

Robotics System Toolbox™

User Guide



MATLAB® & SIMULINK®

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Robotics System Toolbox™ User Guide

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Robotics System Toolbox Examples

Path Planning in Environments of Different Complexity

This example demonstrates how to compute an obstacle free path between two locations on a given map using the Probabilistic Roadmap (PRM) path planner. PRM path planner constructs a roadmap in the free space of a given map using randomly sampled nodes in the free space and connecting them with each other. Once the roadmap has been constructed, you can query for a path from a given start location to a given end location on the map.

In this example, the map is represented as an occupancy grid map using imported data. When sampling nodes in the free space of a map, PRM uses this binary occupancy grid representation to deduce free space. Furthermore, PRM does not take into account the robot dimension while computing an obstacle free path on a map. Hence, you should inflate the map by the dimension of the robot, in order to allow computation of an obstacle free path that accounts for the robot's size and ensures collision avoidance for the actual robot. Define start and end locations on the map for the PRM path planner to find an obstacle free path.

Import Example Maps for Planning a Path

```
load exampleMaps.mat
```

The imported maps are : simpleMap, complexMap and ternaryMap.

```
whos *Map*
```

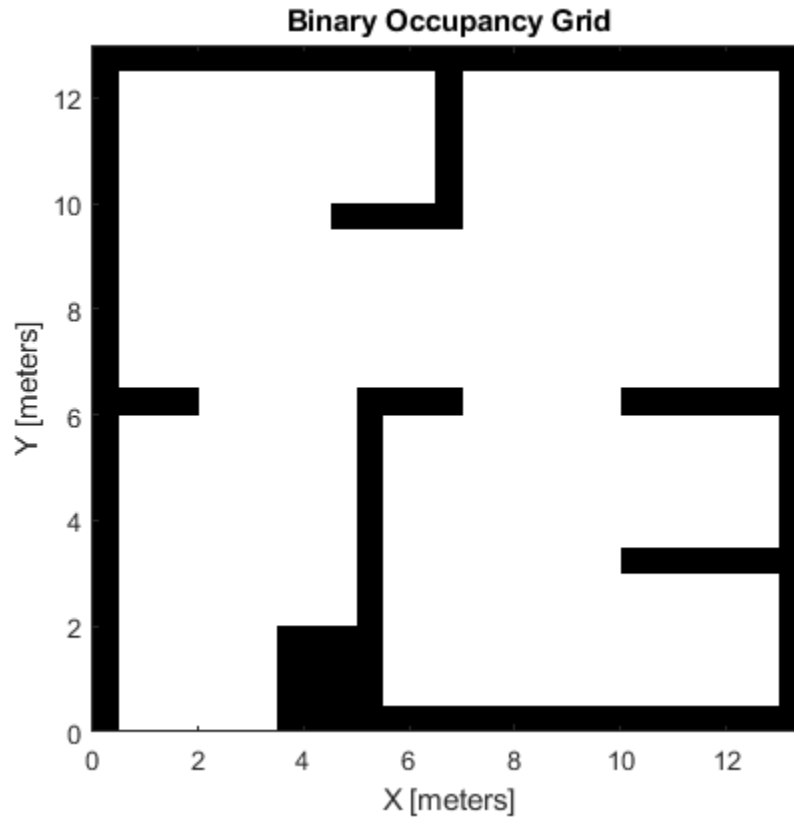
Name	Size	Bytes	Class	Attributes
complexMap	41x52	2132	logical	
emptyMap	26x27	702	logical	
simpleMap	26x27	702	logical	
ternaryMap	501x501	2008008	double	

Use the imported simpleMap data and construct an occupancy grid representation using the binaryOccupancyMap object. Set the resolution to 2 cells per meter for this map.

```
map = binaryOccupancyMap(simpleMap,2);
```

Display the map using the show function on the binaryOccupancyMap object

```
show(map)
```

Define Robot Dimensions and Inflate the Map

To ensure that the robot does not collide with any obstacles, you should inflate the map by the dimension of the robot before supplying it to the PRM path planner.

Here the dimension of the robot can be assumed to be a circle with radius of 0.2 meters. You can then inflate the map by this dimension using the `inflate` function.

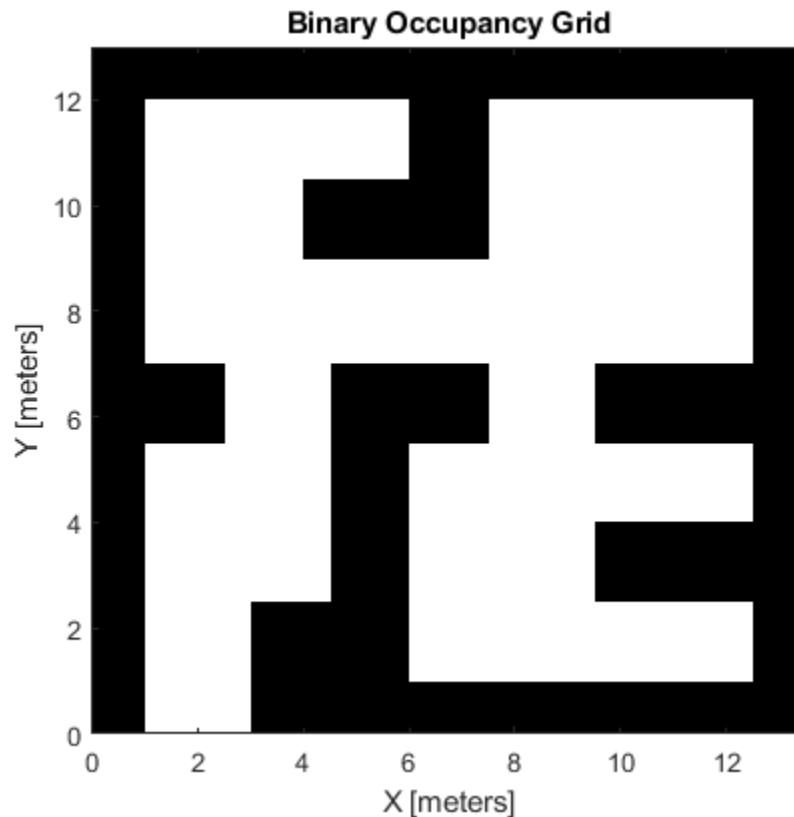
```
robotRadius = 0.2;
```

As mentioned before, PRM does not account for the dimension of the robot, and hence providing an inflated map to the PRM takes into account the robot dimension. Create a copy of the map before using the `inflate` function to preserve the original map.

```
mapInflated = copy(map);
inflate(mapInflated, robotRadius);
```

Display inflated map

```
show(mapInflated)
```



Construct PRM and Set Parameters

Now you need to define a path planner. Create a `mobileRobotPRM` object and define the associated attributes.

```
prm = mobileRobotPRM;
```

Assign the inflated map to the PRM object

```
prm.Map = mapInflated;
```

Define the number of PRM nodes to be used during PRM construction. PRM constructs a roadmap using a given number of nodes on the given map. Based on the dimension and the complexity of the input map, this is one of the primary attributes to tune in order to get a solution between two points on the map. A large number of nodes create a dense roadmap and increases the probability of finding a path. However, having more nodes increases the computation time for both creating the roadmap and finding a solution.

```
prm.NumNodes = 50;
```

Define the maximum allowed distance between two connected nodes on the map. PRM connects all nodes separated by this distance (or less) on the map. This is another attribute to tune in the case of larger and/or complicated input maps. A large connection distance increases the connectivity between nodes to find a path easier, but can increase the computation time of roadmap creation.

```
prm.ConnectionDistance = 5;
```

Find a Feasible Path on the Constructed PRM

Define start and end locations on the map for the path planner to use.

```
startLocation = [2 1];
endLocation = [12 10];
```

Search for a path between start and end locations using the `findpath` function. The solution is a set of waypoints from start location to the end location. Note that the path will be different due to probabilistic nature of the PRM algorithm.

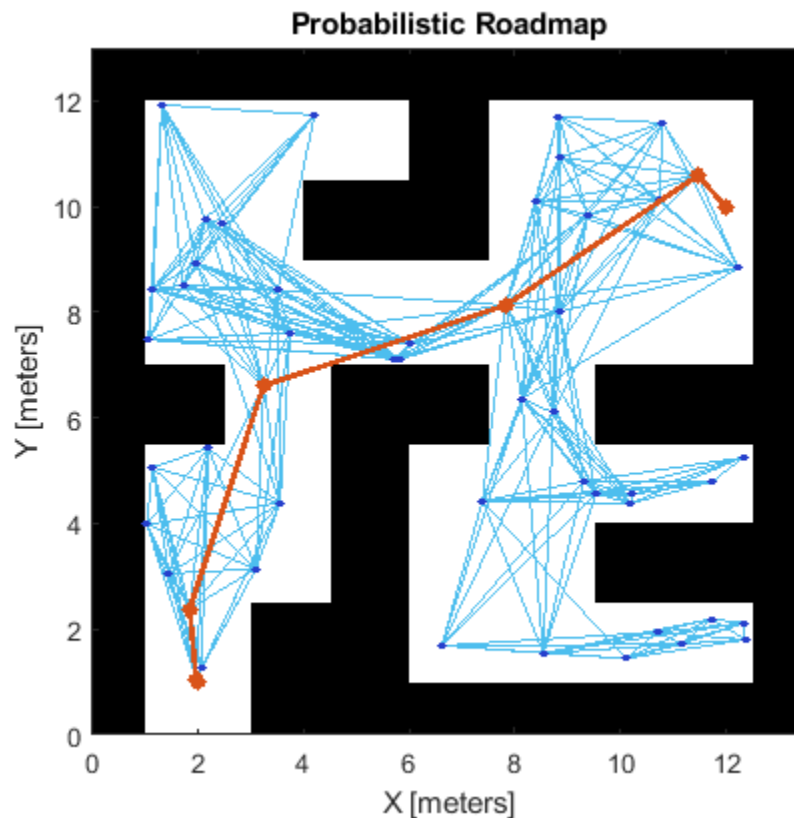
```
path = findpath(prm, startLocation, endLocation)
```

```
path = 7×2
```

```
2.0000    1.0000
1.9569    1.0546
1.8369    2.3856
3.2389    6.6106
7.8260    8.1330
11.4632   10.5857
12.0000   10.0000
```

Display the PRM solution.

```
show(prm)
```



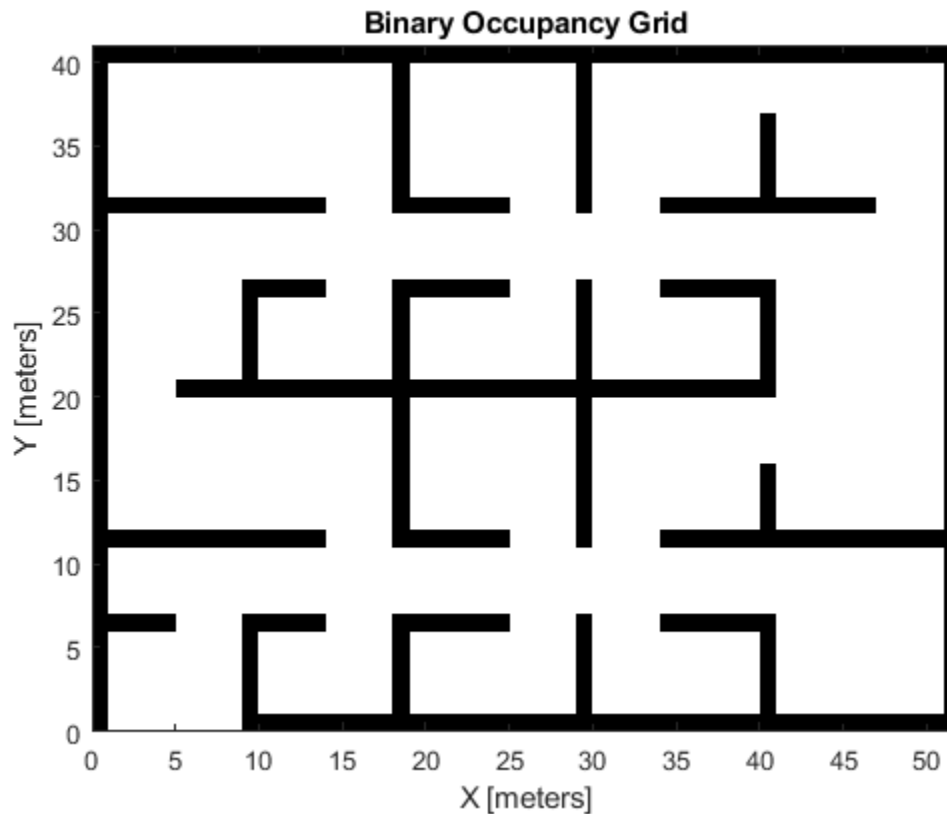
Use PRM for a Large and Complicated Map

Use the imported `complexMap` data, which represents a large and complicated floor plan, and construct a binary occupancy grid representation with a given resolution (1 cell per meter)

```
map = binaryOccupancyMap(complexMap,1);
```

Display the map.

```
show(map)
```



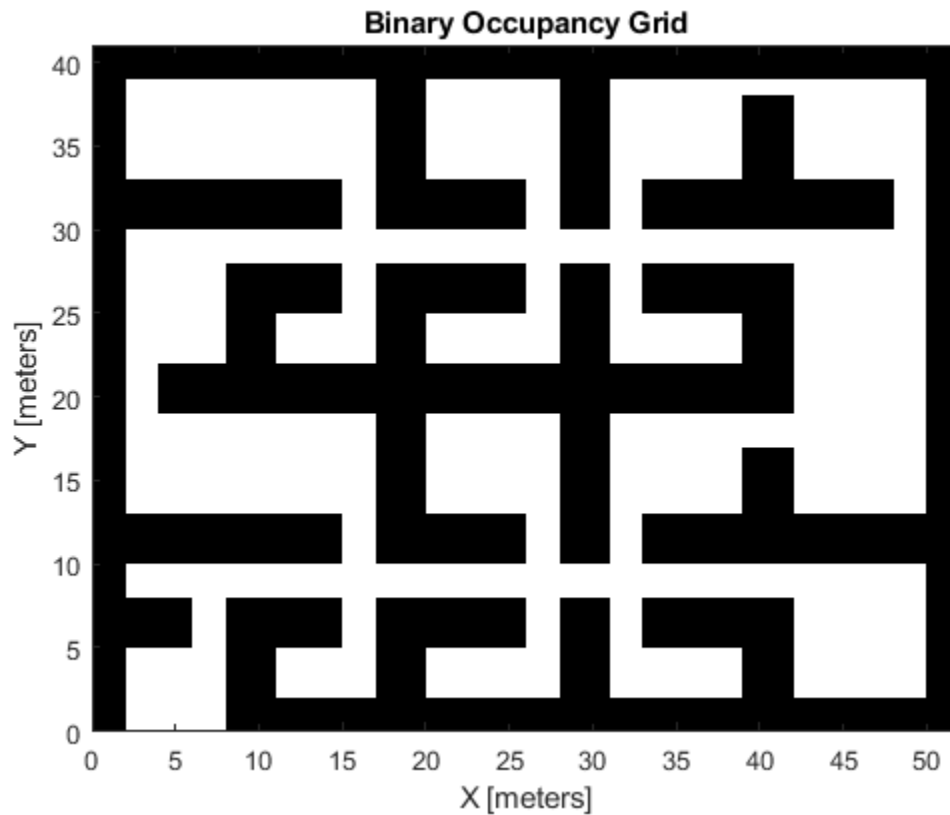
Inflate the Map Based on Robot Dimension

Copy and inflate the map to factor in the robot's size for obstacle avoidance

```
mapInflated = copy(map);  
inflate(mapInflated, robotRadius);
```

Display inflated map.

```
show(mapInflated)
```



Associate the Existing PRM Object with the New Map and Set Parameters

Update PRM object with the newly inflated map and define other attributes.

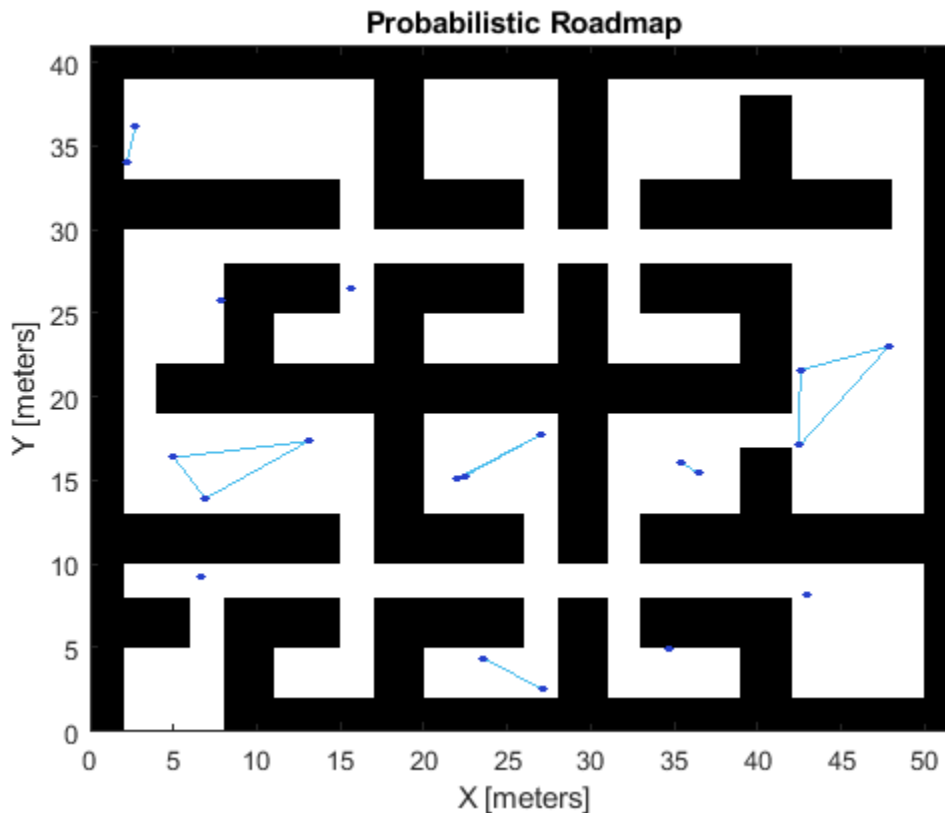
```
prm.Map = mapInflated;
```

Set the NumNodes and the ConnectionDistance properties.

```
prm.NumNodes = 20;  
prm.ConnectionDistance = 15;
```

Display PRM graph.

```
show(prm)
```



Find a Feasible Path on the Constructed PRM

Define start and end location on the map to find an obstacle free path.

```
startLocation = [3 3];
endLocation = [45 35];
```

Search for a solution between start and end location. For complex maps, there may not be a feasible path for a given number of nodes (returns an empty path).

```
path = findpath(prm, startLocation, endLocation);
```

Since you are planning a path on a large and complicated map, larger number of nodes may be required. However, often it is not clear how many nodes will be sufficient. Tune the number of nodes to make sure there is a feasible path between the start and end location.

```
while isempty(path)
    % No feasible path found yet, increase the number of nodes
    prm.NumNodes = prm.NumNodes + 10;

    % Use the |update| function to re-create the PRM roadmap with the changed
    % attribute
    update(prm);

    % Search for a feasible path with the updated PRM
    path = findpath(prm, startLocation, endLocation);
end
```

Display path.

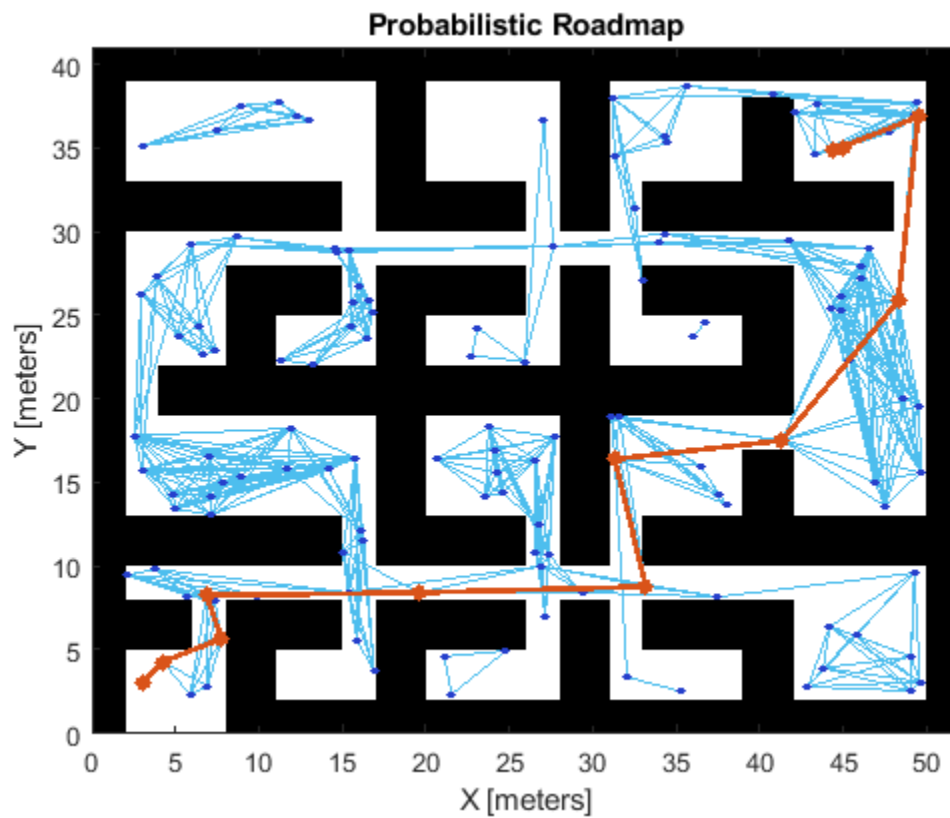
```
path
```

```
path = 12x2
```

```
3.0000    3.0000
4.2287    4.2628
7.7686    5.6520
6.8570    8.2389
19.5613   8.4030
33.1838   8.7614
31.3248   16.3874
41.3317   17.5090
48.3017   25.8527
49.4926   36.8804
:
```

Display PRM solution.

```
show(prm)
```



Path Following for a Differential Drive Robot

This example demonstrates how to control a robot to follow a desired path using a Robot Simulator. The example uses the Pure Pursuit path following controller to drive a simulated robot along a predetermined path. A desired path is a set of waypoints defined explicitly or computed using a path planner (refer to “Path Planning in Environments of Different Complexity” on page 1-2). The Pure Pursuit path following controller for a simulated differential drive robot is created and computes the control commands to follow a given path. The computed control commands are used to drive the simulated robot along the desired trajectory to follow the desired path based on the Pure Pursuit controller.

Note: Starting in R2016b, instead of using the step method to perform the operation defined by the System object™, you can call the object with arguments, as if it were a function. For example, `y = step(obj, x)` and `y = obj(x)` perform equivalent operations.

Define Waypoints

Define a set of waypoints for the desired path for the robot

```
path = [2.00    1.00;  
        1.25    1.75;  
        5.25    8.25;  
        7.25    8.75;  
        11.75   10.75;  
        12.00   10.00];
```

Set the current location and the goal location of the robot as defined by the path.

```
robotInitialLocation = path(1,:);  
robotGoal = path(end,:);
```

Assume an initial robot orientation (the robot orientation is the angle between the robot heading and the positive X-axis, measured counterclockwise).

```
initialOrientation = 0;
```

Define the current pose for the robot [x y theta]

```
robotCurrentPose = [robotInitialLocation initialOrientation]';
```

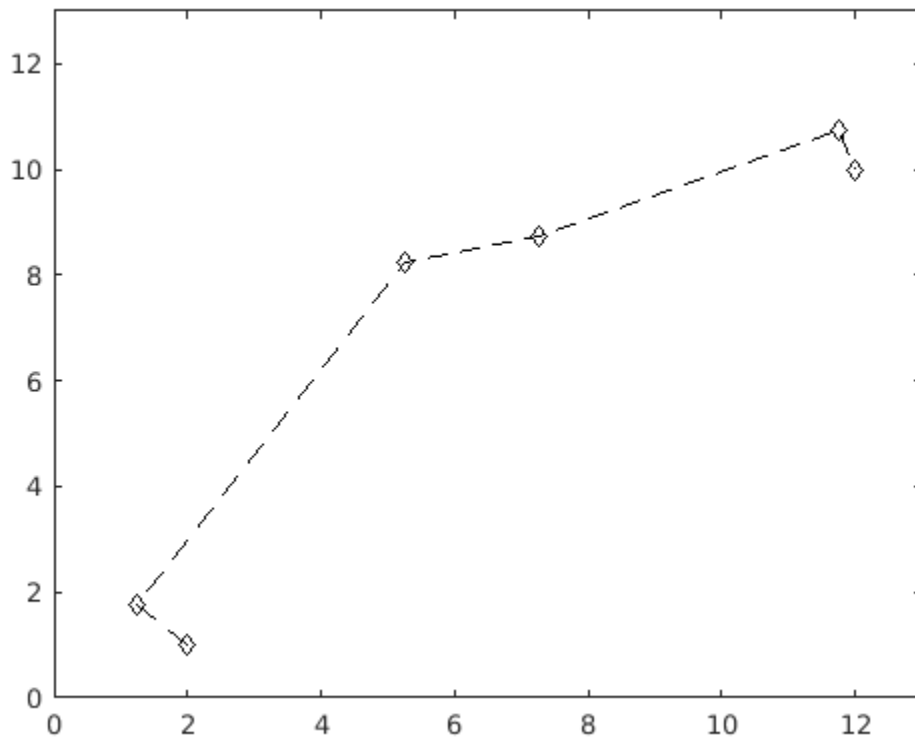
Create a Kinematic Robot Model

Initialize the robot model and assign an initial pose. The simulated robot has kinematic equations for the motion of a two-wheeled differential drive robot. The inputs to this simulated robot are linear and angular velocities.

```
robot = differentialDriveKinematics("TrackWidth", 1, "VehicleInputs", "VehicleSpeedHeadingRate")
```

Visualize the desired path

```
figure  
plot(path(:,1), path(:,2), 'k--d')  
xlim([0 13])  
ylim([0 13])
```

Define the Path Following Controller

Based on the path defined above and a robot motion model, you need a path following controller to drive the robot along the path. Create the path following controller using the `controllerPurePursuit` object.

```
controller = controllerPurePursuit;
```

Use the path defined above to set the desired waypoints for the controller

```
controller.Waypoints = path;
```

Set the path following controller parameters. The desired linear velocity is set to 0.6 meters/second for this example.

```
controller.DesiredLinearVelocity = 0.6;
```

The maximum angular velocity acts as a saturation limit for rotational velocity, which is set at 2 radians/second for this example.

```
controller.MaxAngularVelocity = 2;
```

As a general rule, the lookahead distance should be larger than the desired linear velocity for a smooth path. The robot might cut corners when the lookahead distance is large. In contrast, a small lookahead distance can result in an unstable path following behavior. A value of 0.3 m was chosen for this example.

```
controller.LookaheadDistance = 0.3;
```

Using the Path Following Controller, Drive the Robot over the Desired Waypoints

The path following controller provides input control signals for the robot, which the robot uses to drive itself along the desired path.

Define a goal radius, which is the desired distance threshold between the robot's final location and the goal location. Once the robot is within this distance from the goal, it will stop. Also, you compute the current distance between the robot location and the goal location. This distance is continuously checked against the goal radius and the robot stops when this distance is less than the goal radius.

Note that too small value of the goal radius may cause the robot to miss the goal, which may result in an unexpected behavior near the goal.

```
goalRadius = 0.1;
distanceToGoal = norm(robotInitialLocation - robotGoal);
```

The `controllerPurePursuit` object computes control commands for the robot. Drive the robot using these control commands until it reaches within the goal radius. If you are using an external simulator or a physical robot, then the controller outputs should be applied to the robot and a localization system may be required to update the pose of the robot. The controller runs at 10 Hz.

```
% Initialize the simulation loop
sampleTime = 0.1;
vizRate = rateControl(1/sampleTime);

% Initialize the figure
figure

% Determine vehicle frame size to most closely represent vehicle with plotTransforms
frameSize = robot.TrackWidth/0.8;

while( distanceToGoal > goalRadius )

    % Compute the controller outputs, i.e., the inputs to the robot
    [v, omega] = controller(robotCurrentPose);

    % Get the robot's velocity using controller inputs
    vel = derivative(robot, robotCurrentPose, [v omega]);

    % Update the current pose
    robotCurrentPose = robotCurrentPose + vel*sampleTime;

    % Re-compute the distance to the goal
    distanceToGoal = norm(robotCurrentPose(1:2) - robotGoal(:));

    % Update the plot
    hold off

    % Plot path each instance so that it stays persistent while robot mesh
    % moves
    plot(path(:,1), path(:,2), "k--d")
    hold all

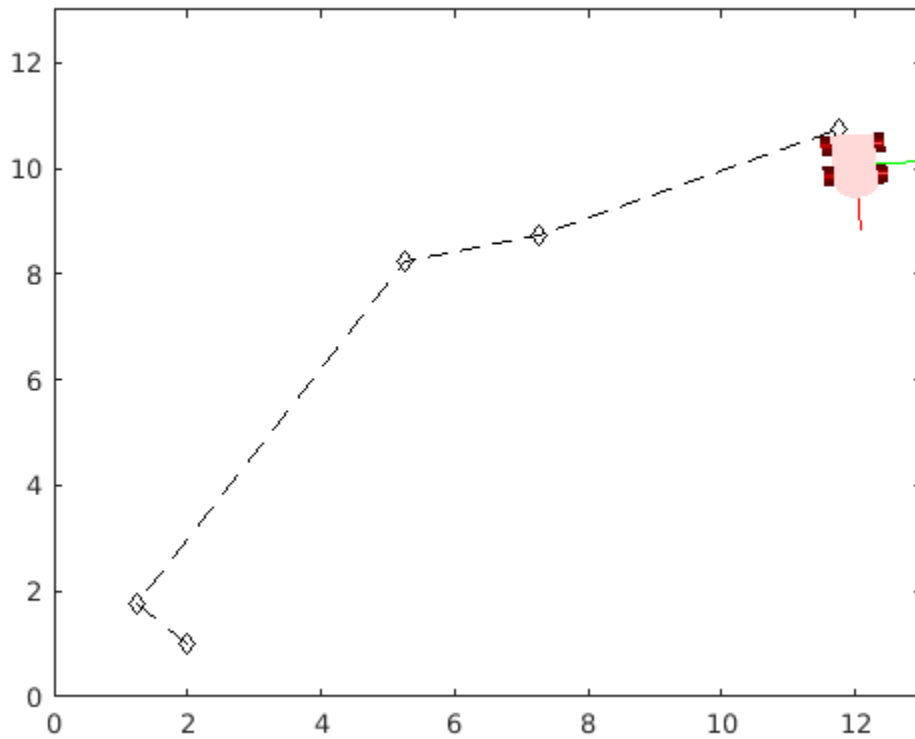
    % Plot the path of the robot as a set of transforms
    plotTrVec = [robotCurrentPose(1:2); 0];
    plotRot = axang2quat([0 0 1 robotCurrentPose(3)]);
    plotTransforms(plotTrVec', plotRot, "MeshFilePath", "groundvehicle.stl", "Parent", gca, "View
```

```

light;
xlim([0 13])
ylim([0 13])

waitfor(vizRate);
end

```



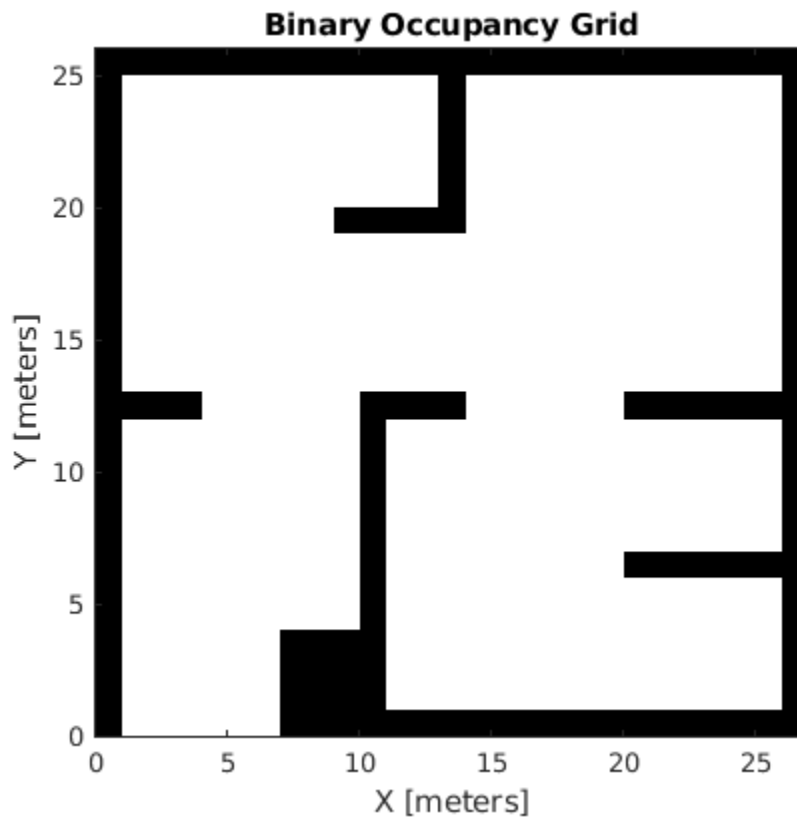
Using the Path Following Controller Along with PRM

If the desired set of waypoints are computed by a path planner, the path following controller can be used in the same fashion. First, visualize the map

```

load exampleMaps
map = binaryOccupancyMap(simpleMap);
figure
show(map)

```



You can compute the path using the PRM path planning algorithm. See “Path Planning in Environments of Different Complexity” on page 1-2 for details.

```
mapInflated = copy(map);
inflate(mapInflated, robot.TrackWidth/2);
prm = robotics.PRM(mapInflated);
prm.NumNodes = 100;
prm.ConnectionDistance = 10;
```

Find a path between the start and end location. Note that the path will be different due to the probabilistic nature of the PRM algorithm.

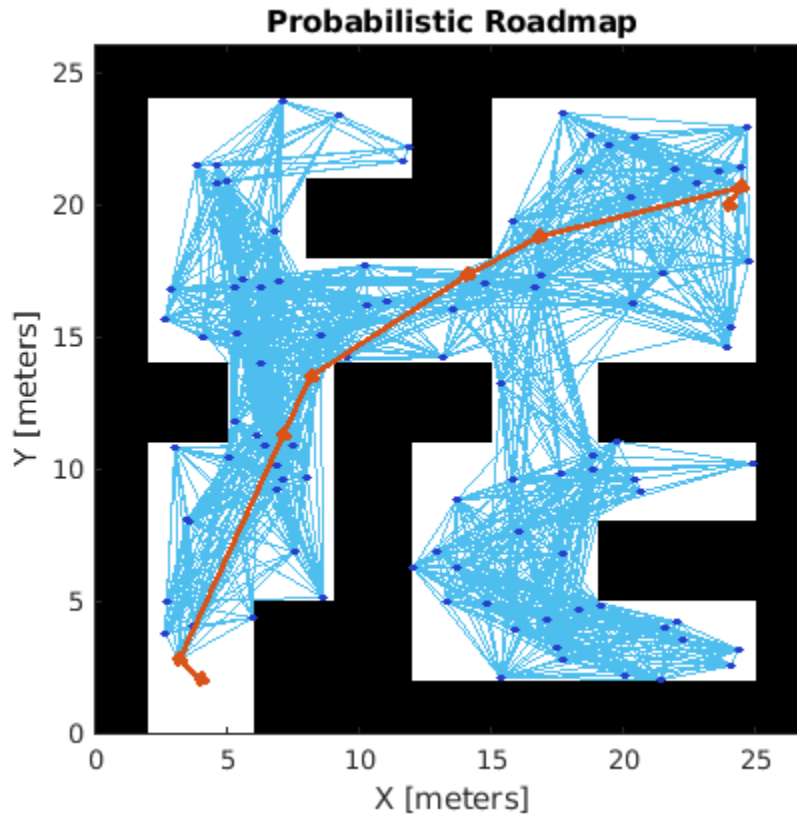
```
startLocation = [4.0 2.0];
endLocation = [24.0 20.0];
path = findpath(prm, startLocation, endLocation)
```

```
path = 8x2
```

```
4.0000    2.0000
3.1703    2.7616
7.0797   11.2229
8.1337   13.4835
14.0707   17.3248
16.8068   18.7834
24.4564   20.6514
24.0000   20.0000
```

Display the inflated map, the road maps, and the final path.

```
show(prm);
```



You defined a path following controller above which you can re-use for computing the control commands of a robot on this map. To re-use the controller and redefine the waypoints while keeping the other information the same, use the release function.

```
release(controller);
controller.Waypoints = path;
```

Set initial location and the goal of the robot as defined by the path

```
robotInitialLocation = path(1,:);
robotGoal = path(end,:);
```

Assume an initial robot orientation

```
initialOrientation = 0;
```

Define the current pose for robot motion [x y theta]

```
robotCurrentPose = [robotInitialLocation initialOrientation]';
```

Compute distance to the goal location

```
distanceToGoal = norm(robotInitialLocation - robotGoal);
```

Define a goal radius

```
goalRadius = 0.1;
```

Drive the robot using the controller output on the given map until it reaches the goal. The controller runs at 10 Hz.

```
reset(vizRate);
```

```
% Initialize the figure  
figure
```

```
while( distanceToGoal > goalRadius )
```

```
    % Compute the controller outputs, i.e., the inputs to the robot  
    [v, omega] = controller(robotCurrentPose);
```

```
    % Get the robot's velocity using controller inputs  
    vel = derivative(robot, robotCurrentPose, [v omega]);
```

```
    % Update the current pose  
    robotCurrentPose = robotCurrentPose + vel*sampleTime;
```

```
    % Re-compute the distance to the goal  
    distanceToGoal = norm(robotCurrentPose(1:2) - robotGoal(:));
```

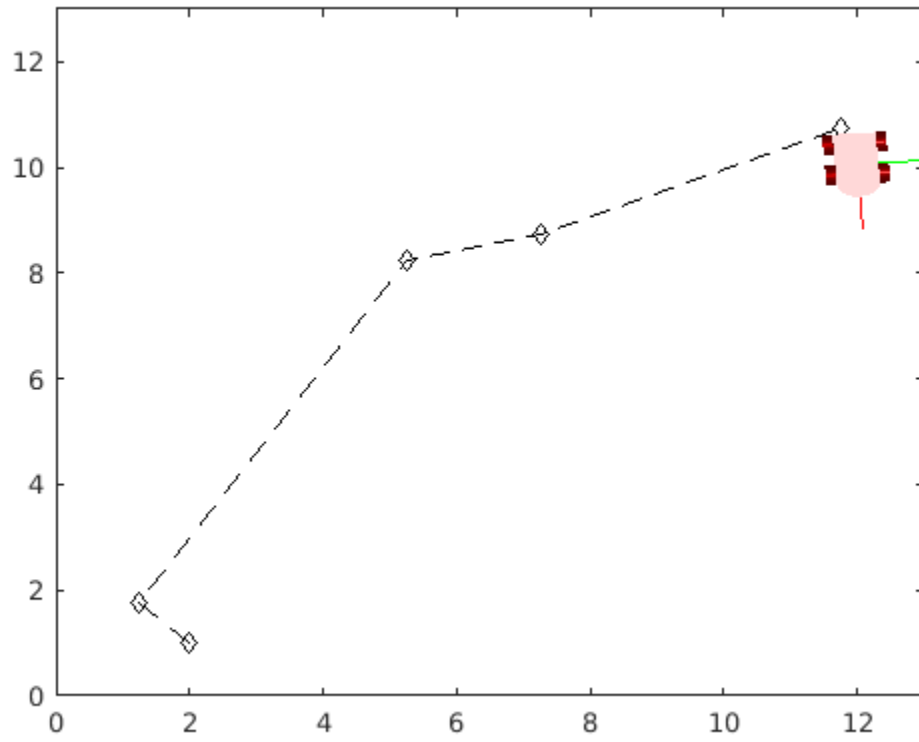
```
    % Update the plot  
    hold off  
    show(map);  
    hold all
```

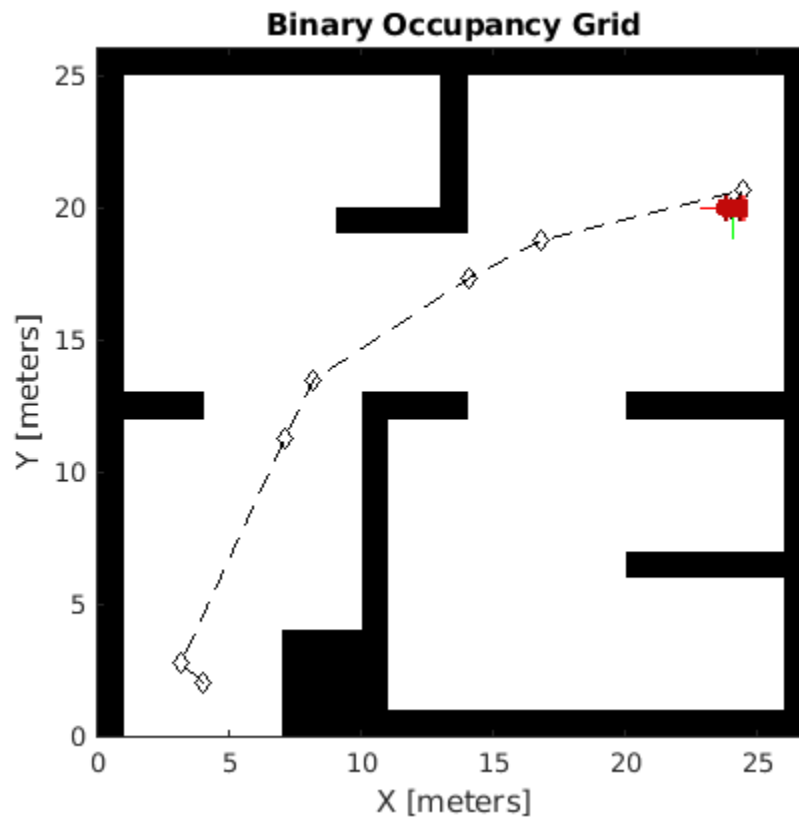
```
    % Plot path each instance so that it stays persistent while robot mesh  
    % moves  
    plot(path(:,1), path(:,2), "k--d")
```

```
    % Plot the path of the robot as a set of transforms  
    plotTrVec = [robotCurrentPose(1:2); 0];  
    plotRot = axang2quat([0 0 1 robotCurrentPose(3)]);  
    plotTransforms(plotTrVec', plotRot, 'MeshFilePath', 'groundvehicle.stl', 'Parent', gca, "View",  
    light;  
    xlim([0 27])  
    ylim([0 26])
```

```
    waitfor(vizRate);
```

```
end
```





See Also

- “Path Planning in Environments of Different Complexity” on page 1-2
- “Mapping with Known Poses” on page 1-19
- “Simulate Different Kinematic Models for Mobile Robots” on page 1-67

Mapping with Known Poses

This example shows how to create a map of an environment using range sensor readings and robot poses for a differential drive robot. You create a map from range sensor readings that are simulated using the `rangeSensor` object. The `differentialDriveKinematics` motion model simulates driving the robot around the room based on velocity commands. The `rangeSensor` gives range readings based on the pose of the robot as it follows the path.

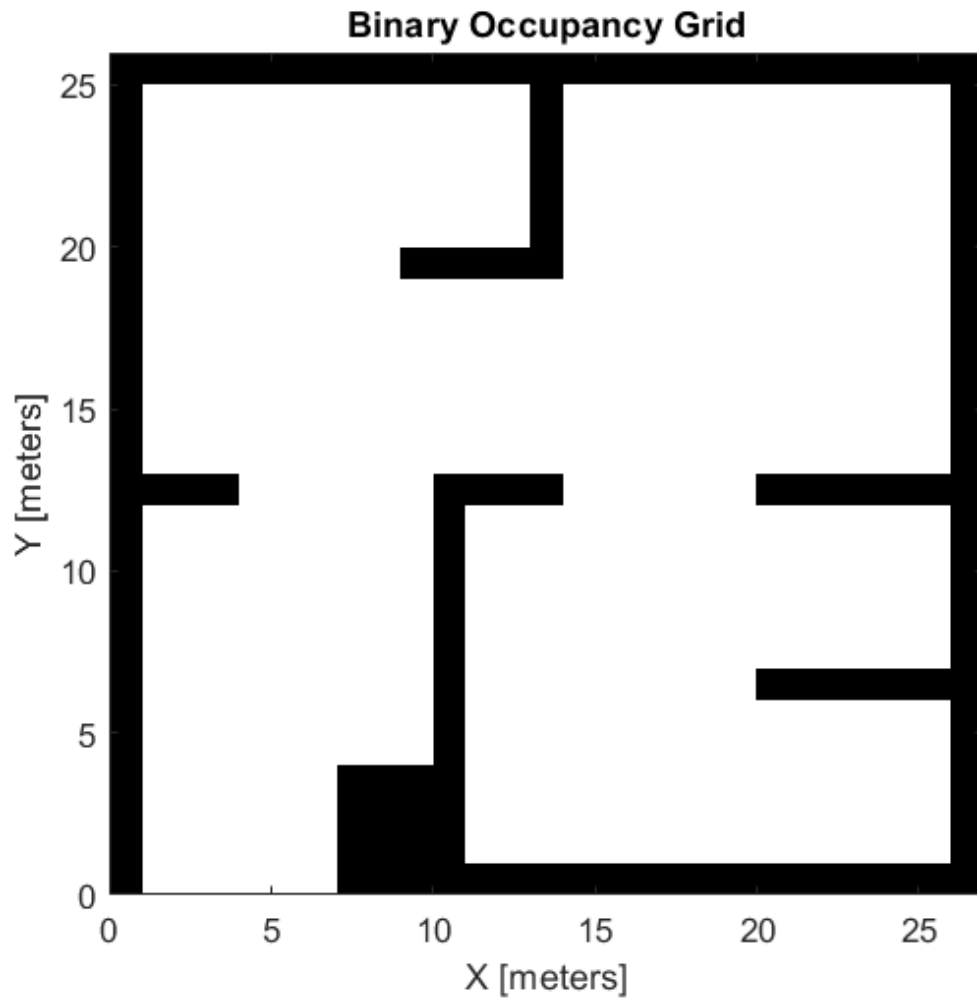
Reference Map and Figures

Load a set of example binary occupancy grids from `exampleMaps`, including `simpleMap`, which this example uses.

```
load exampleMaps.mat
```

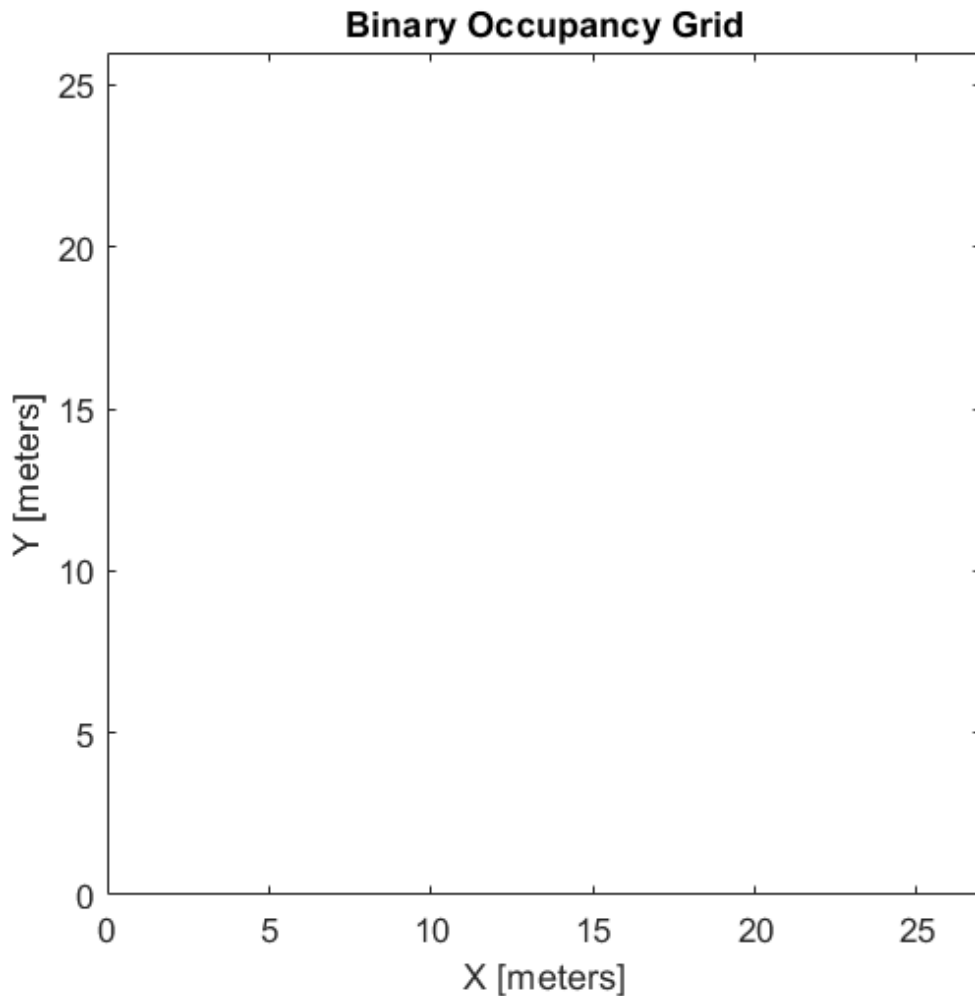
Create the reference binary occupancy map using `simpleMap` with a resolution of 1. Show the figure and save the handle of the figure.

```
refMap = binaryOccupancyMap(simpleMap,1);  
refFigure = figure('Name','SimpleMap');  
show(refMap);
```



Create an empty map of the same dimensions as the selected map with a resolution of 10. Show the figure and save the handle of the figure. Lock the axes at the size of the map.

```
[mapdimx,mapdimy] = size(simpleMap);  
map = binaryOccupancyMap(mapdimy,mapdimx,10);  
mapFigure = figure('Name','Unknown Map');  
show(map);
```



Initialize Motion Model and Controller

Create a differential-drive kinematic motion model. The motion model represents the motion of the simulated differential-drive robot. This model takes left and right wheels speeds or linear and angular velocities for the robot heading. For this example, use the vehicle speed and heading rate for the `VehicleInputs`.

```
diffDrive = differentialDriveKinematics("VehicleInputs","VehicleSpeedHeadingRate");
```

Create a pure pursuit controller. This controller generates the velocity inputs for the simulated robot to follow a desired path. Set your desired linear velocity and maximum angular velocity, specified in meters per second and radians per second respectively.

```
controller = controllerPurePursuit('DesiredLinearVelocity',2,'MaxAngularVelocity',3);
```

Set Up Range Sensor

Create a sensor with a max range of 10 meters. This sensor simulates range readings based on a given pose and map. The reference map is used with this range sensor to simulate collecting sensor readings in an unknown environment.

```
sensor = rangeSensor;  
sensor.Range = [0,10];
```

Create the Planned Path

Create a path to drive through the map for gathering range sensor readings.

```
path = [4 6; 6.5 12.5; 4 22; 12 14; 22 22; 16 12; 20 10; 14 6; 22 3];
```

Plot the path on the reference map figure.

```
figure(refFigure);  
hold on  
plot(path(:,1),path(:,2), 'o-');  
hold off
```

Set the path as the waypoints of the pure pursuit controller.

```
controller.Waypoints = path;
```

Follow Path and Map Environment

Set the initial pose and final goal location based on the path. Create global variables for storing the current pose and an index for tracking the iterations.

```
initPose = [path(1,1) path(1,2), pi/2];  
goal = [path(end,1) path(end,2)]';  
poses(:,1) = initPose';
```

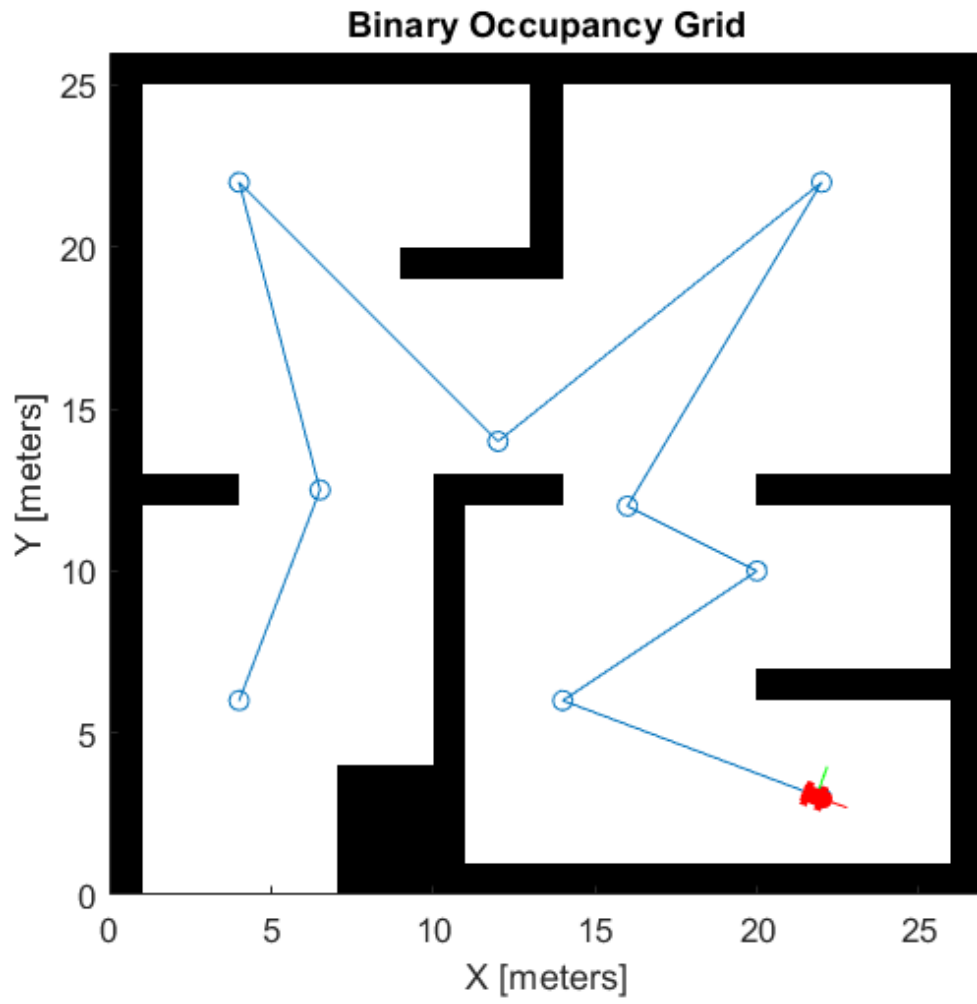
Use the provided helper function `exampleHelperDiffDriveControl`. The helper function contains the main loop for navigation the path, getting range readings, and mapping the environment.

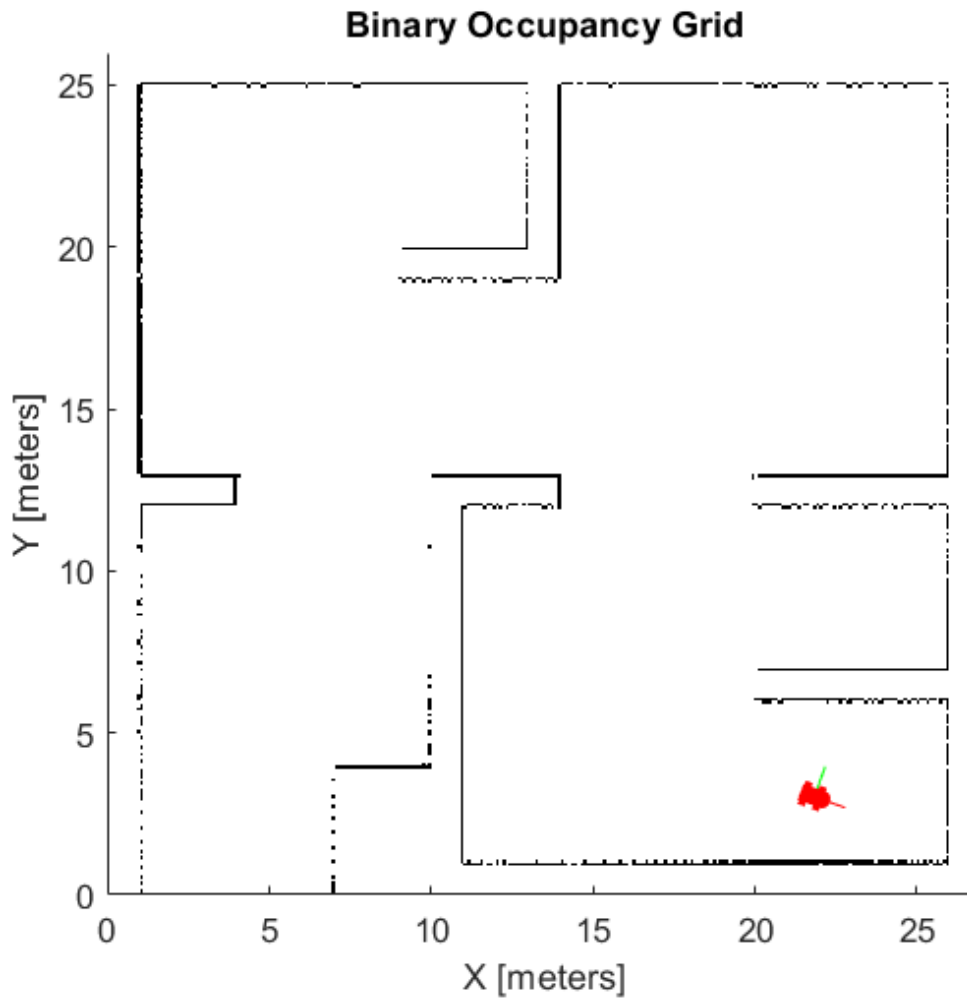
The `exampleHelperDiffDriveControl` function has the following workflow:

- Scan the reference map using the range sensor and the current pose. This simulates normal range readings for driving in an unknown environment.
- Update the map with the range readings.
- Get control commands from pure pursuit controller to drive to next waypoint.
- Calculate derivative of robot motion based on control commands.
- Increment the robot pose based on the derivative.

You should see the robot driving around the empty map and filling in walls as the range sensor detects them.

```
exampleHelperDiffDriveCtrl(diffDrive,controller,initPose,goal,refMap,map,refFigure,mapFigure,sens
```





Goal position reached

Differential Drive Control Function

The `exampleHelperDiffDriveControl` function has the following workflow:

- Scan the reference map using the range sensor and the current pose. This simulates normal range readings for driving in an unknown environment.
- Update the map with the range readings.
- Get control commands from pure pursuit controller to drive to next waypoint.
- Calculate derivative of robot motion based on control commands.
- Increment the robot pose based on the derivative.

```
function exampleHelperDiffDriveControl(diffDrive,ppControl,initPose,goal,map1,map2,fig1,fig2,lid
sampleTime = 0.05;           % Sample time [s]
t = 0:sampleTime:100;       % Time array
poses = zeros(3,numel(t));   % Pose matrix
poses(:,1) = initPose';
```

```

% Set iteration rate
r = rateControl(1/sampleTime);

% Get the axes from the figures
ax1 = fig1.CurrentAxes;
ax2 = fig2.CurrentAxes;

for idx = 1:numel(t)
    position = poses(:,idx)';
    currPose = position(1:2);

    % End if pathfollowing is vehicle has reached goal position within tolerance of 0.2m
    dist = norm(goal'-currPose);
    if (dist < .2)
        disp("Goal position reached")
        break;
    end

    % Update map by taking sensor measurements
    figure(2)
    [ranges, angles] = lidar(position, map1);
    scan = lidarScan(ranges,angles);
    validScan = removeInvalidData(scan,'RangeLimits',[0,lidar.Range(2)]);
    insertRay(map2,position,validScan,lidar.Range(2));
    show(map2);

    % Run the Pure Pursuit controller and convert output to wheel speeds
    [vRef,wRef] = ppControl(poses(:,idx));

    % Perform forward discrete integration step
    vel = derivative(diffDrive, poses(:,idx), [vRef wRef]);
    poses(:,idx+1) = poses(:,idx) + vel*sampleTime;

    % Update visualization
    plotTrvec = [poses(1:2, idx+1); 0];
    plotRot = axang2quat([0 0 1 poses(3, idx+1)]);

    % Delete image of the last robot to prevent displaying multiple robots
    if idx > 1
        items = get(ax1, 'Children');
        delete(items(1));
    end

    %plot robot onto known map
    plotTransforms(plotTrvec', plotRot, 'MeshFilePath', 'groundvehicle.stl', 'View', '2D', 'I
    %plot robot on new map
    plotTransforms(plotTrvec', plotRot, 'MeshFilePath', 'groundvehicle.stl', 'View', '2D', 'I

    % waiting to iterate at the proper rate
    waitfor(r);
end
end

```

Plan Path for a Differential Drive Robot in Simulink

This example demonstrates how to execute an obstacle-free path between two locations on a given map in Simulink®. The path is generated using a probabilistic road map (PRM) planning algorithm (`mobileRobotPRM`). Control commands for navigating this path are generated using the **Pure Pursuit** controller block. A differential drive kinematic motion model simulates the robot motion based on those commands.

Load the Map and Simulink Model

Load the occupancy map, which defines the map limits and obstacles within the map. `exampleMaps.mat` contain multiple maps including `simpleMap`, which this example uses.

```
load exampleMaps.mat
```

Specify a start and end location within the map.

```
startLoc = [5 5];  
goalLoc = [20 20];
```

Model Overview

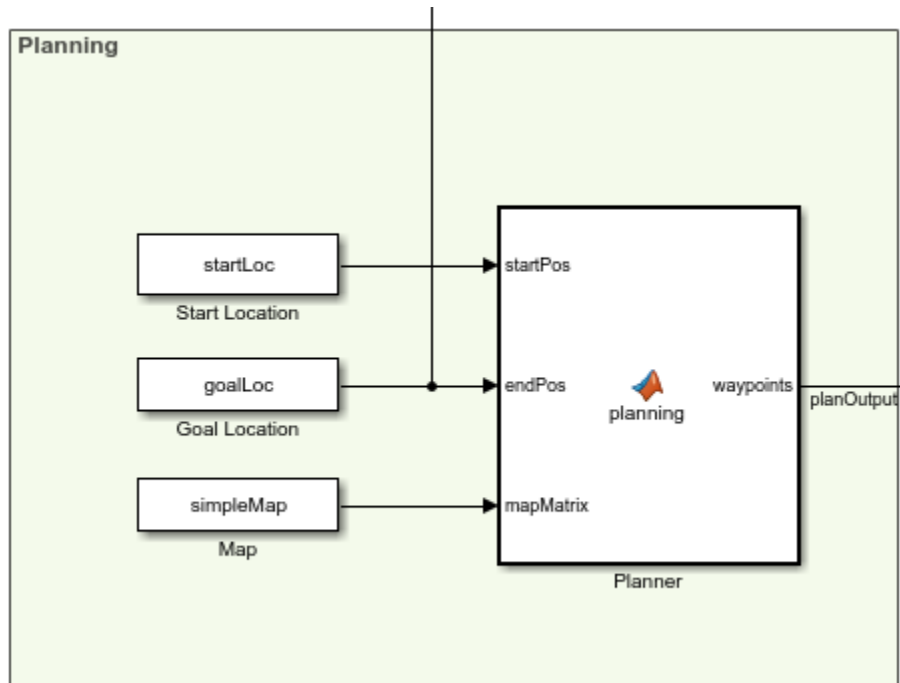
Open the Simulink model.

```
open_system('pathPlanningSimulinkModel.slx')
```

The model is composed of three primary parts:

- **Planning**
- **Control**
- **Plant Model**

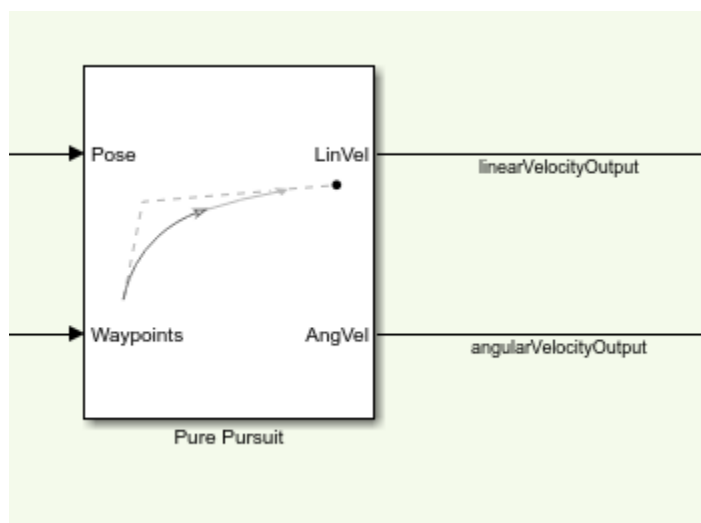
Planning



The **Planner** MATLAB® function block uses the `mobileRobotPRM` path planner and takes a start location, goal location, and map as inputs. The block outputs an array of waypoints that the robot follows. The planned waypoints are used downstream by the **Pure Pursuit** controller block.

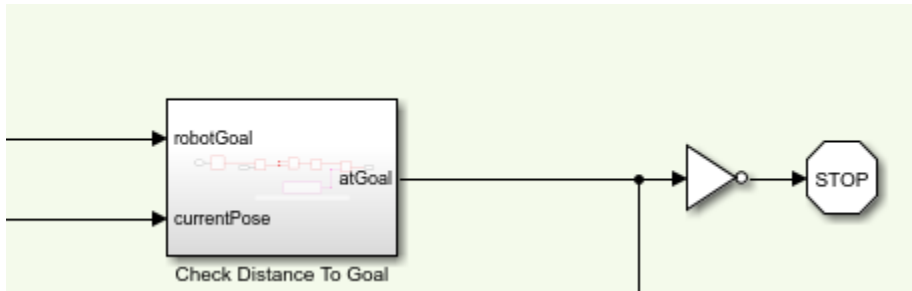
Control

Pure Pursuit



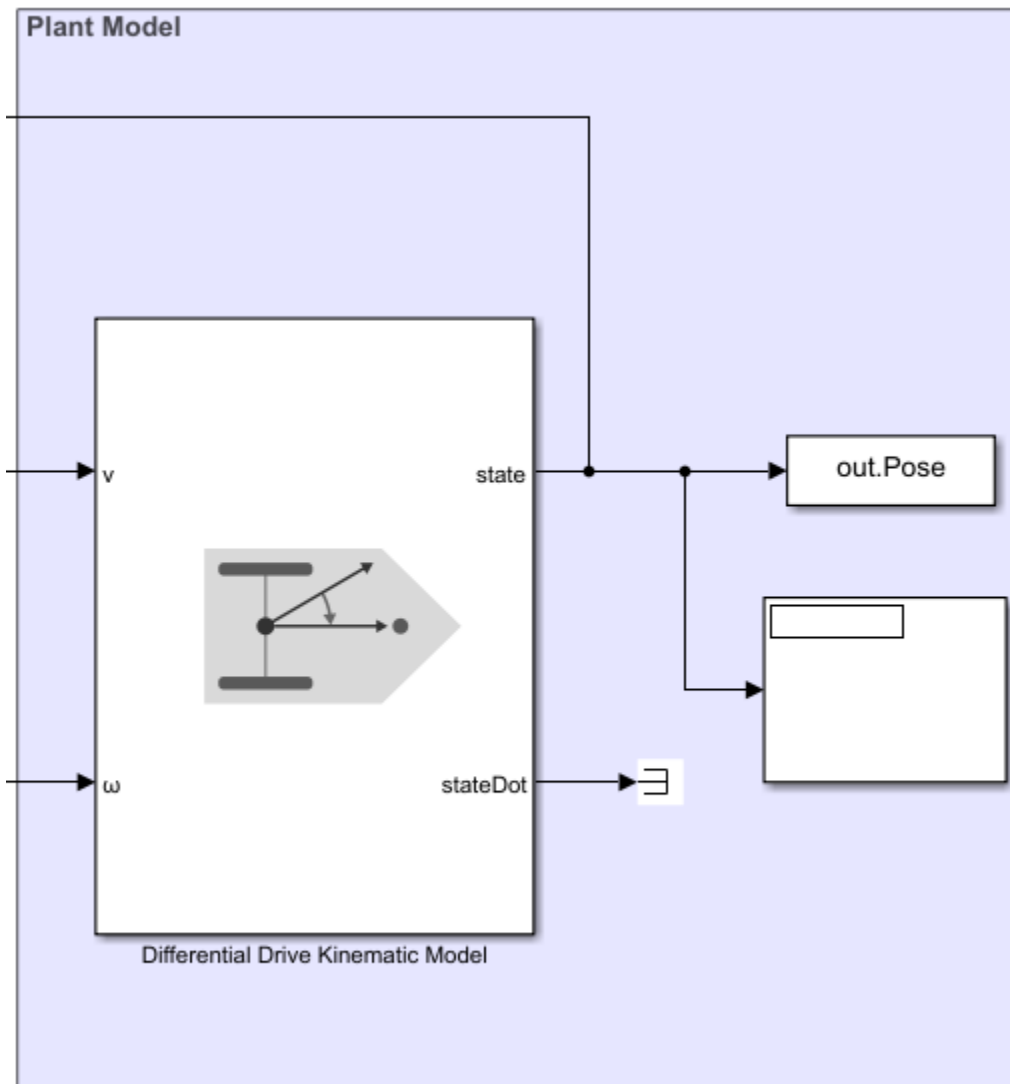
The **Pure Pursuit** controller block generates the linear velocity and angular velocity commands based on the waypoints and the current pose of the robot.

Check if Goal is Reached



The **Check Distance to Goal** subsystem calculates the current distance to the goal and if it is within a threshold, the simulation stops.

Plant Model



The **Differential Drive Kinematic Model** block creates a vehicle model to simulate simplified vehicle kinematics. The block takes linear and angular velocities as command inputs from the **Pure Pursuit** controller block, and outputs the current position and velocity states.

Run the Model

```
simulation = sim('pathPlanningSimulinkModel.slx');
```

Visualize The Motion of Robot

After simulating the model, visualize the robot driving the obstacle-free path in the map.

```
map = binaryOccupancyMap(simpleMap);
robotPose = simulation.Pose;
thetaIdx = 3;

% Translation
xyz = robotPose;
xyz(:, thetaIdx) = 0;

% Rotation in XYZ euler angles
theta = robotPose(:,thetaIdx);
thetaEuler = zeros(size(robotPose, 1), 3 * size(theta, 2));
thetaEuler(:, end) = theta;

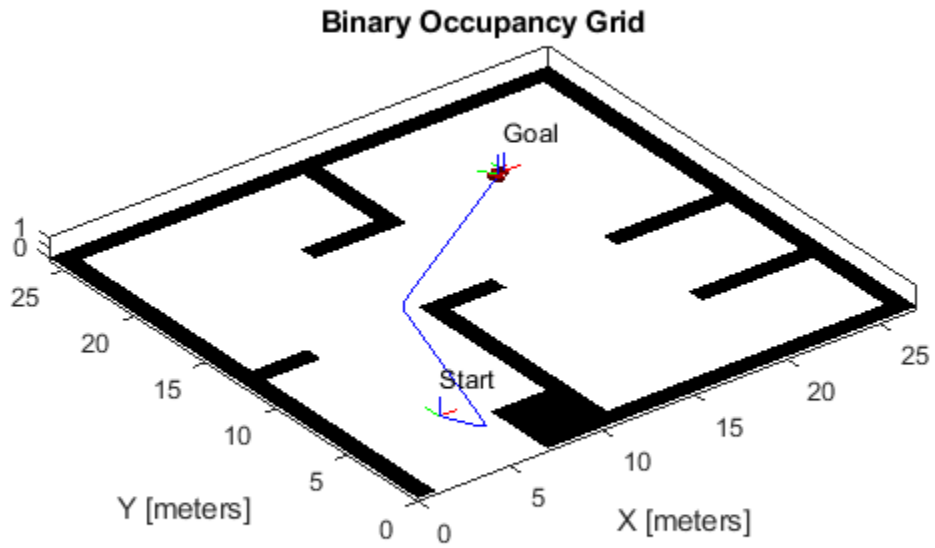
% Plot the robot poses at every 10th step.
for k = 1:10:size(xyz, 1)
    show(map)
    hold on;

    % Plot the start location.
    plotTransforms([startLoc, 0], eul2quat([0, 0, 0]))
    text(startLoc(1), startLoc(2), 2, 'Start');

    % Plot the goal location.
    plotTransforms([goalLoc, 0], eul2quat([0, 0, 0]))
    text(goalLoc(1), goalLoc(2), 2, 'Goal');

    % Plot the xy-locations.
    plot(robotPose(:, 1), robotPose(:, 2), '-b')

    % Plot the robot pose as it traverses the path.
    quat = eul2quat(thetaEuler(k, :), 'xyz');
    plotTransforms(xyz(k,:), quat, 'MeshFilePath',...
        'groundvehicle.stl');
    light;
    drawnow;
    hold off;
end
```



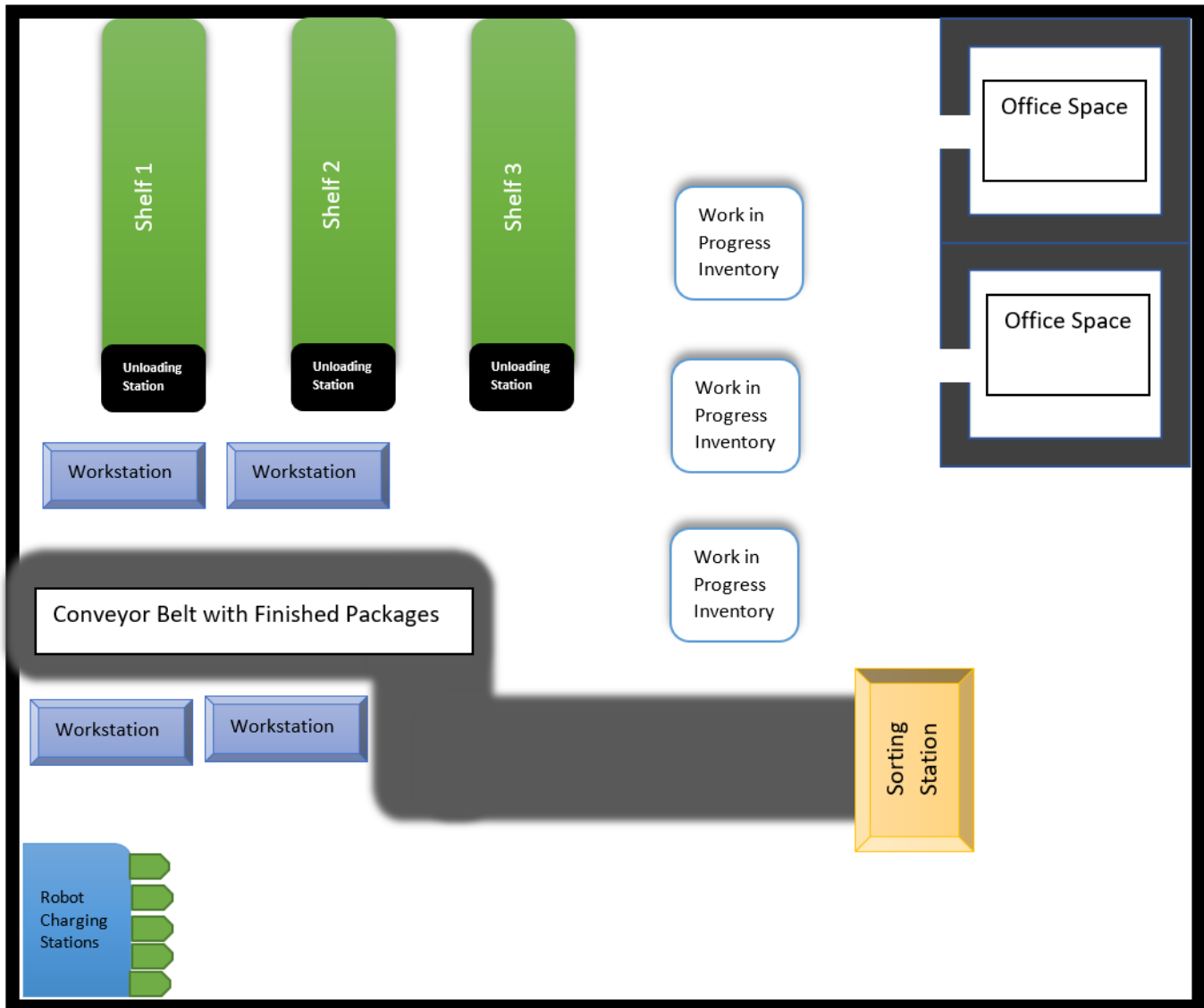
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Execute Tasks for a Warehouse Robot

This example demonstrates how to execute an obstacle free path for a mobile robot between three locations on a given map. The robot is expected to visit the three locations in a warehouse: a charging station, loading station, and unloading location. The sequence in which these locations are visited is dictated by a scheduler. The scheduler gives each robot a goal pose to navigate to. The robot plans a path and uses a Pure Pursuit controller to follow the waypoints based on the current pose of the robot. The **Differential Drive Kinematic Model** block models the simplified kinematics, which takes the linear and angular velocities from the Pure Pursuit Controller. This example builds on top of the “Plan Path for a Differential Drive Robot in Simulink” on page 1-26 example.

Warehouse Map

A typical warehouse of a sorting or distribution facility has packages to be delivered from work stations to storage areas. The warehouse may have off-limit areas like offices and in-progress inventory blocking aisles or walkways. The robots are tasked with picking finished packages as they arrive at the sorting station and are told a location to store them. The warehouse also has a charging station for recharging the robots after a certain time.



This sample warehouse floor-plan can be translated into a binary occupancy map, which indicates all the safe regions in the warehouse facility.

Load the example map file. `logicalMap` is a matrix of logical values indicating free space in the warehouse. Make a `binaryOccupancyMap` from this matrix.

```
load warehouseMaps.mat logicalMap
map = binaryOccupancyMap(logicalMap);
show(map)
```

Assign the `xy`-locations of the charging station, sorting (loading) station, and the unloading location near shelves in the warehouse.

```
chargingStn = [5,5];
loadingStn = [52,15];
unloadingStn = [15,42];
```

Show the various locations on the map

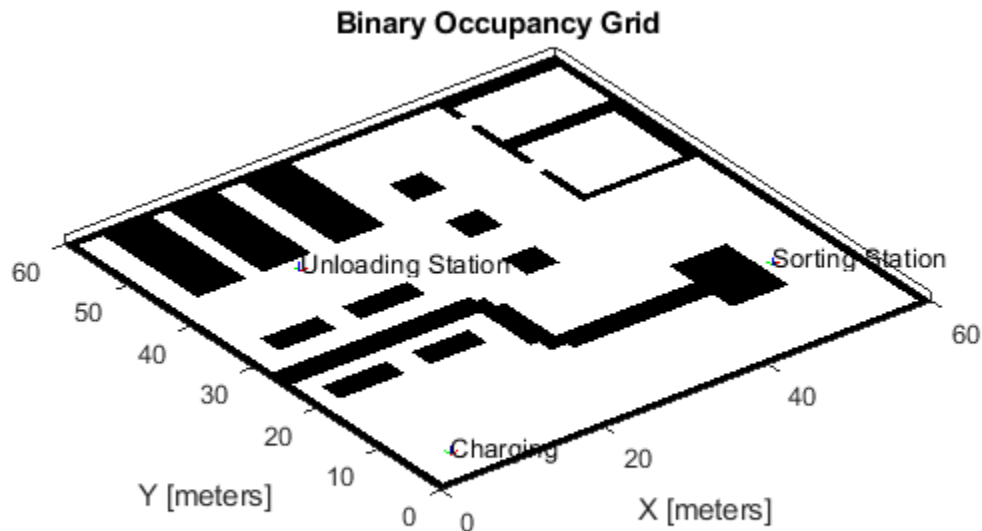
```
hold on;

text(chargingStn(1), chargingStn(2), 1, 'Charging');
plotTransforms([chargingStn, 0], [1 0 0 0])

text(loadingStn(1), loadingStn(2), 1, 'Sorting Station');
plotTransforms([loadingStn, 0], [1 0 0 0])

text(unloadingStn(1), unloadingStn(2), 1, 'Unloading Station');
plotTransforms([unloadingStn, 0], [1 0 0 0])

hold off;
```

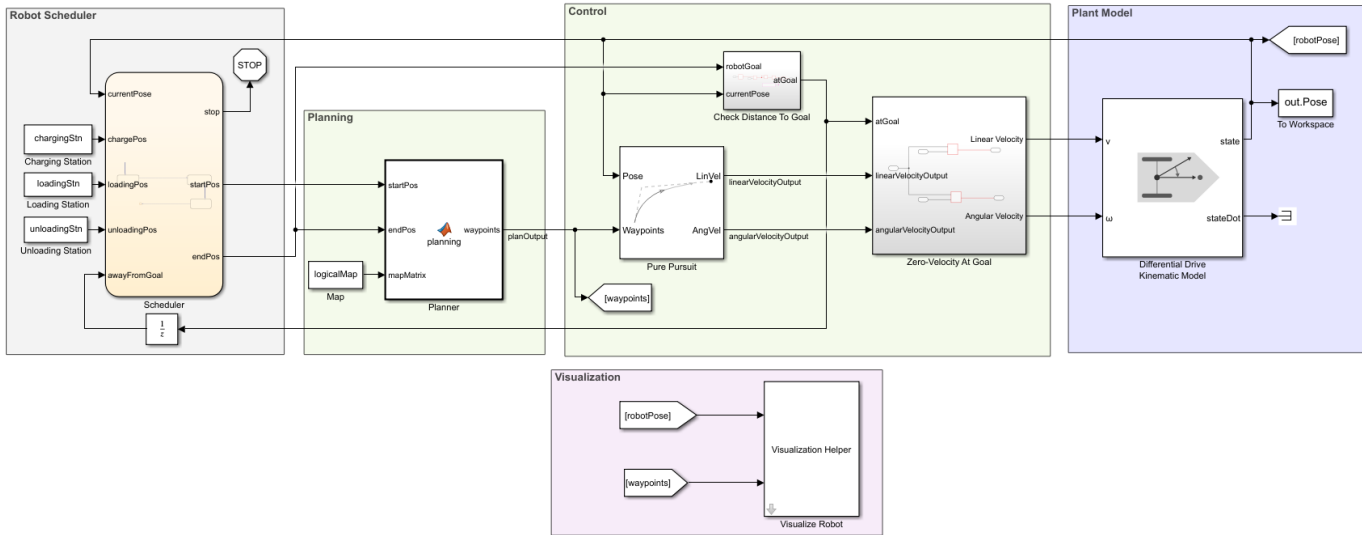


Model Overview

A Simulink® model is provided that models all aspects of the system for scheduling, planning, controlling, and modelling the robot behavior.

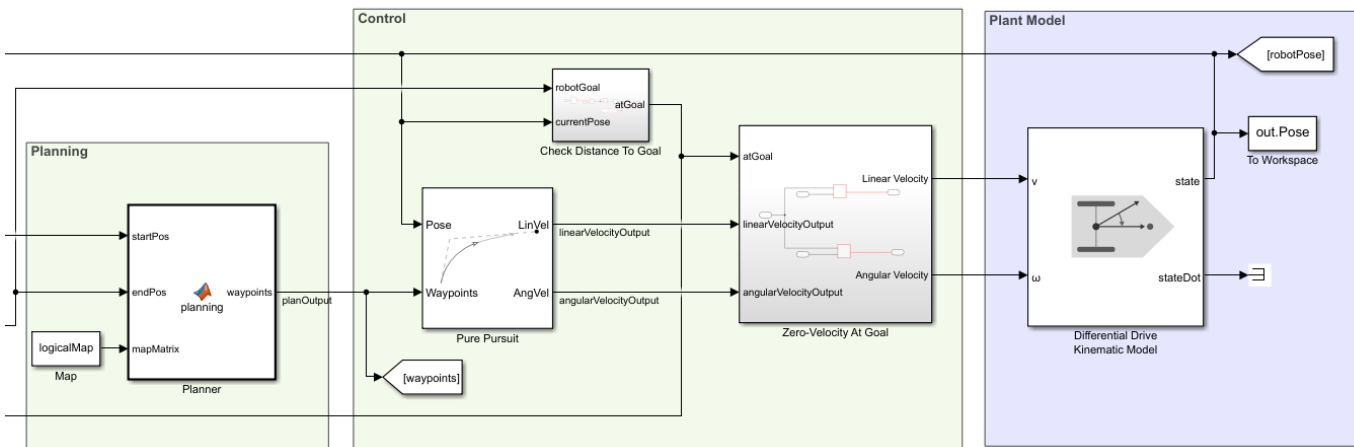
Open the Simulink Model.

```
open_system('warehouseTasksRobotSimulationModel.slx')
```



Planning, Control, and Plant Model

The model uses a planning, control, and plant model similar to the “Plan Path for a Differential Drive Robot in Simulink” on page 1-26 example. The planner takes the start and goal locations from the scheduler and plans an obstacle-free path between them based on the given map. The controller uses a Pure Pursuit controller for generating the linear and angular velocity controls of the robot to navigation the path. These controls are given to the plant model that models the behavior of a differential-drive robot.

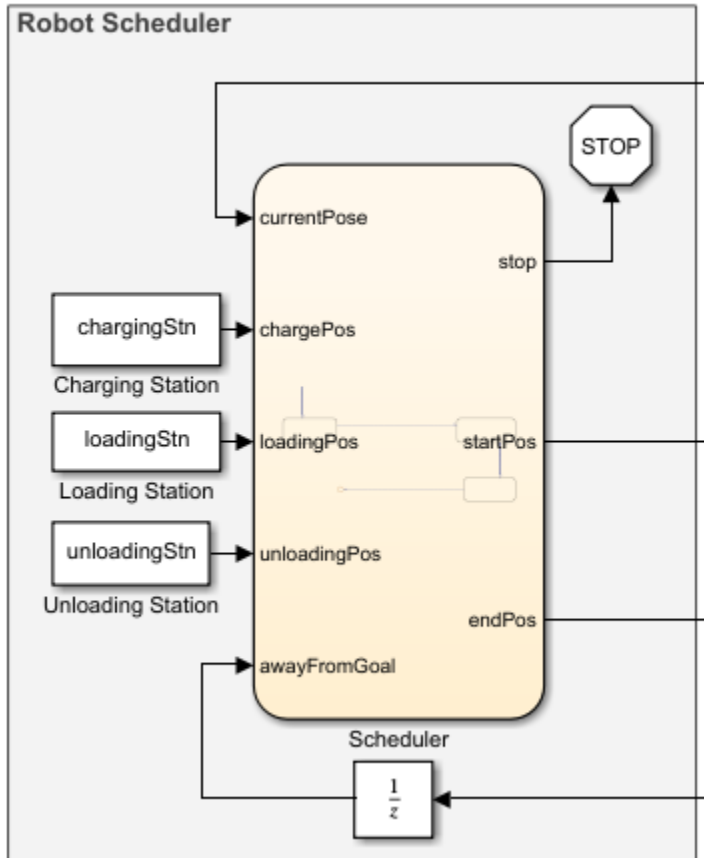


Robot Scheduler

The Scheduler block assigns start and goal locations to the robot. The current pose of the robot is used as a starting location and the end location is determined by a sequence of tasks specified inside the scheduler. The example illustrates the following sequence of tasks for the robot:

- 1 Starts from the charging location, and goes to the loading location.
- 2 Pauses as the loading station to load the package and plans a path to the unloading location.

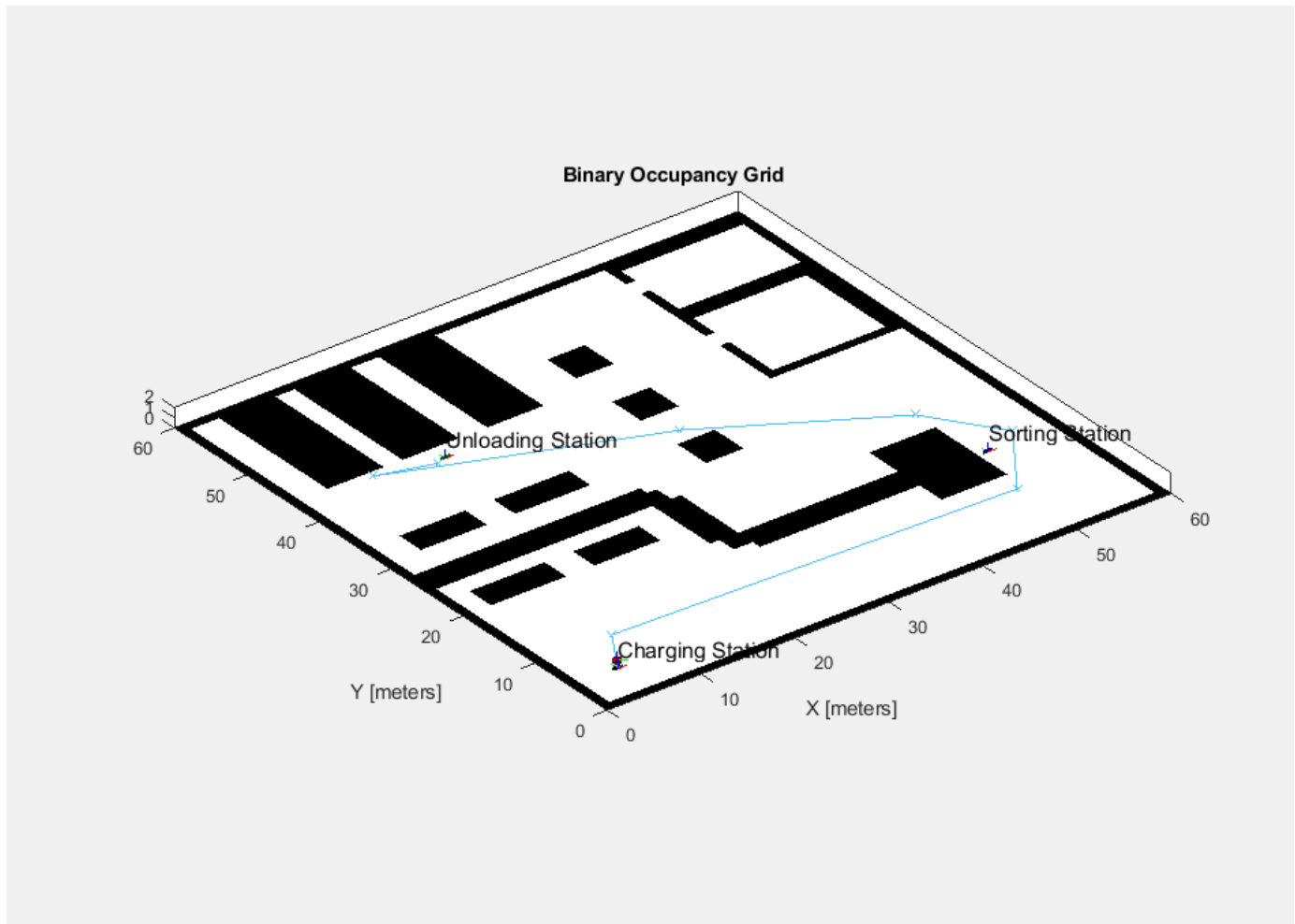
- 3 Navigates to the unloading station to unload the package. Replans a path to the charging station.
- 4 Stops at the charging station.



Simulate The Robot

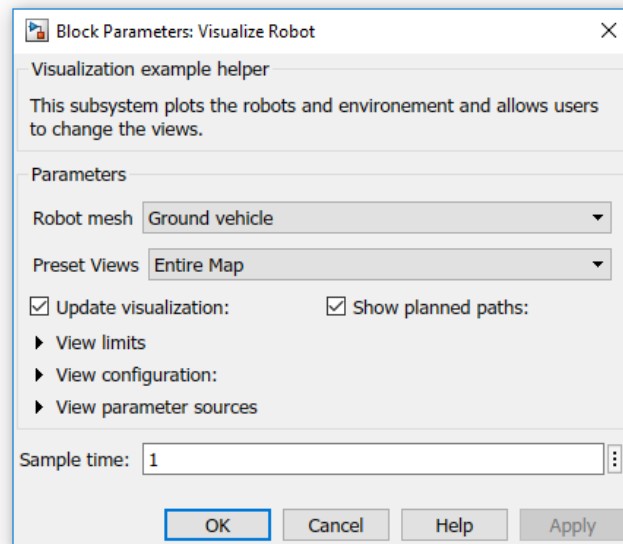
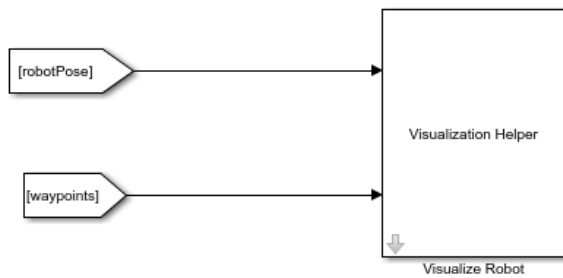
Run the simulation to see the robot execute the tasks.

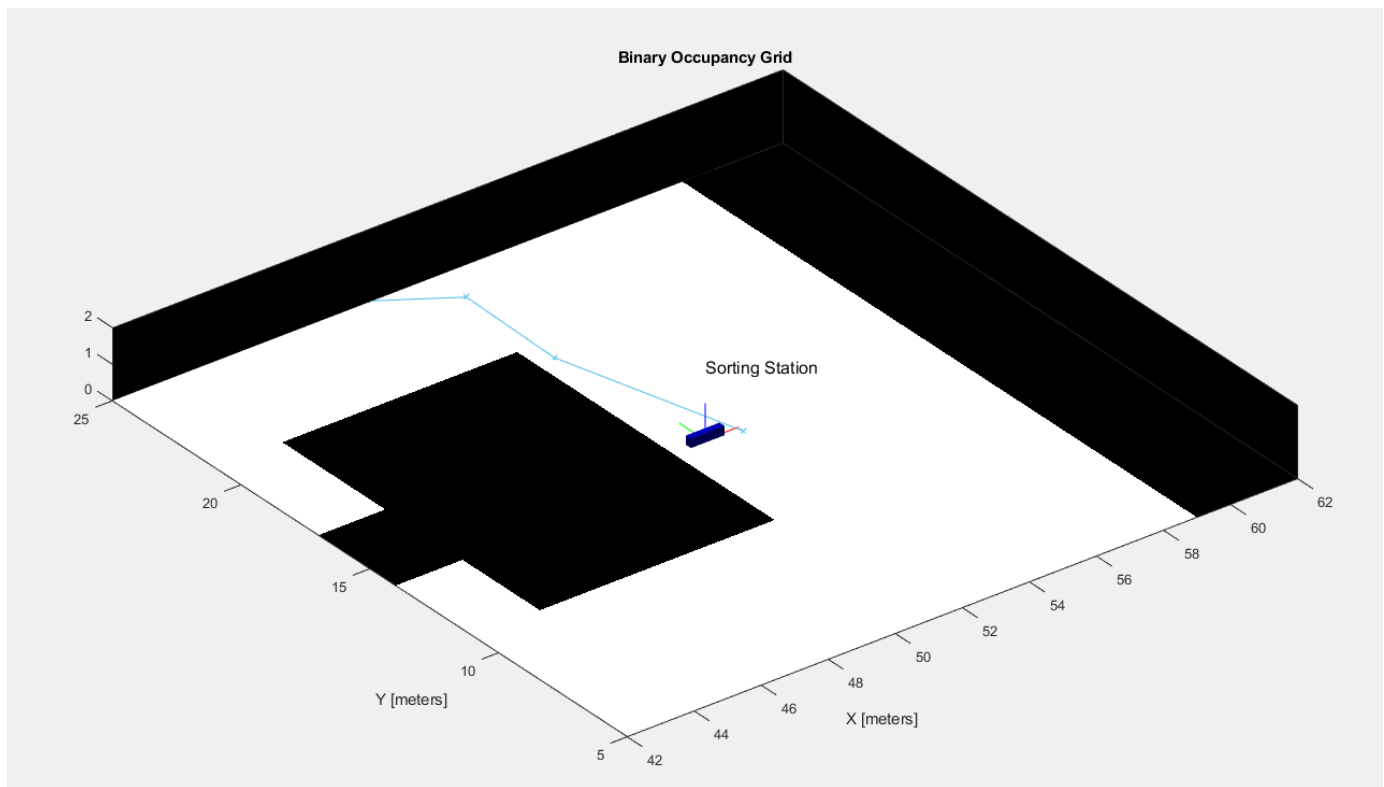
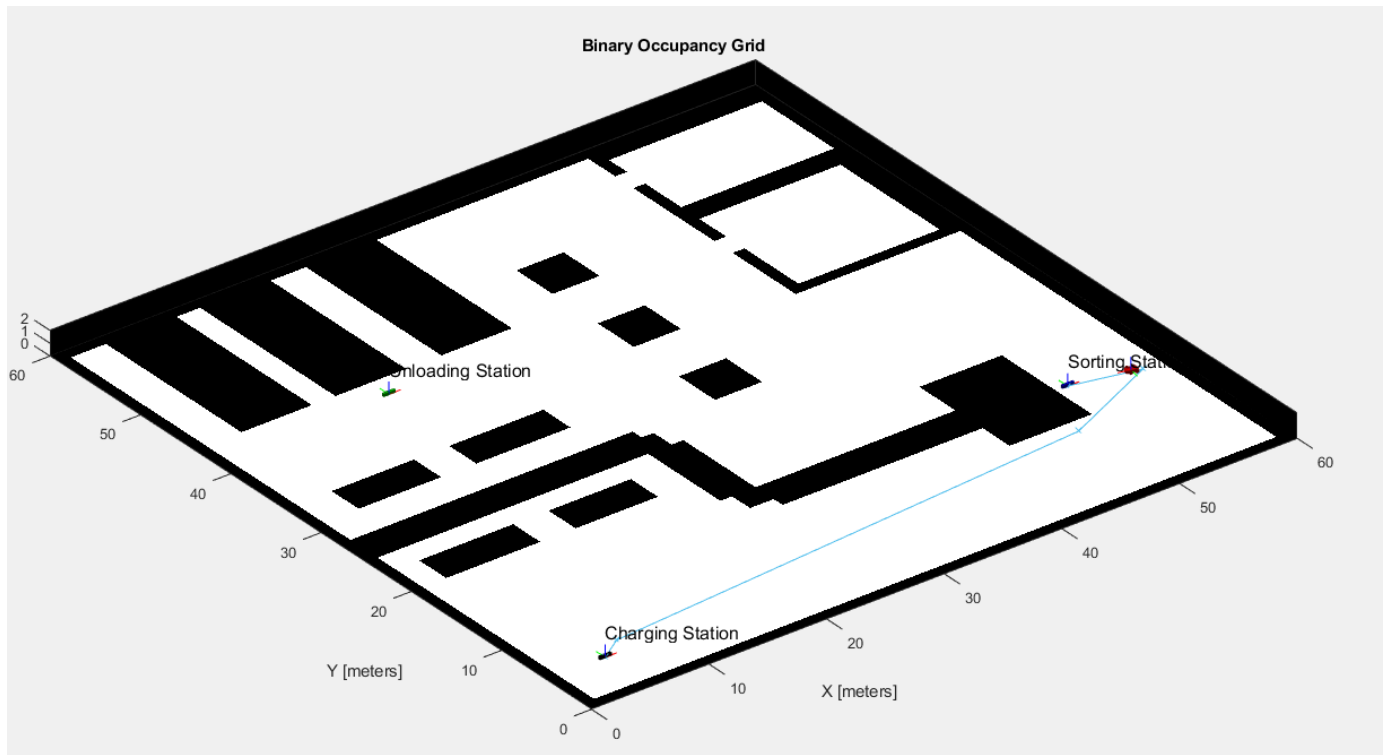
```
simulation = sim('warehouseTasksRobotSimulationModel.slx');
```



Visualize Robot Trajectories

A custom visualization tool is given to mimic a distributed camera system and get more detailed views of the robot trajectory at certain locations in the map. Open the **Visualization Helper** block and use the **Preset Views** drop-down to select different perspectives. The `Sample time` of the visualization has no effect on the simulation of the robot.





See Also

- "Plan Path for a Differential Drive Robot in Simulink" on page 1-26

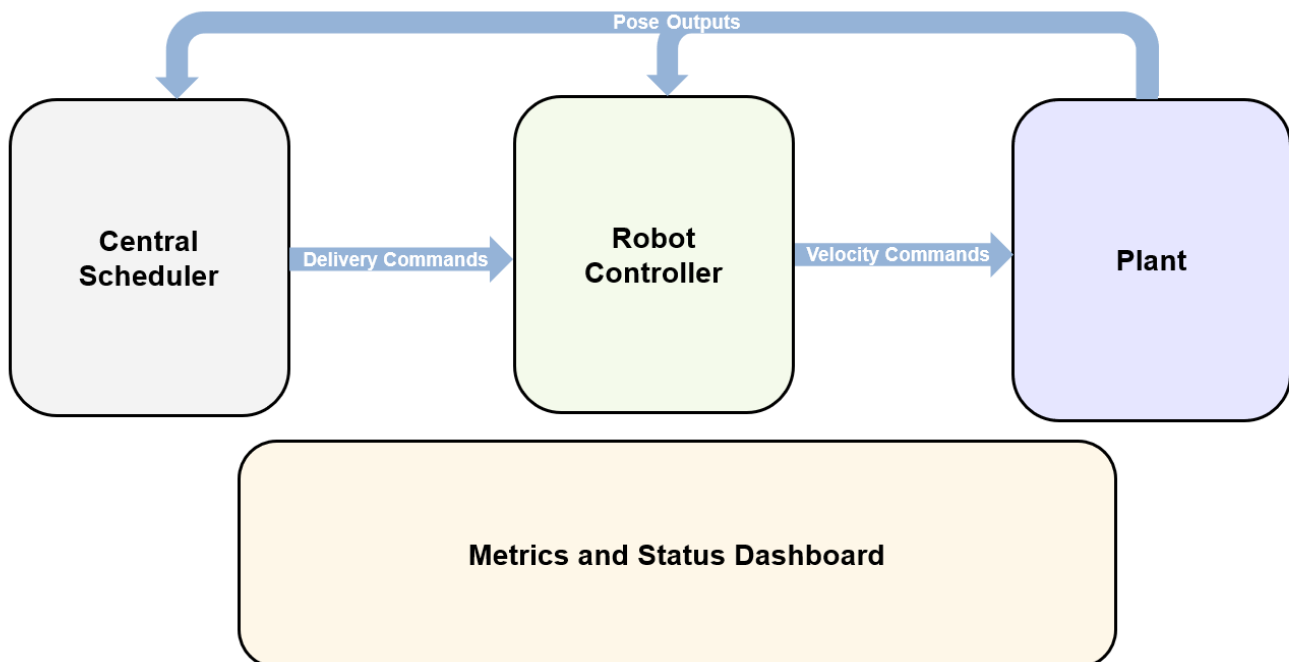
- “Control and Simulate Multiple Warehouse Robots” on page 1-40

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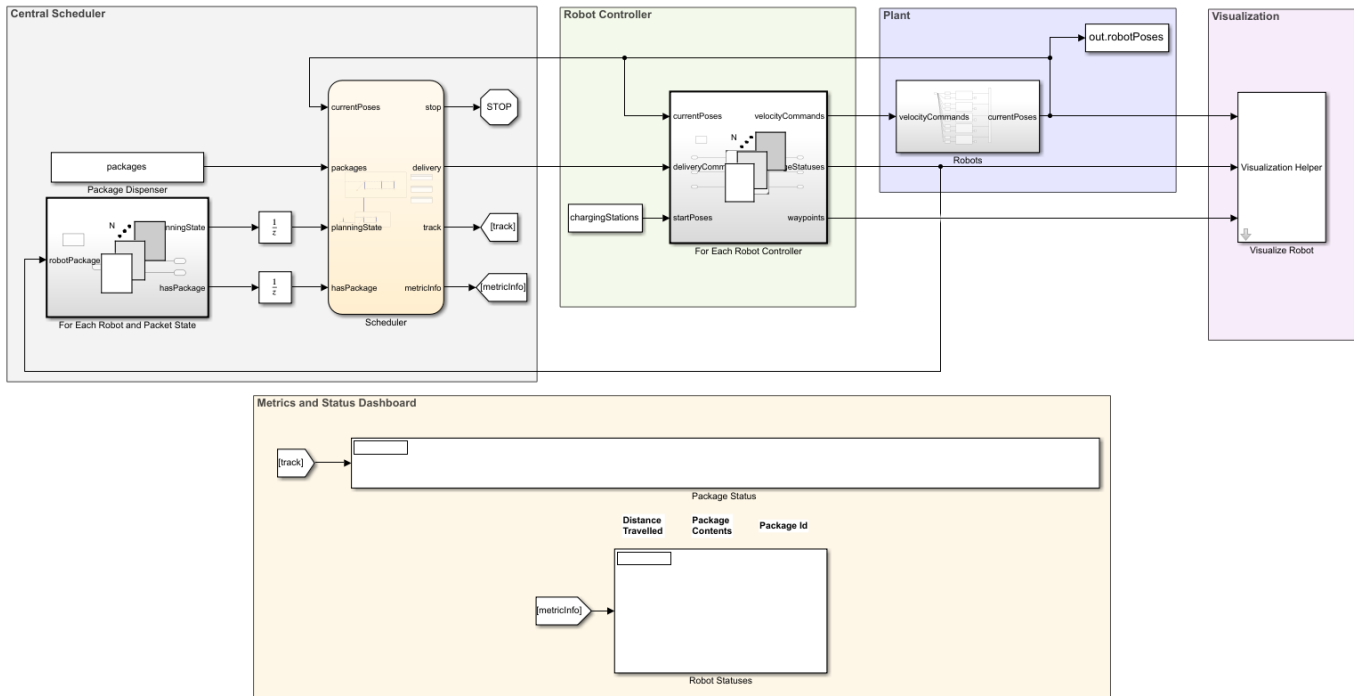
Control and Simulate Multiple Warehouse Robots

This example shows how to control and simulate multiple robots working in a warehouse facility or distribution center. The robots drive around the facility picking up packages and delivering them to stations for storing or processing. This example builds on top of the “Execute Tasks for a Warehouse Robot” on page 1-31 example, which drives a single robot around the same facility.

This package-sorting scenario can be modeled in Simulink® using Stateflow charts and Robotics System Toolbox™ algorithm blocks. A **Central Scheduler** sends commands to robots to pick up packages from the *loading station* and deliver them to a specific *unloading station*. The **Robot Controller** plans the trajectory based on the locations of the loading and unloading stations, and generates velocity commands for the robot. These commands are fed to the **Plant**, which contains a differential-drive robot model for executing the velocity commands and returning ground-truth poses of the robot. The poses are fed back to the scheduler and controller for tracking the robot status. This workflow is done for a group of 5 robots, which are all scheduled, tracked, and modeled simultaneously.



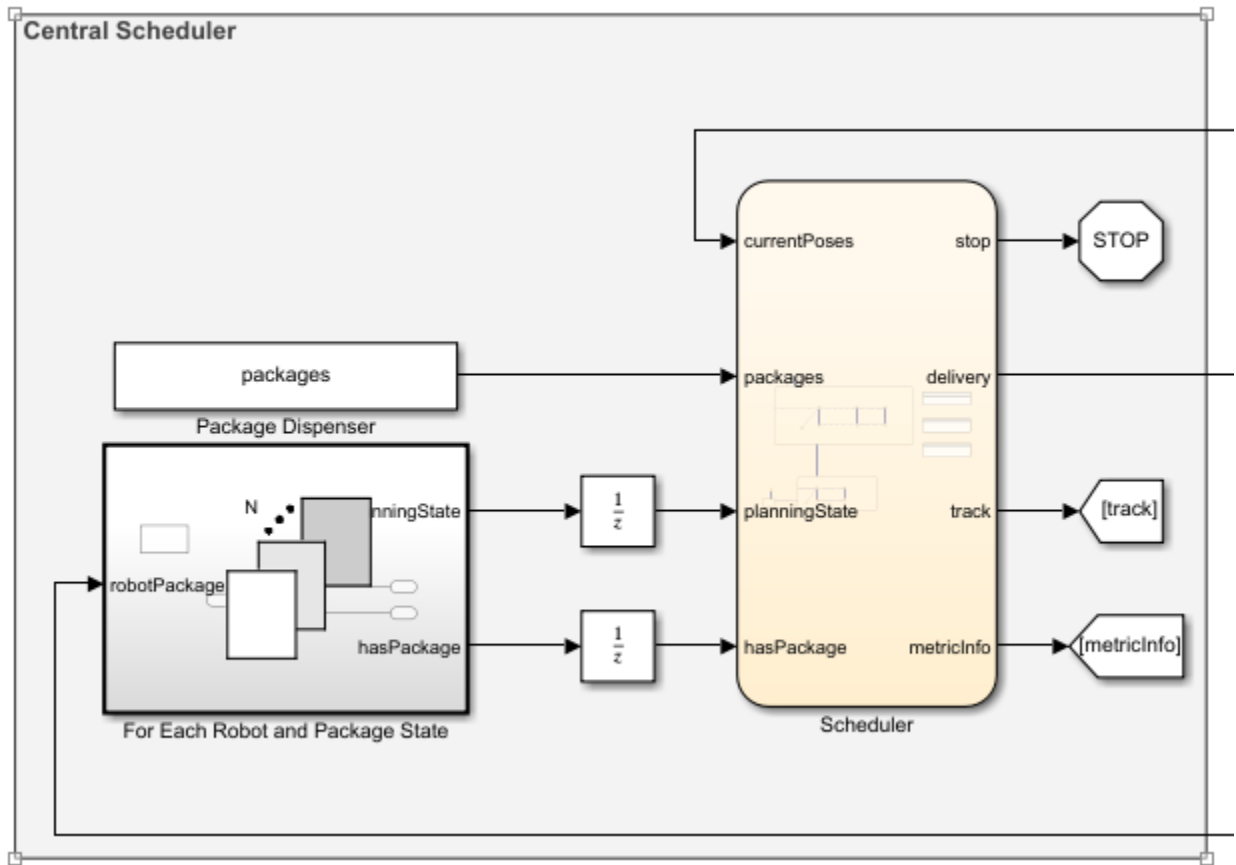
The provided Simulink model, `multiRobotExampleModel`, models the above described scenario.



Central Scheduler

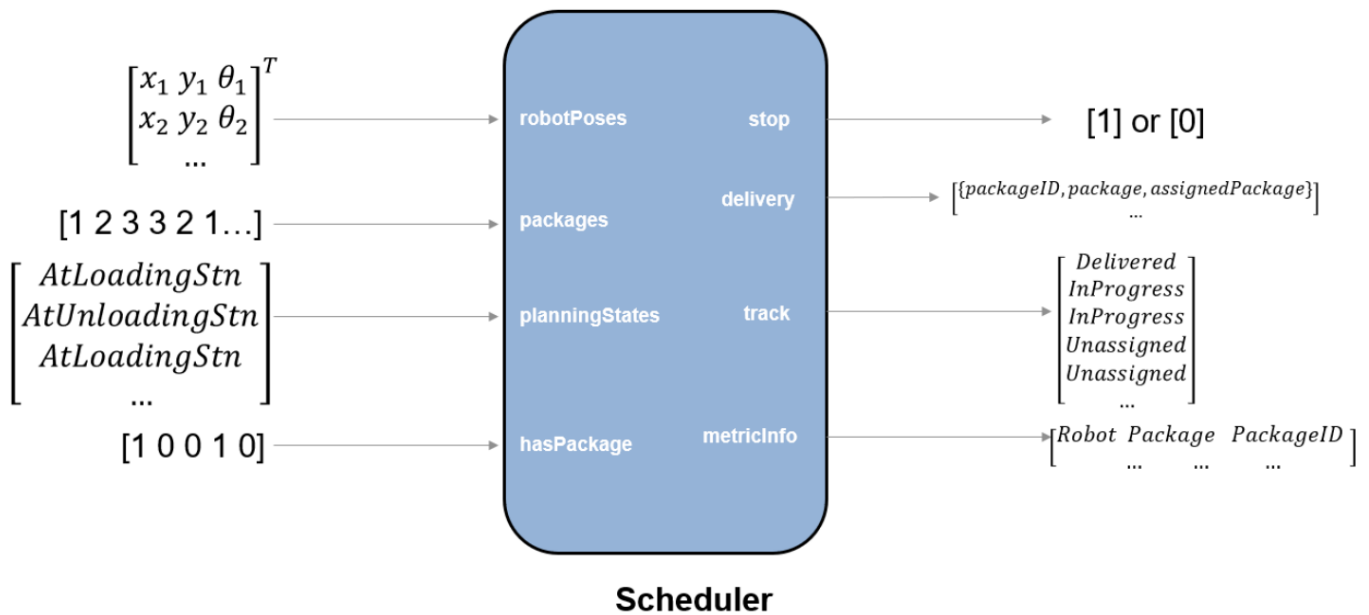
The Central Scheduler uses a Stateflow chart to handle package allocation to the robots from the **Package Dispenser**. Each robot can carry one package at a time and is instructed to go from the loading to an unloading station based on the required location for each package. The scheduler also tracks the status of the packages and robots and updates the **Status Dashboard**. Based on robot poses, the scheduler also sends stop commands to one robot when it detects an imminent collision. This behavior can allow the robots to run local obstacle avoidance if available.

The **For Each Robot and Package State** subsystem is a For Each Subsystem (Simulink) which processes an array of buses for tracking the robot and package states as **RobotPackageStatus** bus object. This makes it easy to update this model for varying number of robots. For more information about processing arrays of buses using a For-Each Subsystem, see “Work with Arrays of Buses” (Simulink).



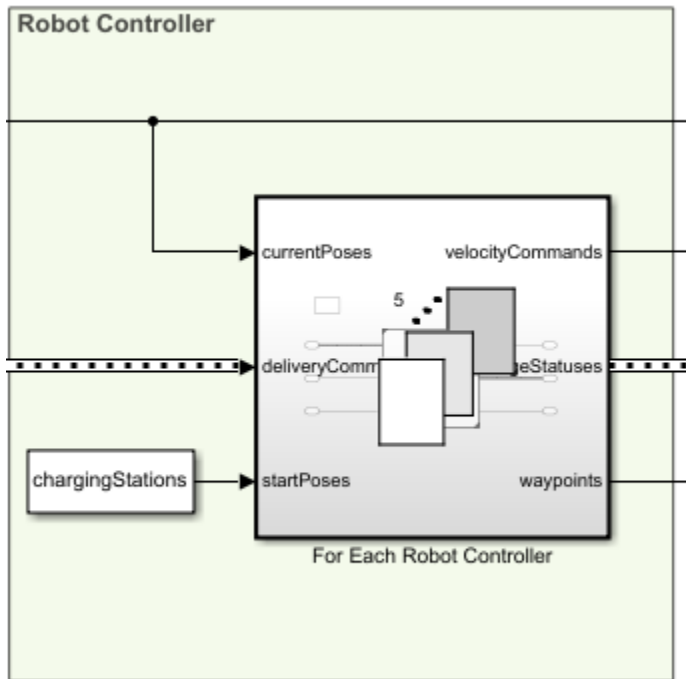
Scheduler

The following schematic details the signal values of the **Scheduler** Stateflow chart.

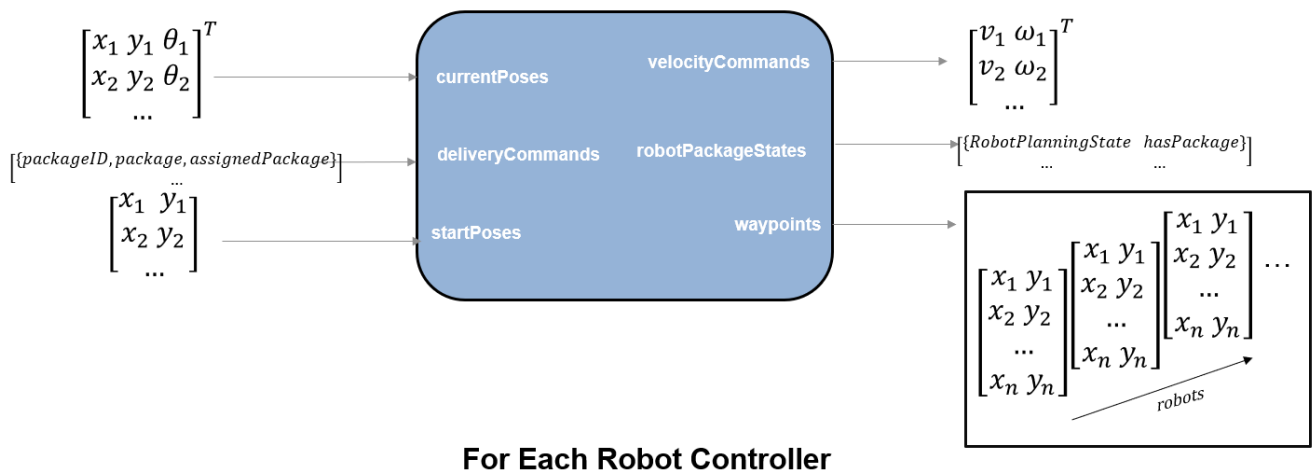


Robot Controller

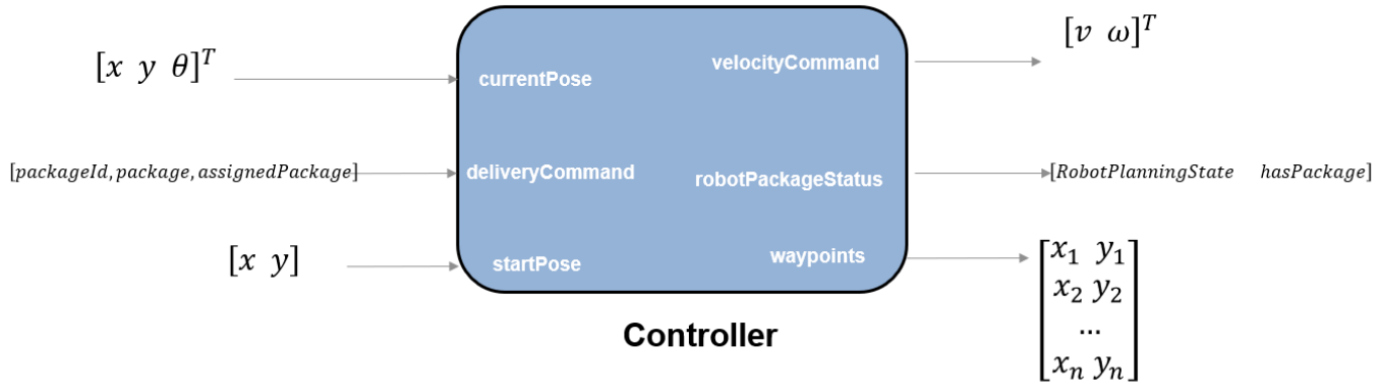
The **Robot Controller** uses a For Each Subsystem (Simulink) to generate an array of robot controllers for your 5 robots.



The following schematic details the type of signal values associated with the **For Each Robot Controller**.

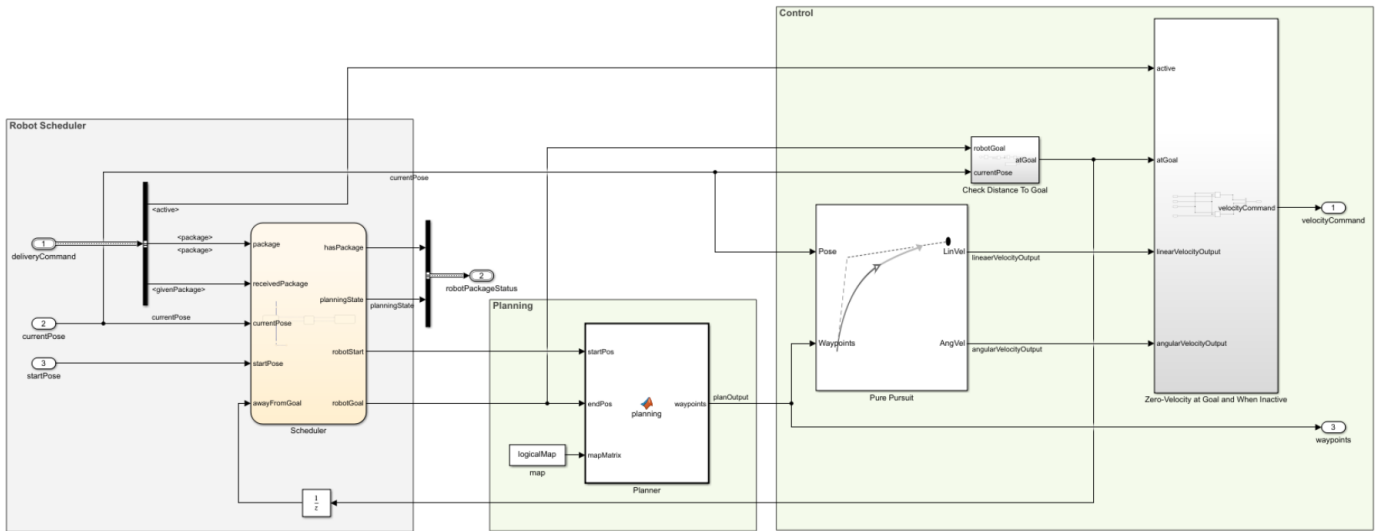


Each robot controller has the following inputs and outputs.



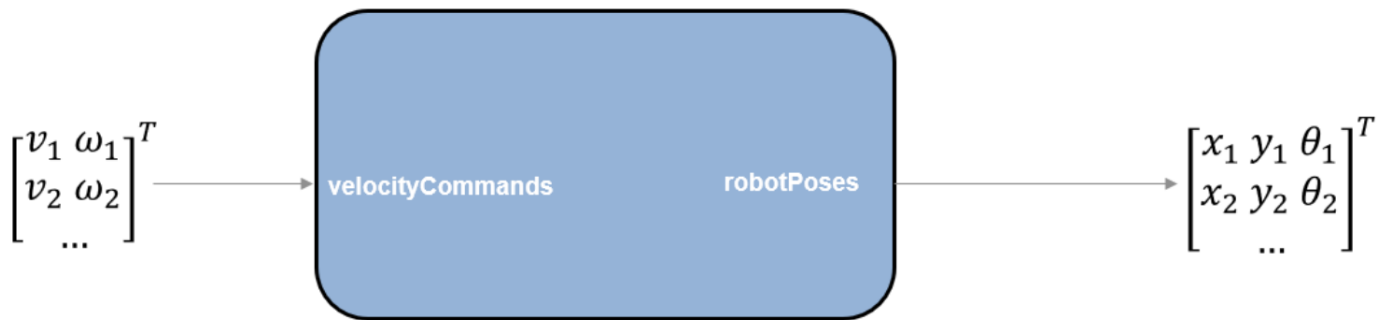
The controller takes delivery commands, which contains the package information, and plans a path for delivering it someone in the warehouse using mobileRobotPRM. The **Pure Pursuit** block takes this path and generates velocity commands for visiting each waypoint. Also, the status of the robot and packages get updated when the robot reaches its goal. Each robot also has its own internal scheduler that tells them the location of unloading stations based on the package information, and sends them back to the loading station when they drop off a package.

The robot controller model uses the same model, warehouseTasksRobotSimulationModel, shown in “Execute Tasks for a Warehouse Robot” on page 1-31.



Plant

The **Plant** subsystem uses a **Differential Drive Kinematic Model** block to model the motion of the robots.



Robots

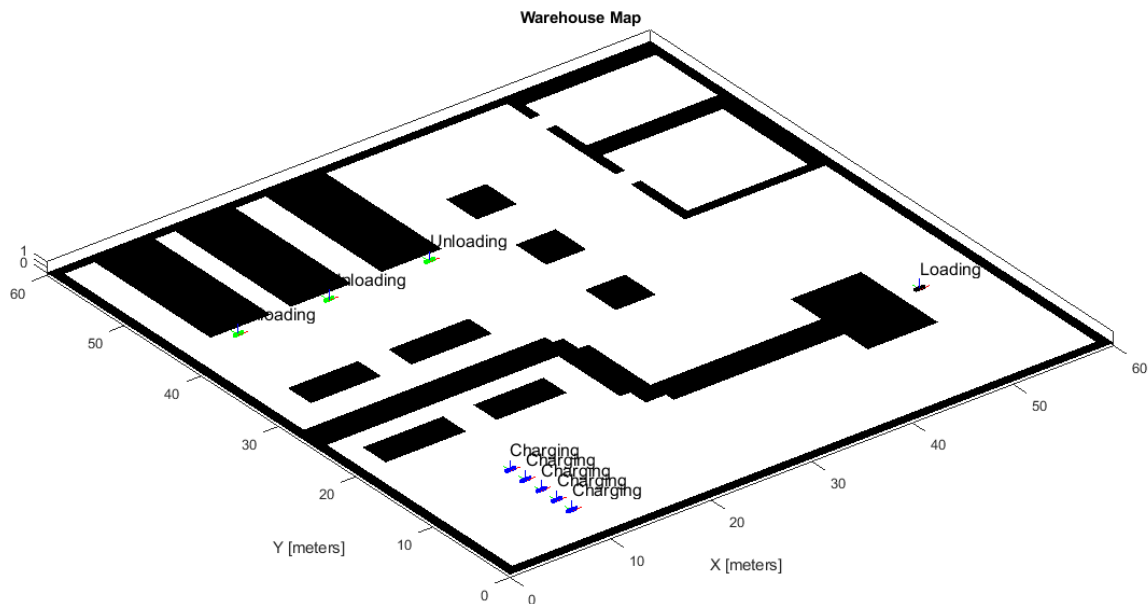
Model Setup

Begin to setup various variables in MATLAB® for the model.

Defining the Warehouse Environment

A logical type matrix, `logicalMap` represents the occupancy map of the warehouse. The warehouse contains obstacles representing walls, shelves, and other processing stations. Loading, unloading, and charging stations are also given in *xy*-coordinates.

```
load multiRobotWarehouseMap.mat logicalMap loadingStation unloadingStations chargingStations
warehouseFig = figure('Name', 'Warehouse Setting', 'Units', "normalized", 'OuterPosition', [0 0 1 1]);
visualizeWarehouse(warehouseFig, logicalMap, chargingStations, unloadingStations, loadingStation);
```



Checking occupancy at stations

Ensure that the stations are not occupied in the map.

```
map = binaryOccupancyMap(logicalMap);
if(any(checkOccupancy(map, [chargingStations; loadingStation; unloadingStations])))
    error("At least one of the station locations is occupied in the map.")
end
```

Central Scheduler

The **Central Scheduler** requires the knowledge of the packages that are to be delivered so as to send the delivery commands to the robot controllers.

Defining Packages

Packages are given as an array of index numbers of the various unloading stations that the packages are supposed to be delivered to. Because this example has three unloading stations, a valid package can take a value of 1, 2, or 3.

```
load packages.mat packages
packages
```

```
packages = 1x11
```

```
    3    2    1    2    3    1    1    1    2    3    1
```

Number of Robots

The number of robots is used to determine the sizes of the various signals in the initialization of the **Scheduler** Stateflow chart

```
numRobots = size(chargingStations, 1); % Each robot has its own charging station;
```

Collision Detection and Goal-Reached Threshold

The **Central Scheduler** and the **Robot Controller** use certain thresholds for collision detection, `collisionThresh`, and a goal-reached condition, `awayFromGoalThresh`.

Collision detection ensures that for any pair of robots within a certain distance-threshold, the robot with a lower index should be allowed to move while the other robot should stop (zero-velocity command). The still moving robot should be able to avoid local static obstacles in their path. You could achieve this with another low-level controller like the Vector Field Histogram (Navigation Toolbox) block.

The goal-reached condition occurs if the robot is within a distance threshold, `awayFromGoalThresh`, from the goal location.

```
load exampleMultiRobotParams.mat awayFromGoalThresh collisionThresh
```

Bus Objects

The `RobotDeliverCommand` and `RobotPackageStatus` bus objects are used to pass robot-package allocations between the **Central Scheduler** and the **Robot Controller**.

```
load warehouseRobotBusObjects.mat RobotDeliverCommand RobotPackageStatus
```

Simulation

Open the Simulink model.

```
open_system("multiRobotExampleModel.slx")
```

Run the simulation. You should see the robots drive plan paths and deliver packages.

```
sim('multiRobotExampleModel');
```

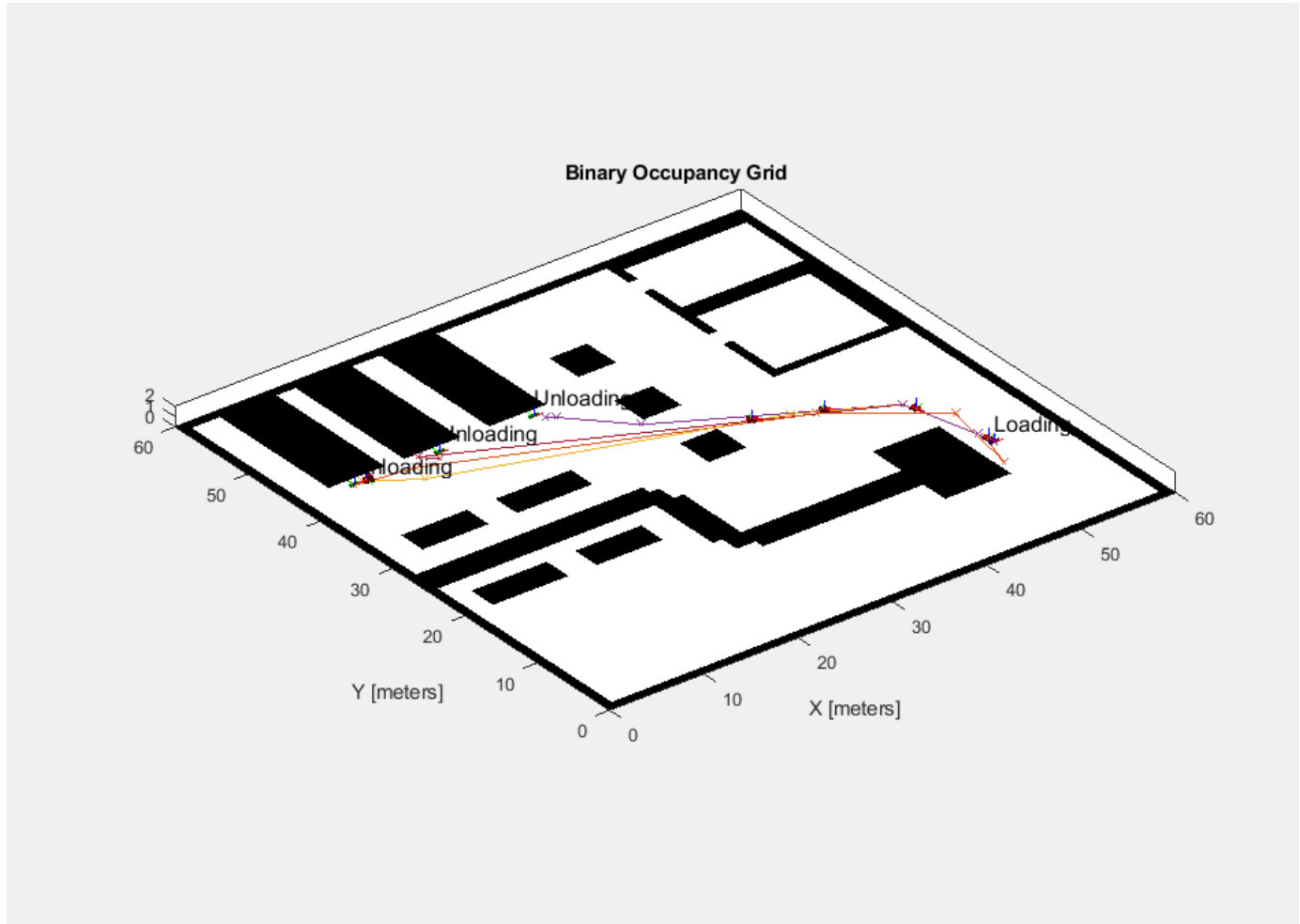
```
### Starting serial model reference simulation build
### Successfully updated the model reference simulation target for: robotController
```

```
Build Summary
```

```
Simulation targets built:
```

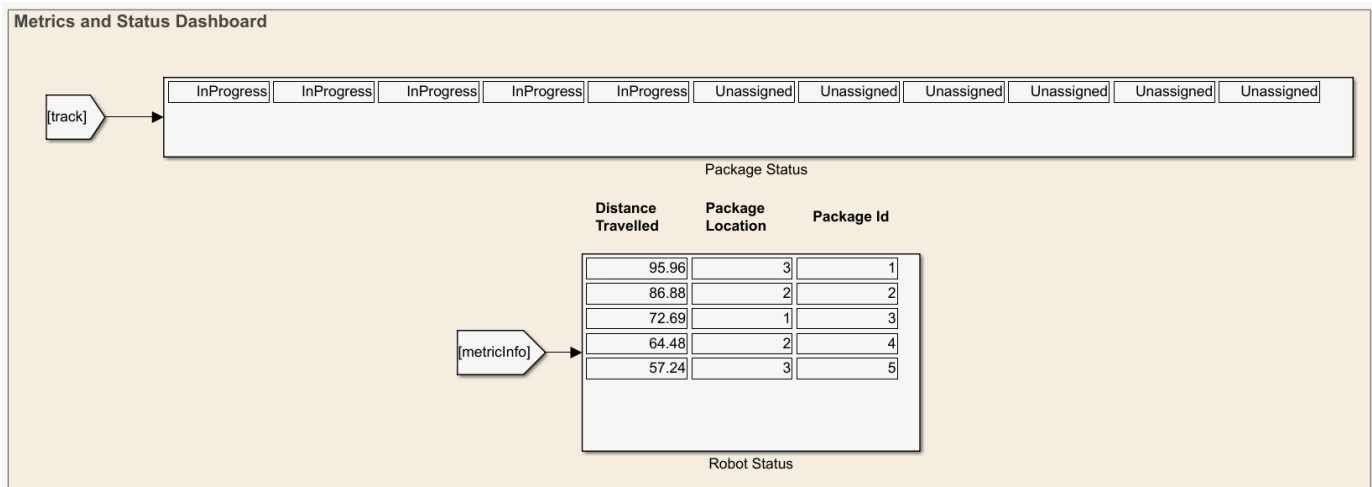
Model	Action	Rebuild Reason
robotController	Code generated and compiled	robotController_msf.mexw64 does not exist.

1 of 1 models built (0 models already up to date)
Build duration: 0h 6m 2.562s



Metrics and Status Dashboard

For each of the packages, the dashboard in the model shows if the package is "InProgress", "Unassigned", or "Delivered". **Robot Status** displays the distance travelled, package location, and a package ID.



Extending the Model

This model is setup to handle modifying the number of robots in the warehouse based on availability. Adding more robots requires defining additional charging stations.

```
chargingStations(6, :) = [10, 15]; % Charging Station for the additional 6th robot
chargingStations(7, :) = [10, 17]; % Charging Station for the additional 7th robot
```

You can also add more unloading stations and assign packages to it.

```
unloadingStations(4, :) = [30, 50];
packages = [packages, 4, 4, 3 1];
```

Additional **Differential Kinematic Model** blocks are also required to match the number of robots. The `exampleHelperReplacePlantSubsystem` adds these by updating `numRobots`.

```
numRobots = size(chargingStations, 1) % As before, each robot has its own charging station
```

```
numRobots = 7
```

```
exampleHelperReplacePlantSubsystem('multiRobotExampleModel/Robots', numRobots);
```

You can also redefine any existing locations. Modify the loading station location.

```
loadingStation = [35, 20];
```

Simulation

After making the modifications, run the simulation again. You should see the updated station locations and an increased number of robots.

```
sim('multiRobotExampleModel');
```

```
### Starting serial model reference simulation build
```

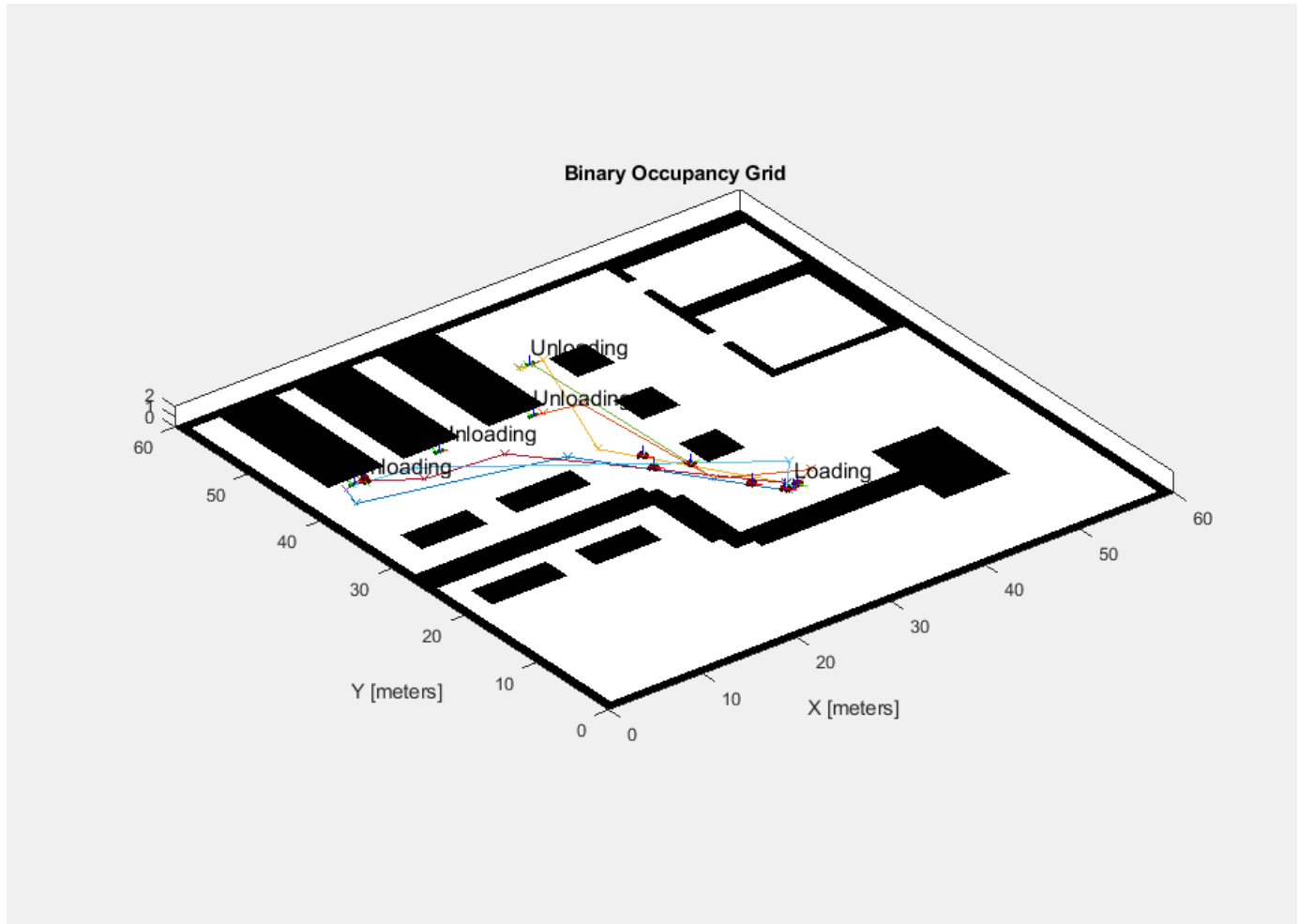
```
### Successfully updated the model reference simulation target for: robotController
```

```
Build Summary
```

```
Simulation targets built:
```

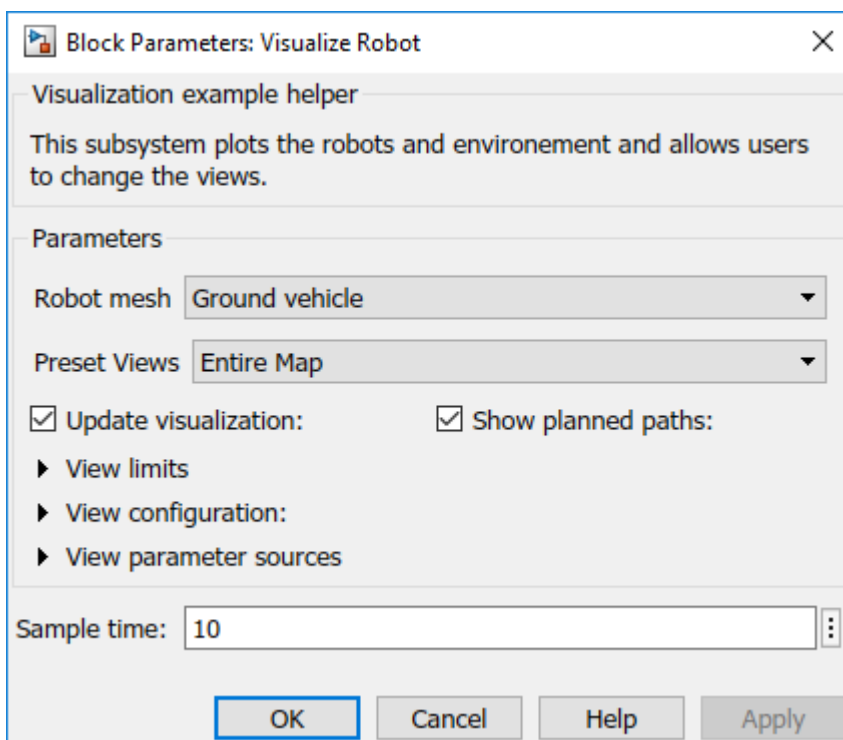
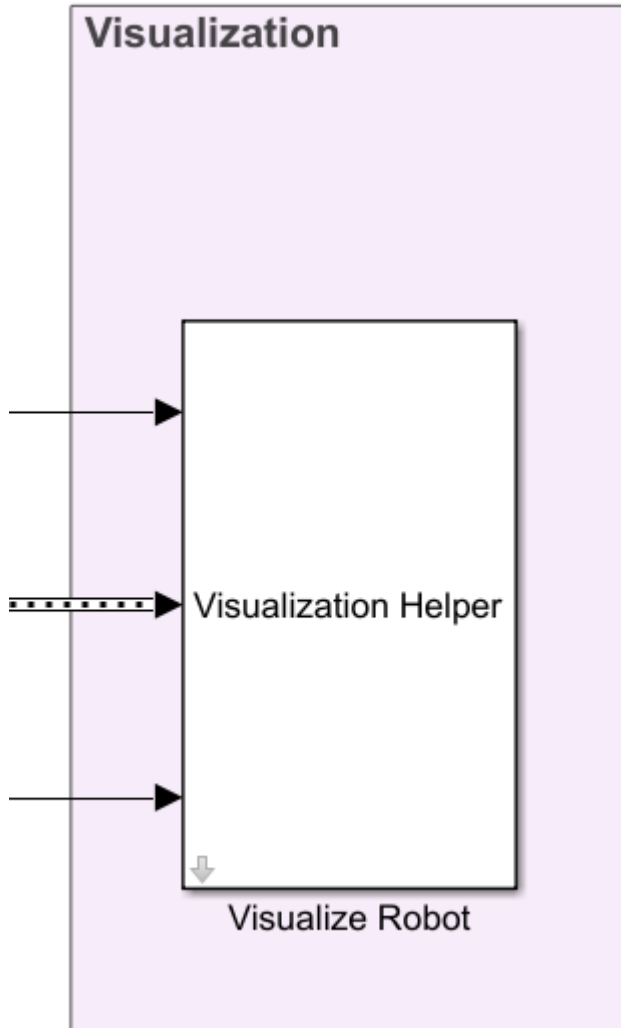
```
Model          Action          Rebuild Reason
=====
robotController Code generated and compiled Global variables have changed.

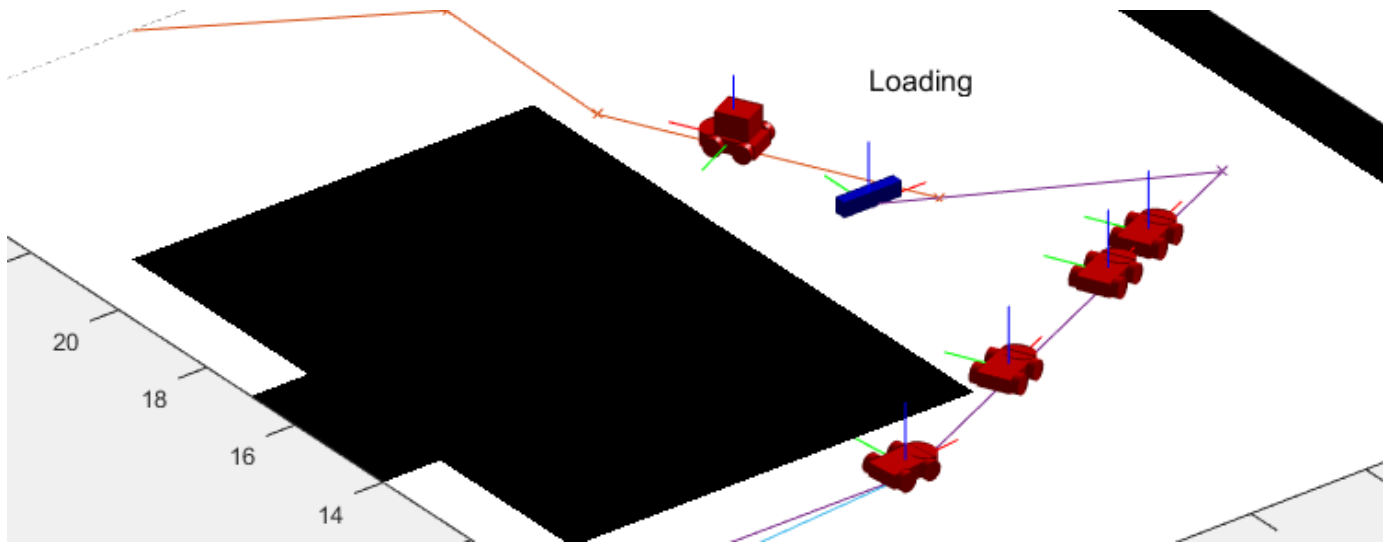
1 of 1 models built (0 models already up to date)
Build duration: 0h 5m 50.87s
```



Visualization

The **Visualization Helper** offers some options for changing the view of the warehouse. Open the block mask to switch between various **Preset Views** of different stations. Toggle path visualization or update robot mesh types. Adjust the **Sample time** to change the rate of the visualization, which does not affect the execution of the actual robot simulation.





Simulate a Mobile Robot in a Warehouse Using Gazebo

This example shows how to simulate a warehouse robot in Gazebo. Gazebo enabled you to simulate a mobile robot that uses a range sensor, while executing certain tasks in a simulated environment. This example details how to use a simulator to apply the “Execute Tasks for a Warehouse Robot” on page 1-31 example, where a robot delivers packages in a warehouse scenario. The robot makes use of the simulated range sensor in Gazebo to detect possible collisions with a dynamic environment and avoid them.

Prerequisites

- Download a Virtual Machine with ROS and Gazebo to set up a simulated robot.
- Review the “Execute Tasks for a Warehouse Robot” on page 1-31 example for the workflow of path planning and navigating in a warehouse scenario.
- Review the “Control A Differential-Drive Robot in Gazebo With Simulink” on page 1-70 example for basic steps of collecting sensor data and controlling a robot in Gazebo.

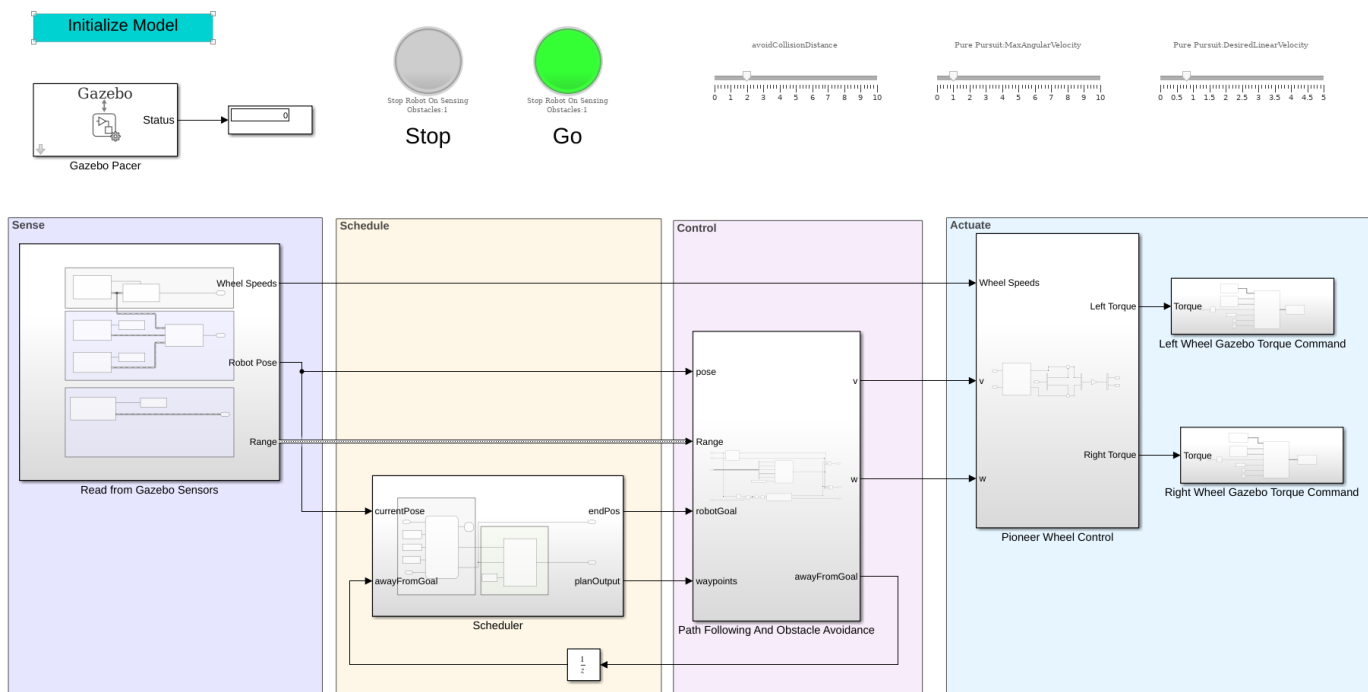
Model Overview

Open the model.

```
open_system('simulateWarehouseRobotInGazebo.slx')
```

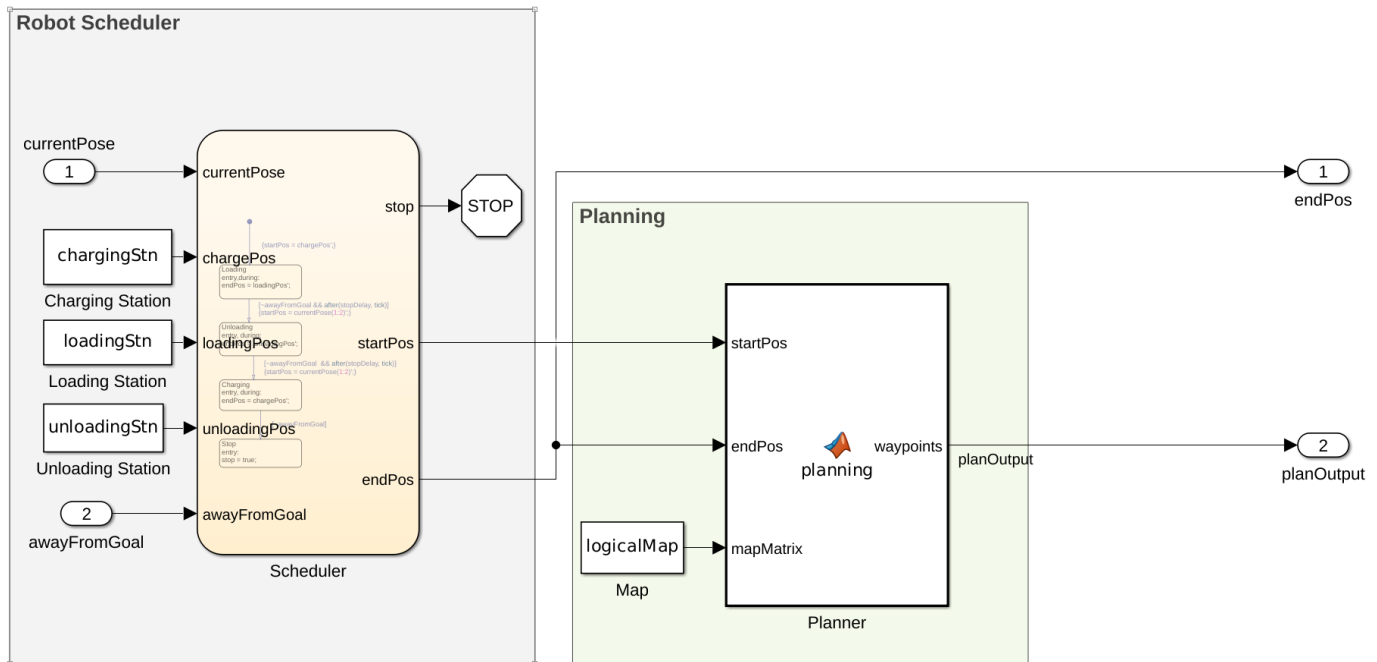
The model can be divided into the following elements:

- **Sense:** Read data from sensors in Gazebo.
- **Schedule:** Assign packages and plan paths for robots to deliver the packages.
- **Control:** Generate commands to follow the predefined path and avoid obstacles.
- **Actuate:** Send commands to Gazebo to actuate the robot in the environment.



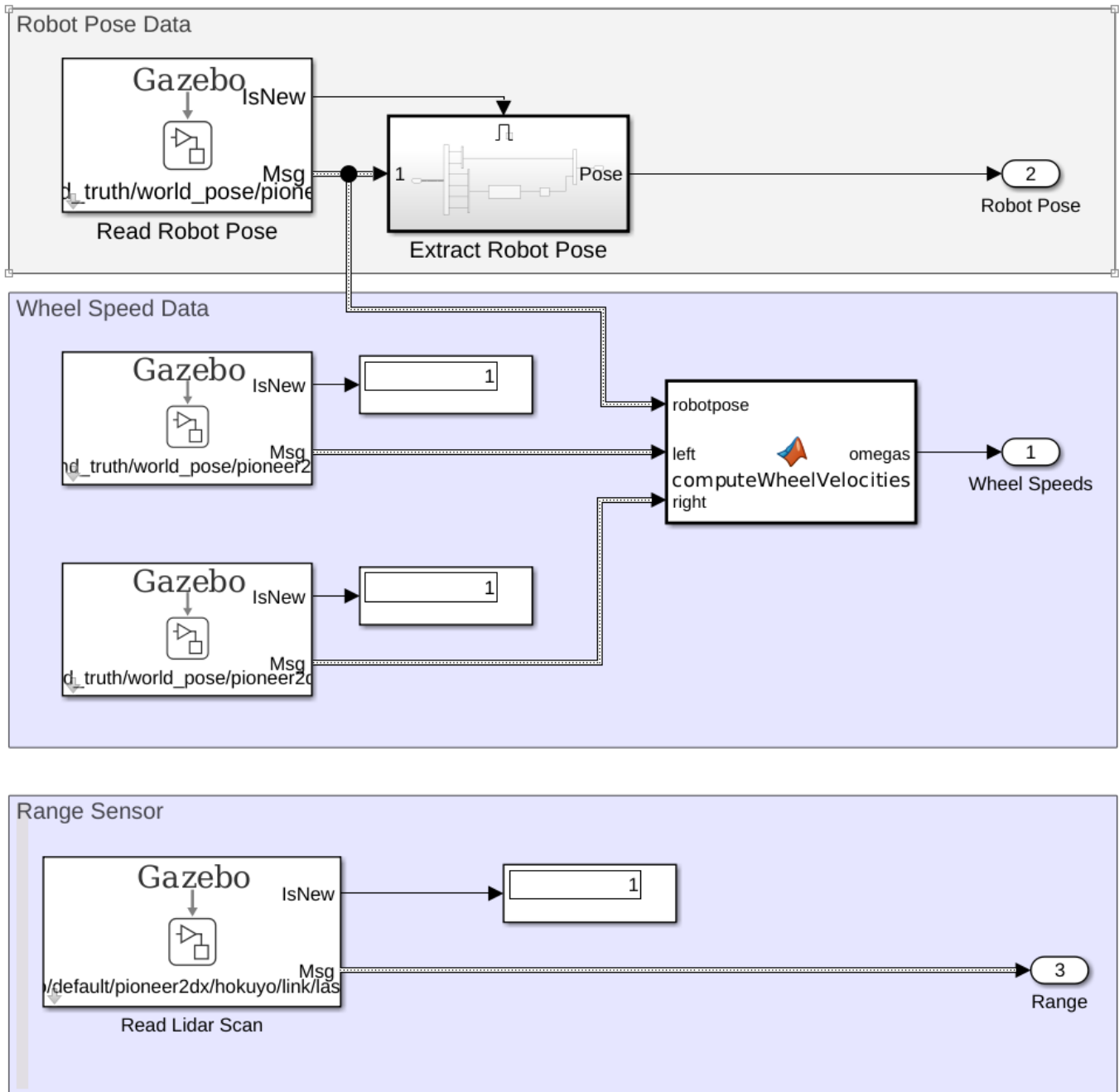
Schedule

The robot performs the task of going between the charging station, the loading station, and the unloading station as guided by the **Scheduler**.



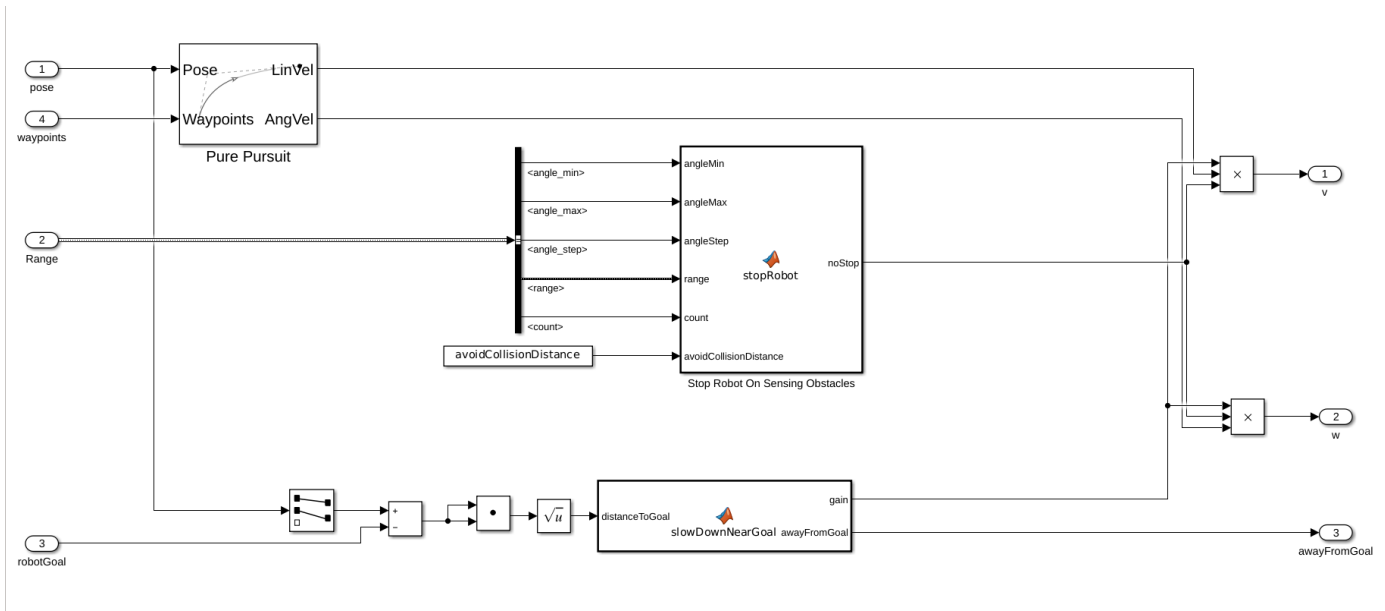
Sense

The current robot pose, the wheel speeds, and the range sensor readings are read from the simulated environment in Gazebo. The figure below is the expanded view of the **Read From Gazebo Sensors** subsystem.



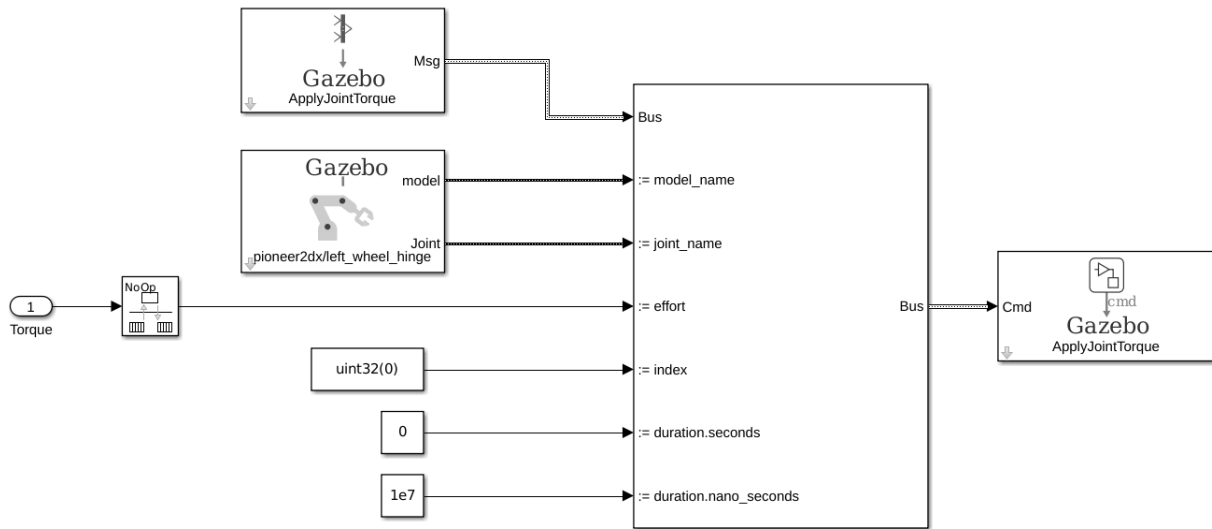
Control

The controller generates control commands for following the waypoints using the **Pure Pursuit** block. If the range sensor on the robot detects an obstacle within the `avoidCollisionDistance` threshold, the robot stops. Also, the robot stops when gets near enough to the goal.



Actuate

Based on the generated control commands, the **Pioneer Wheel Control** subsystem generates a torque value for each wheel. The torque is applied as an `ApplyJointTorque` command.



Setup

Warehouse Facility

Load the example map file, `map`, which is a matrix of logical values indicating occupied space in the warehouse. Invert this matrix to indicate free space, and make a `binaryOccupancyMap` object. Specify a resolution of 100 cells per meter.

The map is based off of the `warehouseExtensions.world` file, which was made using the Building Editor on the same scaling factor as mentioned below. A `.png` file for the map can be made using the `collision_map_creator_plugin` plugin to generate the map matrix. The details on how to install the plugin can be found at [Collision Map Creator Plugin](#).

```
mapScalingFactor = 100;
load gazeboWarehouseMap.mat map
logicalMap = ~map;
map = binaryOccupancyMap(logicalMap,mapScalingFactor);
show(map)
```

Assign the `xy`-locations of the charging station, sorting station, and the unloading location near shelves in the warehouse. The values chosen are based on the simulated world in Gazebo.

```
chargingStn = [12,5];
loadingStn = [24,5];
unloadingStn = [15,24];
```

Show the various locations on the map.

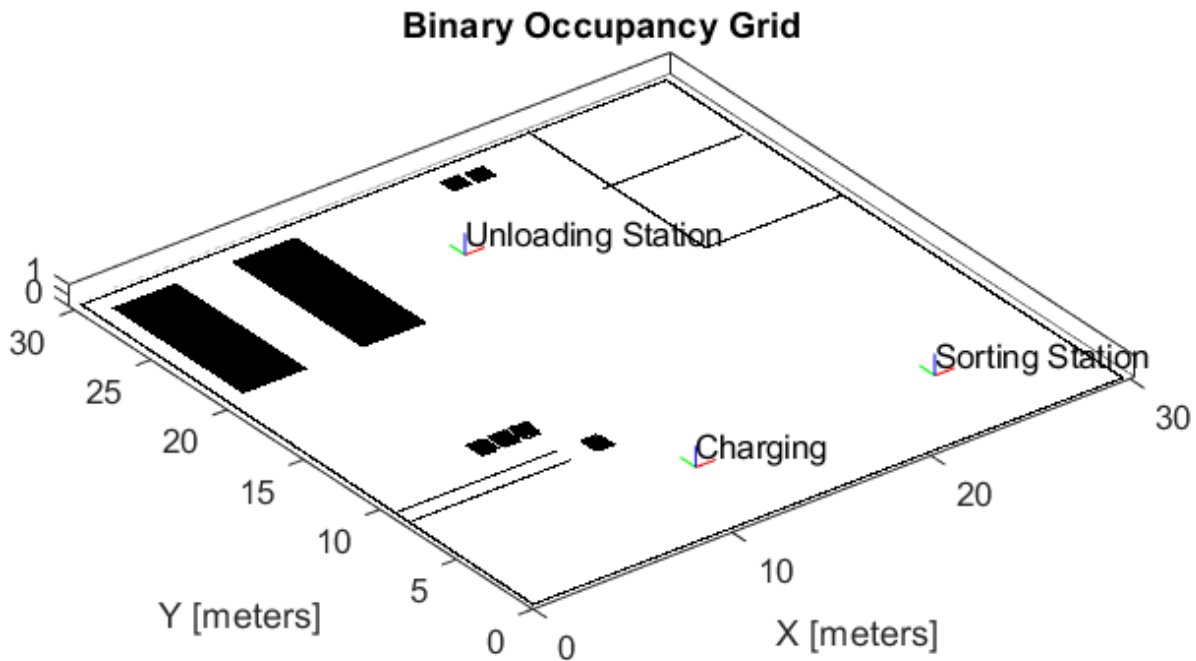
```
hold on;

text(chargingStn(1), chargingStn(2), 1, 'Charging');
plotTransforms([chargingStn, 0], [1 0 0 0])

text(loadingStn(1), loadingStn(2), 1, 'Sorting Station');
plotTransforms([loadingStn, 0], [1 0 0 0])

text(unloadingStn(1), unloadingStn(2), 1, 'Unloading Station');
plotTransforms([unloadingStn, 0], [1 0 0 0])

hold off;
```



Range Sensor

The **Read Lidar Scan** block in the Sensing on page 1-0 section is used to read the range values from the simulated range sensor. The `warehouseExtensions.world` file contains the details of the various models and actors (warehouse workers) in the scene. Because `<actor>` tags are static links with only visual meshes, the sensor type of the range sensor is `gpu_ray`.

Additionally, the range sensor uses 640 range, but the default is 128. This requires modification of the buses used in the in the **Read Lidar Scan** block. Load the `exampleHelperWarehouseRobotWithGazeboBuses.mat` file to get a modified bus with `Gazebo_SL_Bus_gazebo_msgs_LaserScan.range` set to 640. The modified buses were saved to a `.mat` file using the Bus Editor.

```
load exampleHelperWarehouseRobotWithGazeboBuses.mat
```

Collision Avoidance

The actors in the world are walking a predefined trajectory. The robot makes use of a range sensor to check for obstacles within a range of 2.0 m (`avoidCollisionDistance`) with range angles from $[-\pi/10, \pi/10]$. Upon a non-zero reading within that range and view, the robot stops and only

resumes after the range is clear. The "Stop Robot On Sensing Obstacles" function block incorporates this logic.

While running the simulation, the **Stop** lamp turns green when the robot senses that it is good to proceed. If it has stopped the lamp turns red.

```
avoidCollisionDistance = 2;
```

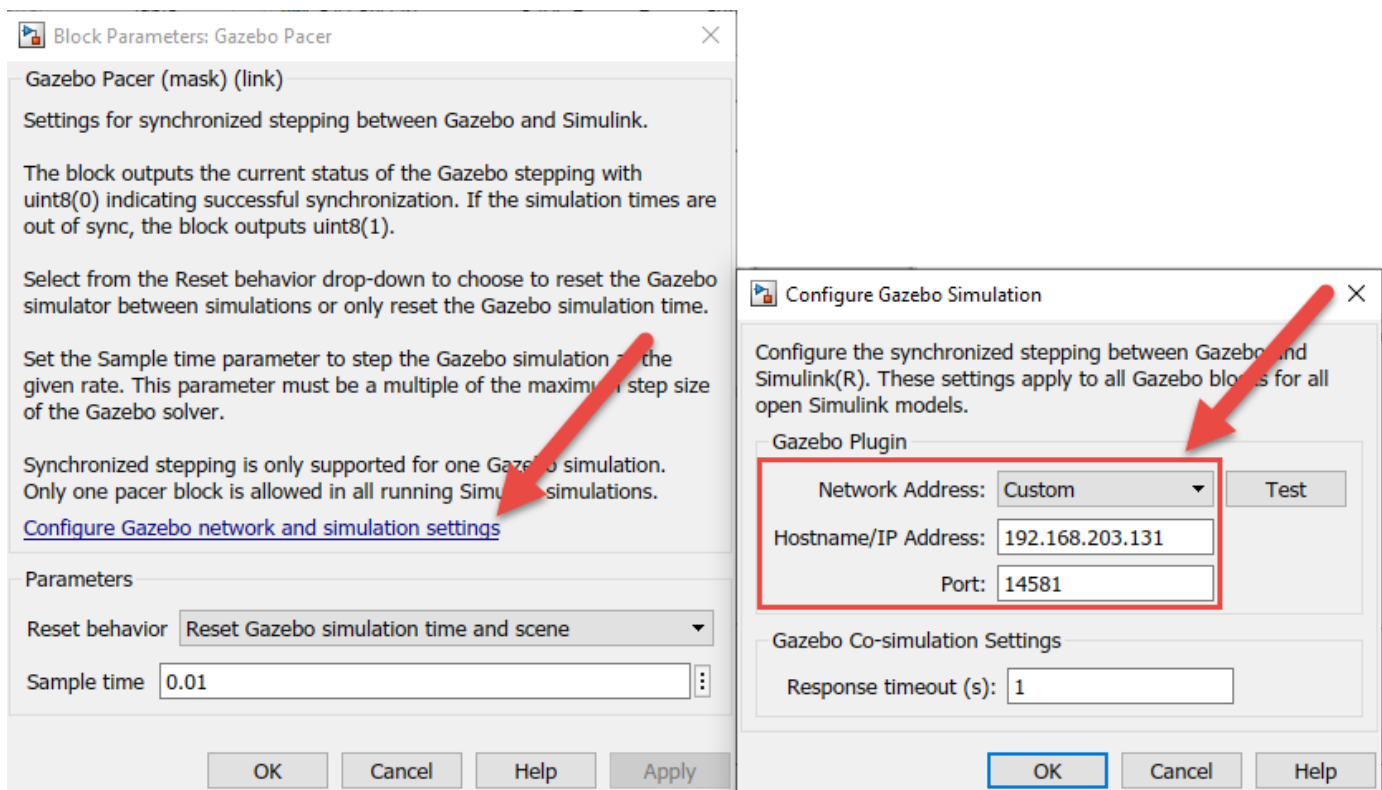
Simulate

To simulate the scenario, set up the connection to Gazebo.

First, run the Gazebo Simulator. In the virtual machine, click the **Gazebo Warehouse Robot** icon.

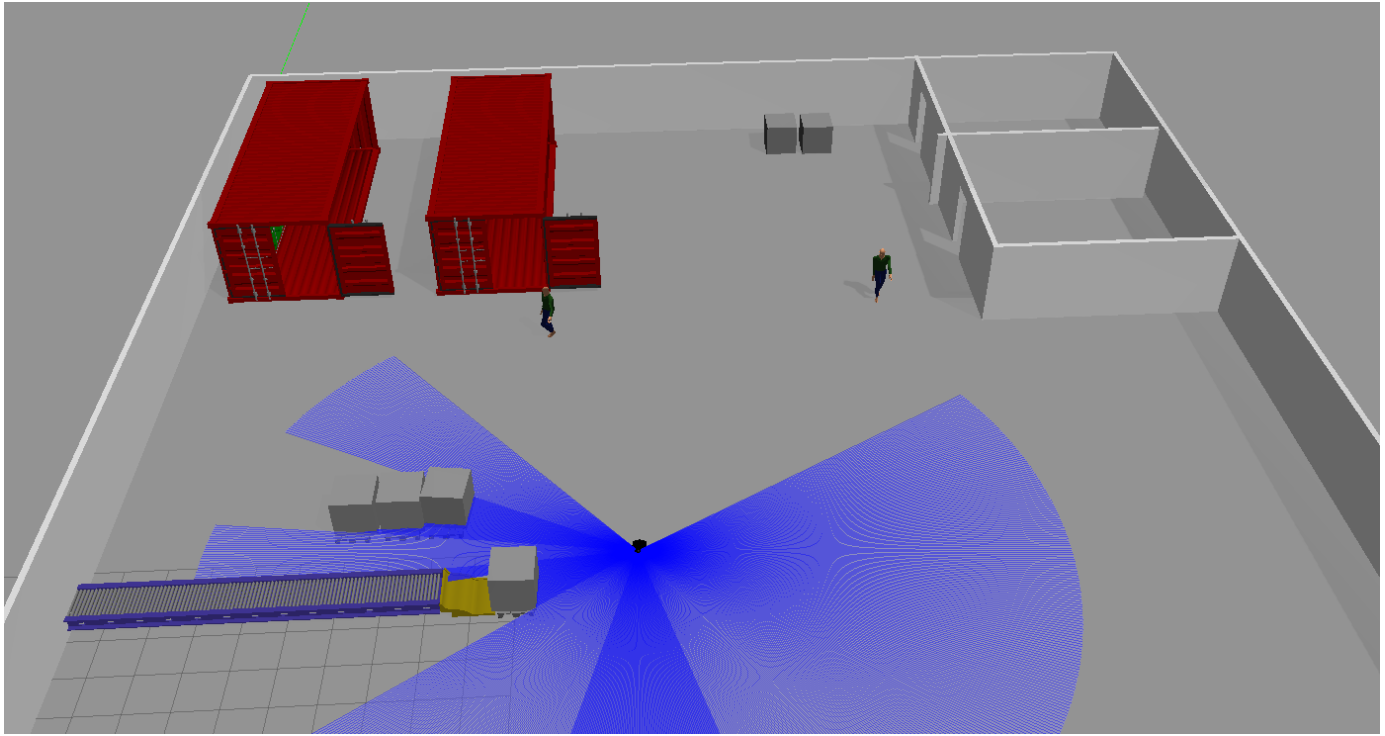
In Simulink, open the **Gazebo Pacer** block and click **Configure Gazebo network and simulation settings**. Specify the **Network Address** as **Custom**, the **Hostname/IP Address** for your Gazebo simulation, and a **Port** of 14581, which is the default port for Gazebo. The desktop of the VM displays the IP address.

For more information about connecting to Gazebo to enable co-simulation, see "Perform Co-Simulation between Simulink and Gazebo" on page 1-257.



Click the **Initialize Model** button at the top of the model to initialize all the variables declared above.

Run the simulation. The robot drives around the environment and stops whenever a worker gets within the defined threshold.



Track a Car-Like Robot Using Particle Filter

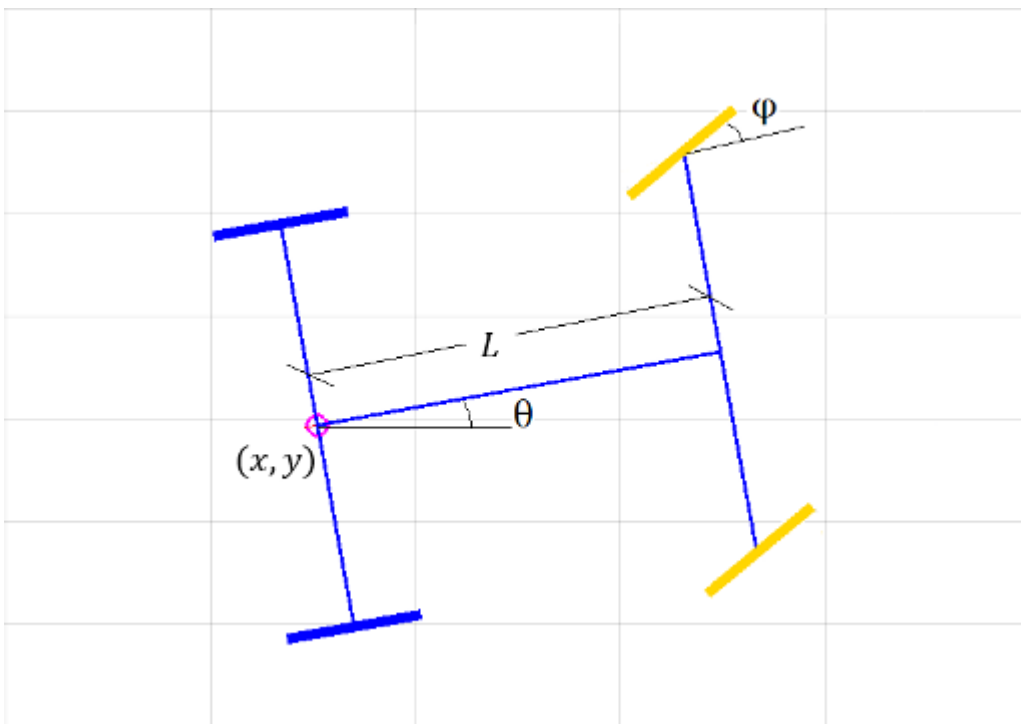
Particle filter is a sampling-based recursive Bayesian estimation algorithm, which is implemented in the `stateEstimatorPF` object. In this example, a remote-controlled car-like robot is being tracked in the outdoor environment. The robot pose measurement is provided by an on-board GPS, which is noisy. There are known motion commands sent to the robot, but the robot will not execute the exact commanded motion due to mechanical slack or model inaccuracy. This example will show how to use `stateEstimatorPF` to reduce the effects of noise in the measurement data and get a more accurate estimation of the pose of the robot. The kinematic model of a car-like robot is described by the following non-linear system. The particle filter is ideally suited for estimating the state of such kind of systems, as it can deal with the inherent non-linearities.

$$\dot{x} = v\cos(\theta)$$

$$\dot{y} = v\sin(\theta)$$

$$\dot{\theta} = \frac{v}{L}\tan\phi$$

$$\dot{\phi} = \omega$$



Scenario: The car-like robot drives and changes its velocity and steering angle continuously. The pose of the robot is measured by some noisy external system, e.g. a GPS or a Vicon system. Along the path it will drive through a roofed area where no measurement can be made.

Input:

- The noisy measurement on robot's partial pose (x, y, θ) . **Note** this is not a full state measurement. No measurement is available on the front wheel orientation (ϕ) as well as all the velocities $(\dot{x}, \dot{y}, \dot{\theta}, \dot{\phi})$.

- The linear and angular velocity command sent to the robot (v_c, ω_c). **Note** there will be some difference between the commanded motion and the actual motion of the robot.

Goal: Estimate the partial pose (x, y, θ) of the car-like robot. **Note** again that the wheel orientation (ϕ) is not included in the estimation. **From the observer's perspective**, the full state of the car is only $[x, y, \theta, \dot{x}, \dot{y}, \dot{\theta}]$.

Approach: Use `stateEstimatorPF` to process the two noisy inputs (neither of the inputs is reliable by itself) and make best estimation of current (partial) pose.

- At the **predict** stage, we update the states of the particles with a simplified, unicycle-like robot model, as shown below. Note that the system model used for state estimation is not an exact representation of the actual system. This is acceptable, as long as the model difference is well-captured in the system noise (as represented by the particle swarm). For more details, see `predict`.

$$\dot{x} = v \cos(\theta)$$

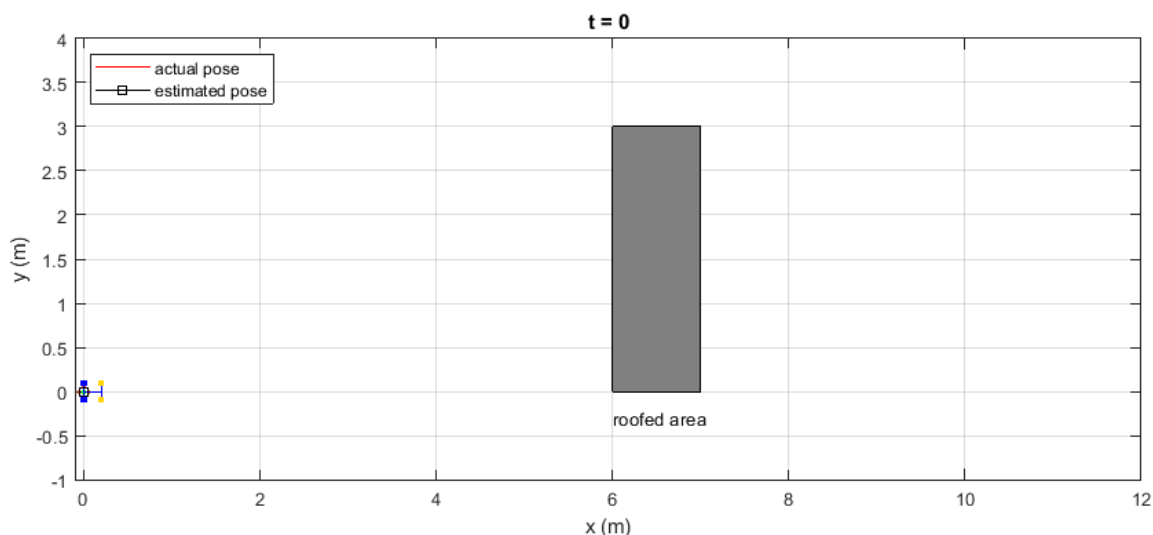
$$\dot{y} = v \sin(\theta)$$

$$\dot{\theta} = \omega$$

- At the **correct** stage, the importance weight (likelihood) of a particle is determined by its error norm from current measurement ($\sqrt{(\Delta x)^2 + (\Delta y)^2 + (\Delta \theta)^2}$), as we only have measurement on these three components. For more details, see `correct`.

Initialize a Car-like Robot

```
rng('default'); % for repeatable result
dt = 0.05; % time step
initialPose = [0 0 0 0]';
carbot = ExampleHelperCarBot(initialPose, dt);
```



Set up the Particle Filter

This section configures the particle filter using 5000 particles. Initially all particles are randomly picked from a normal distribution with mean at initial state and unit covariance. Each particle contains 6 state variables (x , y , θ , \dot{x} , \dot{y} , $\dot{\theta}$). Note that the third variable is marked as Circular since it is the car orientation. It is also very important to specify two callback functions `StateTransitionFcn` and `MeasurementLikelihoodFcn`. These two functions directly determine the performance of the particle filter. The details of these two functions can be found in the last two sections of this example.

```
pf = stateEstimatorPF;

initialize(pf, 5000, [initialPose(1:3)', 0, 0, 0], eye(6), 'CircularVariables',[0 0 1 0 0 0]);
pf.StateEstimationMethod = 'mean';
pf.ResamplingMethod = 'systematic';

% StateTransitionFcn defines how particles evolve without measurement
pf.StateTransitionFcn = @exampleHelperCarBotStateTransition;

% MeasurementLikelihoodFcn defines how measurement affect the our estimation
pf.MeasurementLikelihoodFcn = @exampleHelperCarBotMeasurementLikelihood;

% Last best estimation for x, y and theta
lastBestGuess = [0 0 0];
```

Main Loop

Note in this example, the commanded linear and angular velocities to the robot are arbitrarily-picked time-dependent functions. Also, note the fixed-rate timing of the loop is realized through `rateControl`.

Run loop at 20 Hz for 20 seconds using fixed-rate support.

```
r = rateControl(1/dt);

Reset the fixed-rate object to restart the timer. Reset the timer right before running the time-
dependent code.

reset(r);

simulationTime = 0;

while simulationTime < 20 % if time is not up

    % Generate motion command that is to be sent to the robot
    % NOTE there will be some discrepancy between the commanded motion and the
    % motion actually executed by the robot.
    uCmd(1) = 0.7*abs(sin(simulationTime)) + 0.1; % linear velocity
    uCmd(2) = 0.08*cos(simulationTime);         % angular velocity

    drive(carbot, uCmd);

    % Predict the carbot pose based on the motion model
    [statePred, covPred] = predict(pf, dt, uCmd);

    % Get GPS reading
    measurement = exampleHelperCarBotGetGPSReading(carbot);
```

```

% If measurement is available, then call correct, otherwise just use
% predicted result
if ~isempty(measurement)
    [stateCorrected, covCorrected] = correct(pf, measurement');
else
    stateCorrected = statePred;
    covCorrected = covPred;
end

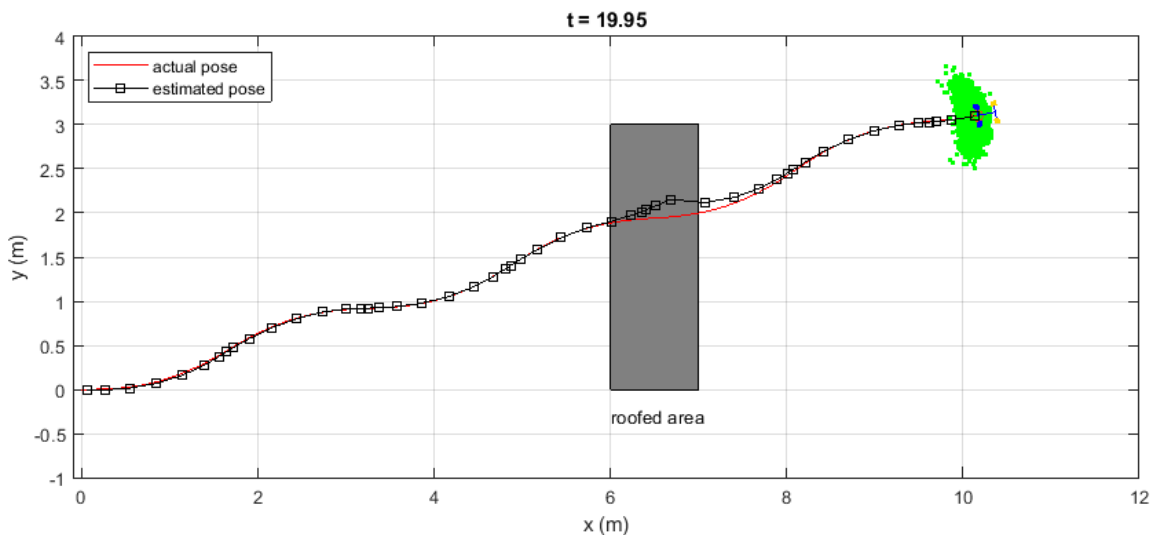
lastBestGuess = stateCorrected(1:3);

% Update plot
if ~isempty(get(groot, 'CurrentFigure')) % if figure is not prematurely killed
    updatePlot(carbot, pf, lastBestGuess, simulationTime);
else
    break
end

waitfor(r);

% Update simulation time
simulationTime = simulationTime + dt;
end

```



Details of the Result Figures

The three figures show the tracking performance of the particle filter.

- In the first figure, the particle filter is tracking the car well as it drives away from the initial pose.
- In the second figure, the robot drives into the roofed area, where no measurement can be made, and the particles only evolve based on prediction model (marked with orange color). You can see

the particles gradually form a horseshoe-like front, and the estimated pose gradually deviates from the actual one.

- In the third figure, the robot has driven out of the roofed area. With new measurements, the estimated pose gradually converges back to the actual pose.

State Transition Function

The sampling-based state transition function evolves the particles based on a prescribed motion model so that the particles will form a representation of the proposal distribution. Below is an example of a state transition function based on the velocity motion model of a unicycle-like robot. For more details about this motion model, please see Chapter 5 in [1]. Decrease `sd1`, `sd2` and `sd3` to see how the tracking performance deteriorates. Here `sd1` represents the uncertainty in the linear velocity, `sd2` represents the uncertainty in the angular velocity. `sd3` is an additional perturbation on the orientation.

```
function predictParticles = exampleHelperCarBotStateTransition(pf, prevParticles, dT, u)

    thetas = prevParticles(:,3);

    w = u(2);
    v = u(1);

    l = length(prevParticles);

    % Generate velocity samples
    sd1 = 0.3;
    sd2 = 1.5;
    sd3 = 0.02;
    vh = v + (sd1)^2*randn(l,1);
    wh = w + (sd2)^2*randn(l,1);
    gamma = (sd3)^2*randn(l,1);

    % Add a small number to prevent div/0 error
    wh(abs(wh)<1e-19) = 1e-19;

    % Convert velocity samples to pose samples
    predictParticles(:,1) = prevParticles(:,1) - (vh./wh).*sin(thetas) + (vh./wh).*sin(thetas + wh*dT);
    predictParticles(:,2) = prevParticles(:,2) + (vh./wh).*cos(thetas) - (vh./wh).*cos(thetas + wh*dT);
    predictParticles(:,3) = prevParticles(:,3) + wh*dT + gamma*dT;
    predictParticles(:,4) = (- (vh./wh).*sin(thetas) + (vh./wh).*sin(thetas + wh*dT))/dT;
    predictParticles(:,5) = ( (vh./wh).*cos(thetas) - (vh./wh).*cos(thetas + wh*dT))/dT;
    predictParticles(:,6) = wh + gamma;

end
```

Measurement Likelihood Function

The measurement likelihood function computes the likelihood for each predicted particle based on the error norm between particle and the measurement. The importance weight for each particle will be assigned based on the computed likelihood. In this particular example, `predictParticles` is a $N \times 6$ matrix (N is the number of particles), and `measurement` is a 1×3 vector.

```
function likelihood = exampleHelperCarBotMeasurementLikelihood(pf, predictParticles, measurement)

    % The measurement contains all state variables
    predictMeasurement = predictParticles;

    % Calculate observed error between predicted and actual measurement
    % NOTE in this example, we don't have full state observation, but only
```

```
% the measurement of current pose, therefore the measurementErrorNorm
% is only based on the pose error.
measurementError = bsxfun(@minus, predictMeasurement(:,1:3), measurement);
measurementErrorNorm = sqrt(sum(measurementError.^2, 2));

% Normal-distributed noise of measurement
% Assuming measurements on all three pose components have the same error distribution
measurementNoise = eye(3);

% Convert error norms into likelihood measure.
% Evaluate the PDF of the multivariate normal distribution
likelihood = 1/sqrt((2*pi).^3 * det(measurementNoise)) * exp(-0.5 * measurementErrorNorm)

end
```

Reference

[1] S. Thrun, W. Burgard, D. Fox, Probabilistic Robotics, MIT Press, 2006

Simulate Different Kinematic Models for Mobile Robots

This example shows how to model different robot kinematics models in an environment and compare them.

Define Mobile Robots with Kinematic Constraints

There are a number of ways to model the kinematics of mobile robots. All dictate how the wheel velocities are related to the robot state: $[x \ y \ \theta]$, as xy -coordinates and a robot heading, θ , in radians.

Unicycle Kinematic Model

The simplest way to represent mobile robot vehicle kinematics is with a unicycle model, which has a wheel speed set by a rotation about a central axle, and can pivot about its z -axis. Both the differential-drive and bicycle kinematic models reduce down to unicycle kinematics when inputs are provided as vehicle speed and vehicle heading rate and other constraints are not considered.

```
unicycle = unicycleKinematics("VehicleInputs", "VehicleSpeedHeadingRate");
```

Differential-Drive Kinematic Model

The differential drive model uses a rear driving axle to control both vehicle speed and head rate. The wheels on the driving axle can spin in both directions. Since most mobile robots have some interface to the low-level wheel commands, this model will again use vehicle speed and heading rate as input to simplify the vehicle control.

```
diffDrive = differentialDriveKinematics("VehicleInputs", "VehicleSpeedHeadingRate");
```

To differentiate the behavior from the unicycle model, add a wheel speed velocity constraint to the differential-drive kinematic model

```
diffDrive.WheelSpeedRange = [-10 10]*2*pi;
```

Bicycle Kinematic Model

The bicycle model treats the robot as a car-like model with two axles: a rear driving axle, and a front axle that turns about the z -axis. The bicycle model works under the assumption that wheels on each axle can be modeled as a single, centered wheel, and that the front wheel heading can be directly set, like a bicycle.

```
bicycle = bicycleKinematics("VehicleInputs", "VehicleSpeedHeadingRate", "MaxSteeringAngle", pi/8);
```

Other Models

The Ackermann kinematic model is a modified car-like model that assumes Ackermann steering. In most car-like vehicles, the front wheels do not turn about the same axis, but instead turn on slightly different axes to ensure that they ride on concentric circles about the center of the vehicle's turn. This difference in turning angle is called Ackermann steering, and is typically enforced by a mechanism in actual vehicles. From a vehicle and wheel kinematics standpoint, it can be enforced by treating the steering angle as a rate input.

```
carLike = ackermannKinematics;
```

Set up Simulation Parameters

These mobile robots will follow a set of waypoints that is designed to show some differences caused by differing kinematics.

```
waypoints = [0 0; 0 10; 10 10; 5 10; 11 9; 4 -5];
% Define the total time and the sample rate
sampleTime = 0.05;           % Sample time [s]
tVec = 0:sampleTime:20;     % Time array

initPose = [waypoints(1,:)'; 0]; % Initial pose (x y theta)
```

Create a Vehicle Controller

The vehicles follow a set of waypoints using a Pure Pursuit controller. Given a set of waypoints, the robot current state, and some other parameters, the controller outputs vehicle speed and heading rate.

```
% Define a controller. Each robot requires its own controller
controller1 = controllerPurePursuit("Waypoints",waypoints,"DesiredLinearVelocity",3,"MaxAngularVelocity",3);
controller2 = controllerPurePursuit("Waypoints",waypoints,"DesiredLinearVelocity",3,"MaxAngularVelocity",3);
controller3 = controllerPurePursuit("Waypoints",waypoints,"DesiredLinearVelocity",3,"MaxAngularVelocity",3);
```

Simulate the Models Using an ODE Solver

The models are simulated using the derivative function to update the state. This example uses an ordinary differential equation (ODE) solver to generate a solution. Another way would be to update the state using a loop, as shown in “Path Following for a Differential Drive Robot” on page 1-10.

Since the ODE solver requires all outputs to be provided as a single output, the pure pursuit controller must be wrapped in a function that outputs the linear velocity and heading angular velocity as a single output. An example helper, `exampleHelperMobileRobotController`, is used for that purpose. The example helper also ensures that the robot stops when it is within a specified radius of the goal.

```
goalPoints = waypoints(end,:)';
goalRadius = 1;
```

`ode45` is called once for each type of model. The derivative function computes the state outputs with initial state set by `initPose`. Each derivative accepts the corresponding kinematic model object, the current robot pose, and the output of the controller at that pose.

```
% Compute trajectories for each kinematic model under motion control
[tUnicycle,unicyclePose] = ode45(@(t,y)derivative(unicycle,y,exampleHelperMobileRobotController(controller1,y,goalPoints,goalRadius)),tVec,initPose);
[tBicycle,bicyclePose] = ode45(@(t,y)derivative(bicycle,y,exampleHelperMobileRobotController(controller2,y,goalPoints,goalRadius)),tVec,initPose);
[tDiffDrive,diffDrivePose] = ode45(@(t,y)derivative(diffDrive,y,exampleHelperMobileRobotController(controller3,y,goalPoints,goalRadius)),tVec,initPose);
```

Plot Results

The results of the ODE solver can be easily viewed on a single plot using `plotTransforms` to visualize the results of all trajectories at once.

The pose outputs must first be converted to indexed matrices of translations and quaternions.

```
unicycleTranslations = [unicyclePose(:,1:2) zeros(length(unicyclePose),1)];
unicycleRot = axang2quat([repmat([0 0 1],length(unicyclePose),1) unicyclePose(:,3)]);
```

```

bicycleTranslations = [bicyclePose(:,1:2) zeros(length(bicyclePose),1)];
bicycleRot = axang2quat([repmat([0 0 1],length(bicyclePose),1) bicyclePose(:,3)]);

diffDriveTranslations = [diffDrivePose(:,1:2) zeros(length(diffDrivePose),1)];
diffDriveRot = axang2quat([repmat([0 0 1],length(diffDrivePose),1) diffDrivePose(:,3)]);

```

Next, the set of all transforms can be plotted and viewed from the top. The paths of the unicycle, bicycle, and differential-drive robots are red, blue, and green, respectively. To simplify the plot, only show every tenth output.

```

figure
plot(waypoints(:,1),waypoints(:,2),"kx-","MarkerSize",20);
hold all
plotTransforms(unicycleTranslations(1:10:end,:),unicycleRot(1:10:end:),'MeshFilePath','groundvel
plotTransforms(bicycleTranslations(1:10:end,:),bicycleRot(1:10:end:),'MeshFilePath','groundvehic
plotTransforms(diffDriveTranslations(1:10:end,:),diffDriveRot(1:10:end:),'MeshFilePath','ground
view(0,90)

```



Control A Differential-Drive Robot in Gazebo With Simulink

This example shows how to control a differential drive robot in Gazebo co-simulation using Simulink. The robot follows a set of waypoints by reading the pose and wheel encoder positions and generates torque-control commands to drive it.

To download the virtual machine (VM) used in this example, see [Virtual Machine with ROS and Gazebo](#).

For an introduction to Gazebo co-simulation and getting connected for the first time, see “Perform Co-Simulation between Simulink and Gazebo” on page 1-257.

Run the VM

Open the virtual machine installed from [Virtual Machine with ROS and Gazebo](#).

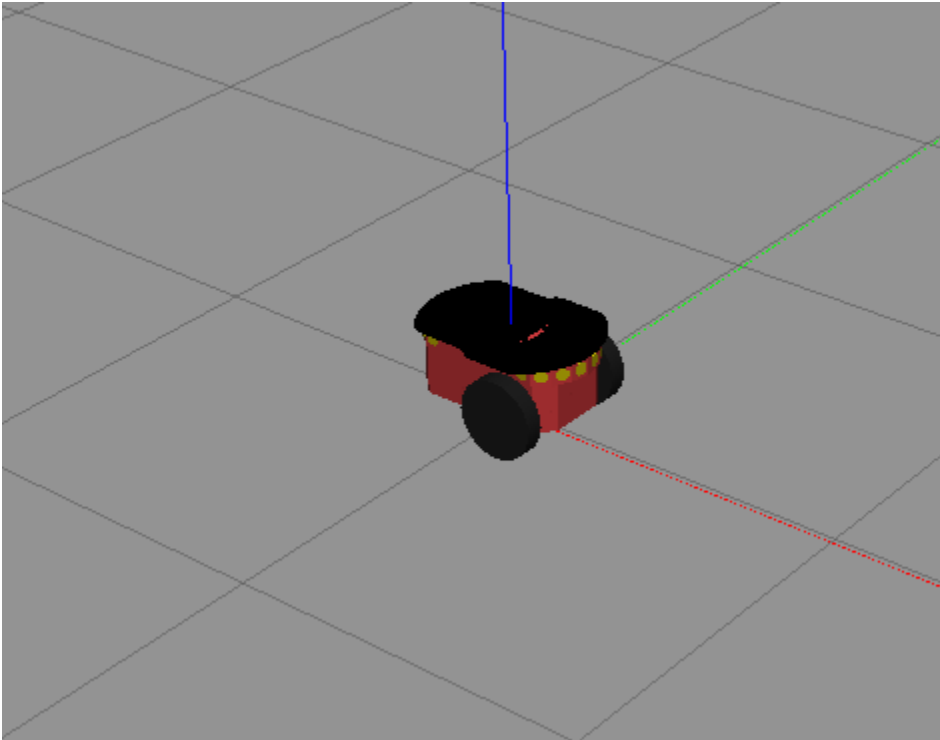
Gazebo World

This example uses a world given in the VM, `differentialDriveRobot.world`, as a simple ground plane with default physics settings. The world uses a Pioneer robot with the default controllers removed, so that the built-in controllers do not compete with torques provided from Simulink. The Pioneer robot is available in default Gazebo installs. The Gazebo plugin references the plugin required for the connection to Simulink, as detailed in “Perform Co-Simulation between Simulink and Gazebo” on page 1-257.

Double-click the **Gazebo Differential Drive Robot** icon.

Alternative, run these commands in the terminal:

```
cd /home/user/src/GazeboPlugin/export
export SVGA_VGPU10=0
gazebo ../world/differentialDriveRobot.world
```



Model Overview

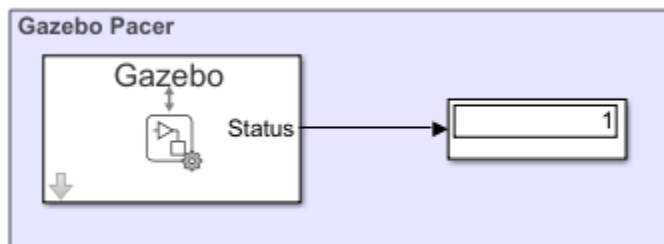
Open the model:

```
open_system('GazeboDifferentialDriveControl')
```

The model has four sections:

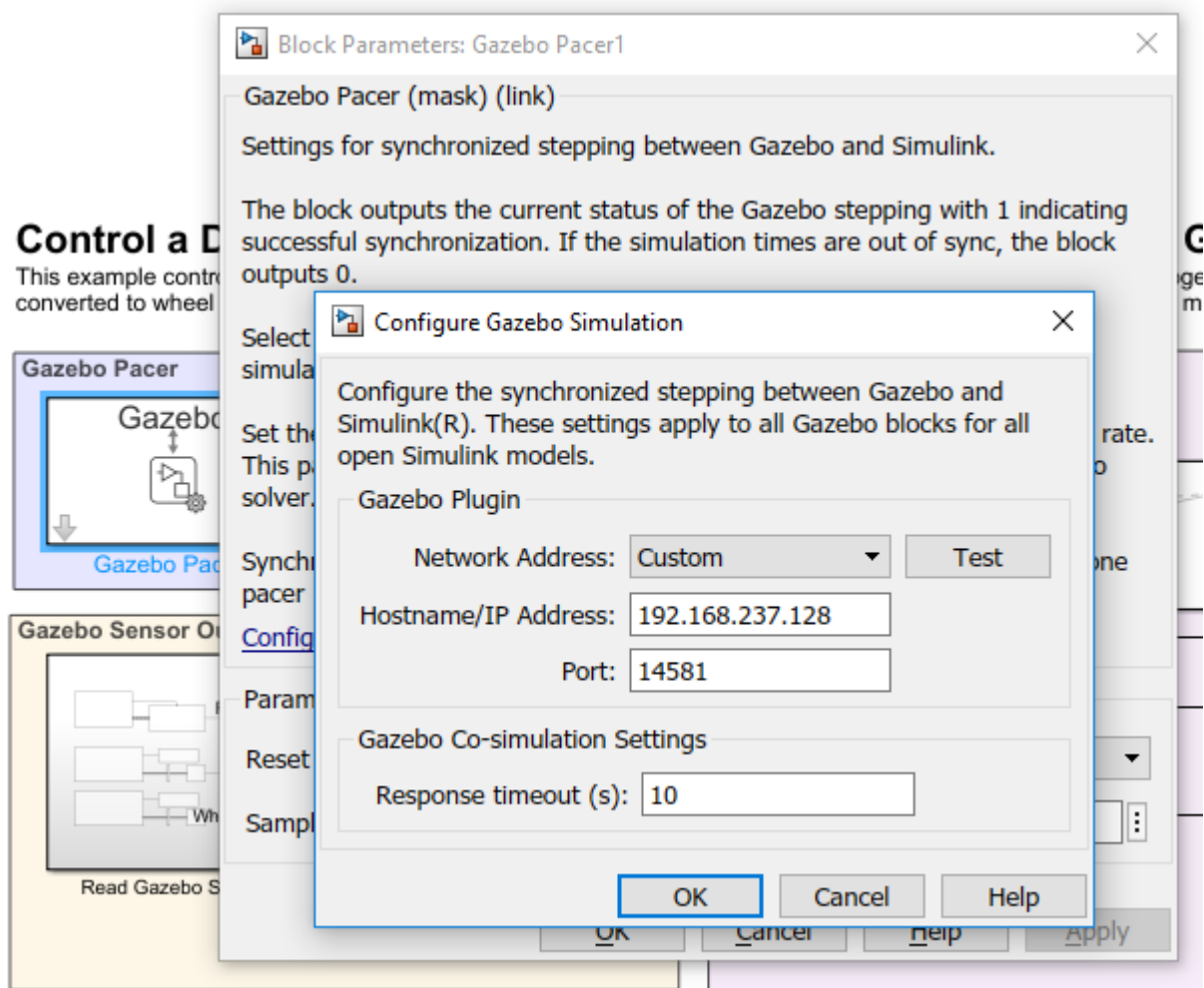
- Gazebo Pacer
- Read Sensor Data
- Control Mobile Robot
- Send Actuation Data to Gazebo

Gazebo Pacer



This section establishes the connection to Gazebo. Double-click the **Gazebo Pacer** block to open its parameters, and then click the **Configure Gazebo network and simulation settings** link. This will open a dialog.

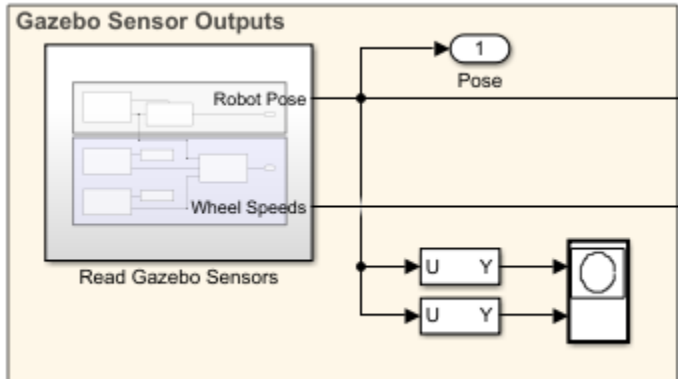
Specify the **IP Address** for your VM. By default, Gazebo connects on the 14581 port. Click the **Test** button to verify the connection to Gazebo.



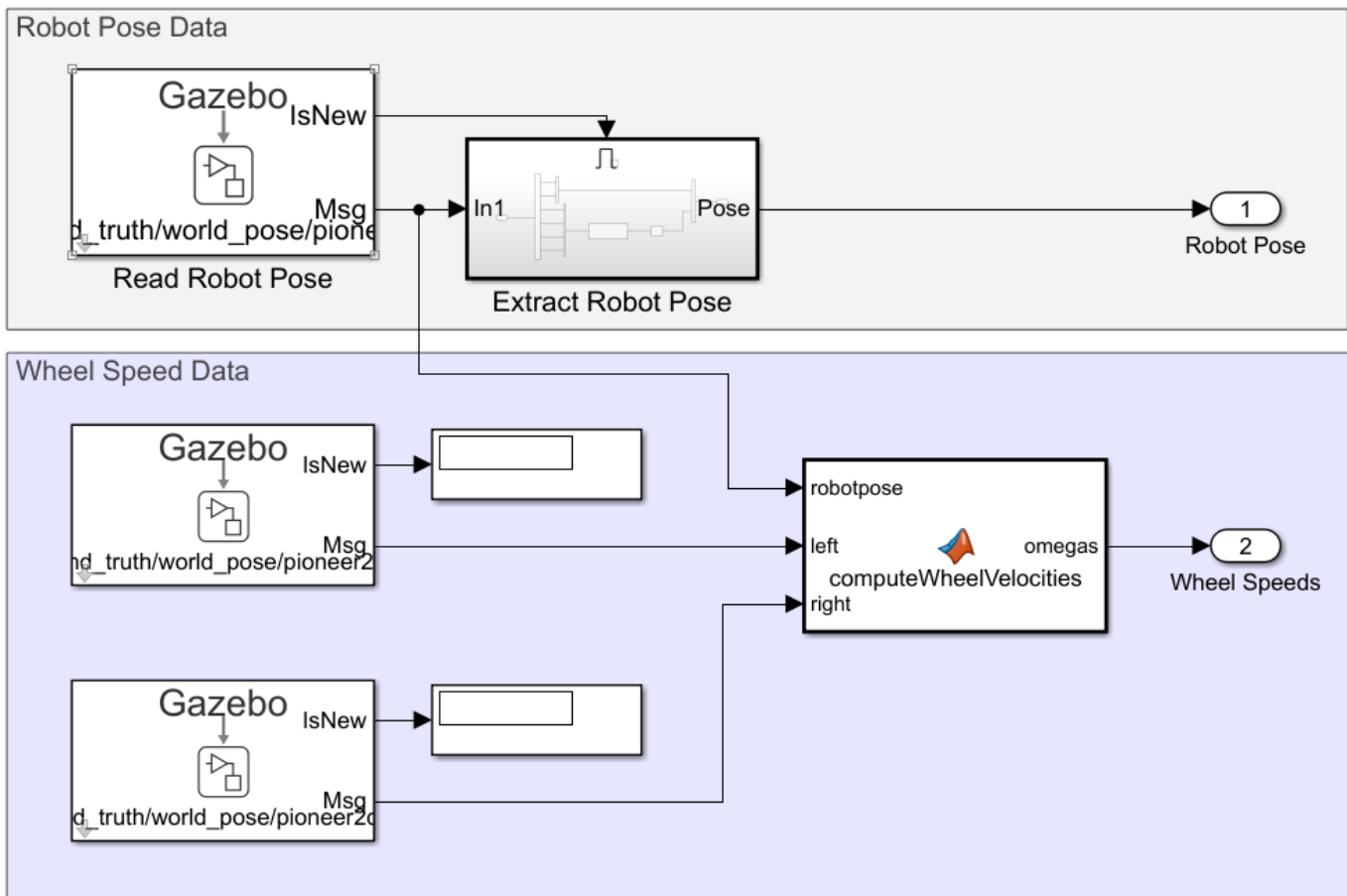
If the test is not successful, make sure to check the instructions in “Perform Co-Simulation between Simulink and Gazebo” on page 1-257 and ensure that Gazebo is properly configured and the associated world is up and running.

Gazebo Sensor Outputs

The sensor outputs read sensor data from Gazebo and passes it to the appropriate Simulink blocks. An XY graph plots the current robot position, and pose data is saved to the simulation output.

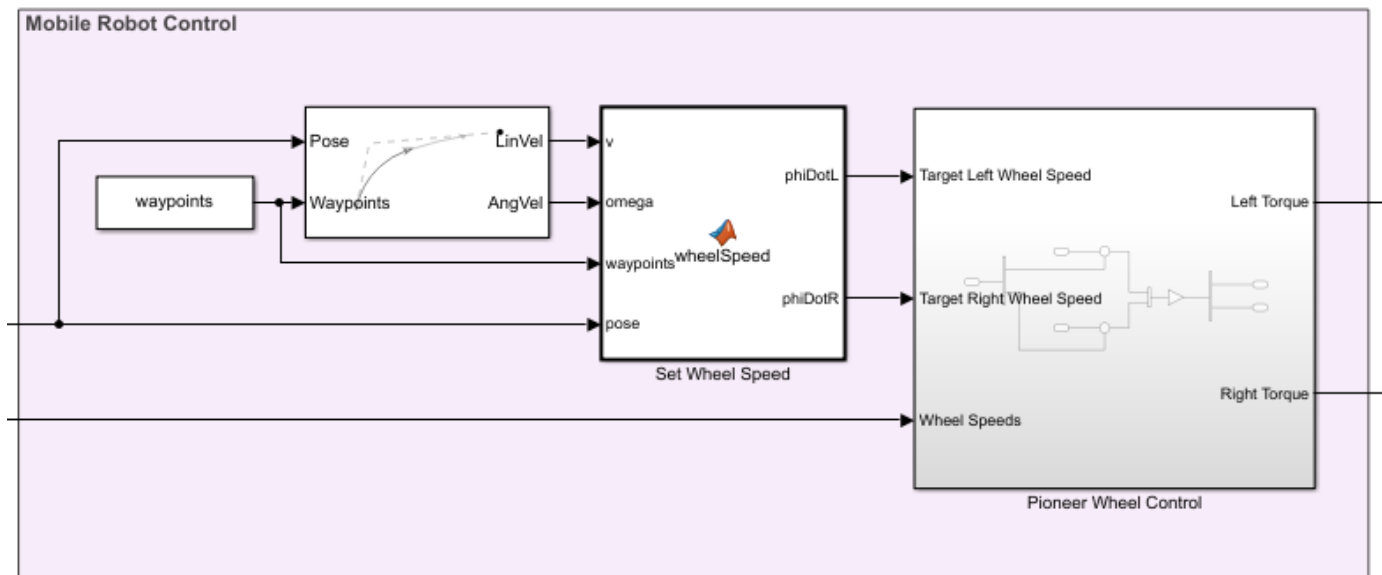


The **Read Gazebo Sensors** subsystem extracts the robot pose and wheel sensor data. The pose data are the xy-coordinates and a four-element quaternion for orientation. The wheel speeds are computed based on rate of change of the wheel positions as they rotate.



Mobile Robot Control

The **Mobile Robot Control** section accepts a set of target waypoints, current pose, and the current wheel speeds, and outputs the wheel torques needed to have the robot follow a path that pursues the waypoints.



There are three main components.

The **Pure Pursuit** block is a controller that specifies the vehicle speed and heading angular velocity of the vehicle needed to follow the waypoints at a fixed speed, given the current pose.

The **Set Wheel Speed** MATLAB Function block converts vehicle speed and heading angular velocity to left and right wheel speed, using the kinematics of a differential-drive robot:

$$\dot{\phi}_L = \frac{1}{r} \left(v - \frac{\omega d}{2} \right)$$

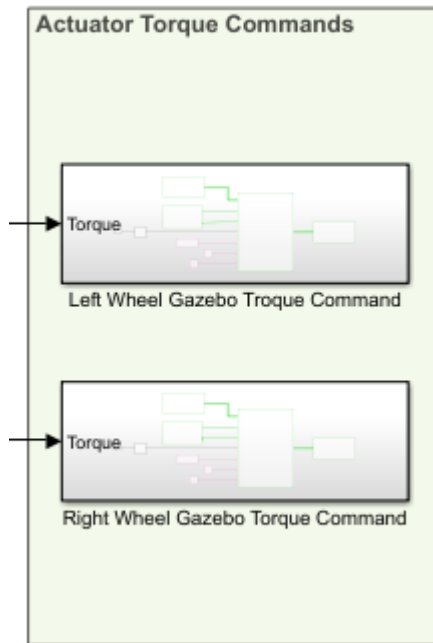
$$\dot{\phi}_R = \frac{1}{r} \left(v + \frac{\omega d}{2} \right)$$

$\dot{\phi}_L$ and $\dot{\phi}_R$ are the left and right wheel speeds, v is the vehicle speed, ω is the vehicle heading angular velocity, d is the track width, and r is the wheel radius. Additionally, this MATLAB® Function includes code to throttle the wheel speed. Since the **Pure Pursuit** block uses a fixed speed throughout, inside the MATLAB Function block, there are two if-statements. The first slows the velocity at a rate proportional to the distance to the goal when the robot is within a certain distance threshold. The second if-statement stops the robot when it is within a tight threshold. This helps the robot to come to a gentle stop.

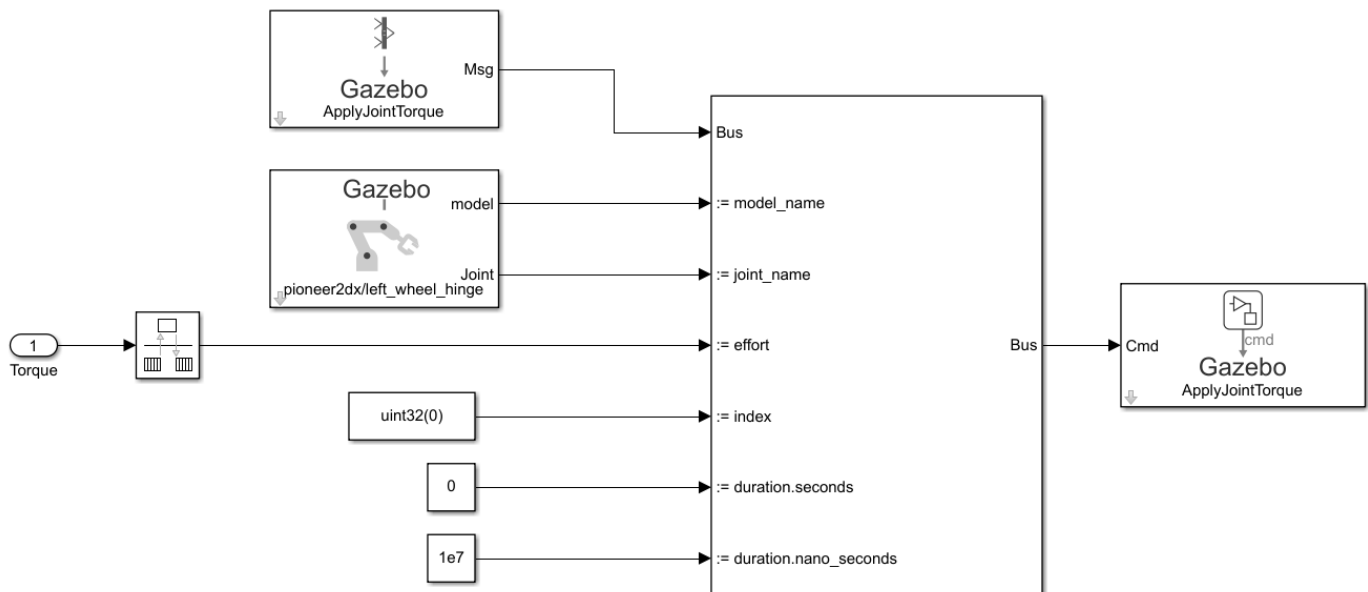
Finally, the **Pioneer Wheel Control** subsystem converts the desired wheel speeds to torques using a proportional controller.

Actuator Torque Commands

The last section of the model takes the torque commands produced by the controller and sends it to Simulink using blocks from the **Gazebo Co-Simulation Library**.



Inside each of the subsystems in this block, a **Bus Assignment** block is used to assign the joint torque to the correct joint.



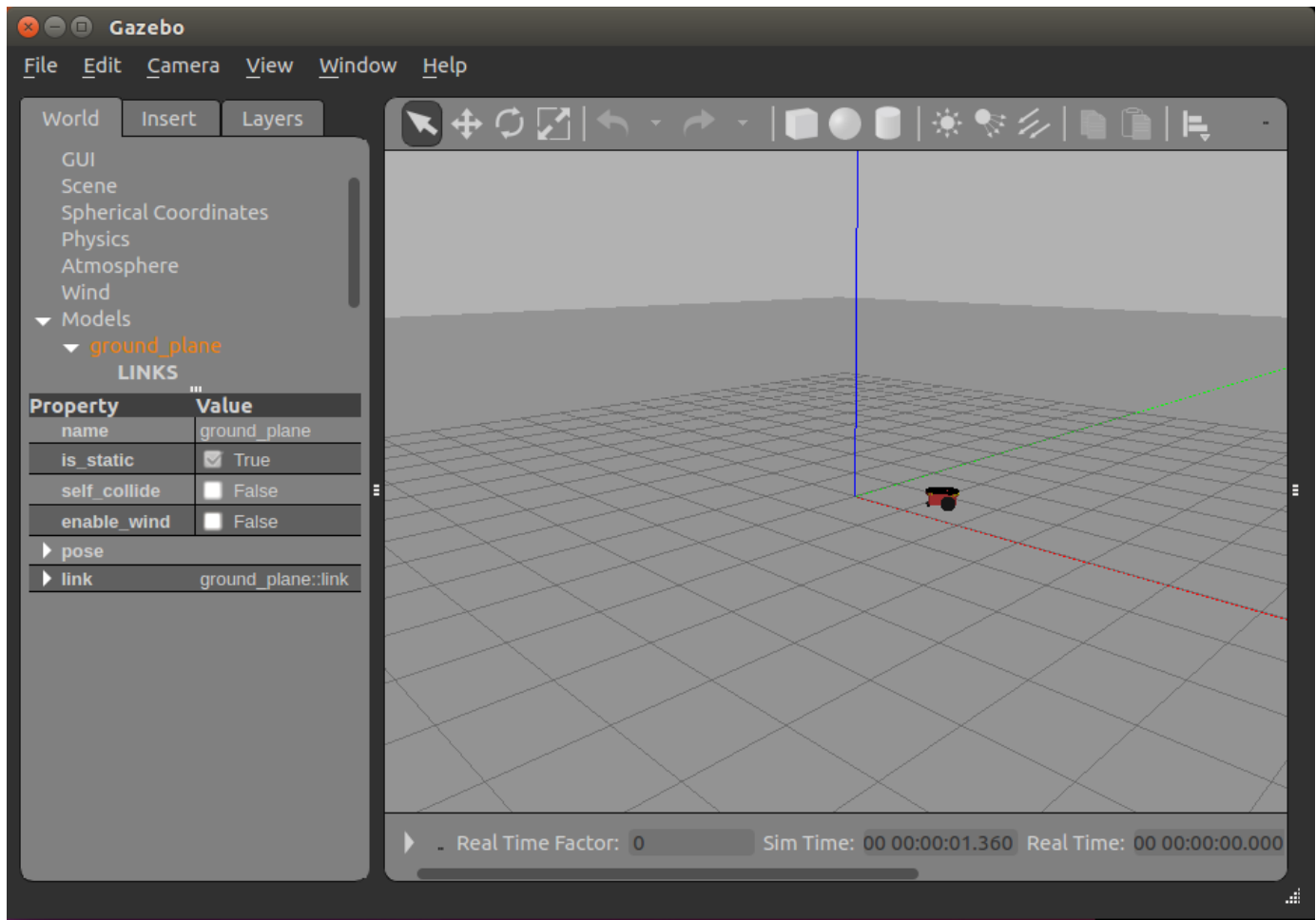
For example, inside the **Left Wheel Gazebo Torque Command** subsystem, shown above, a **Gazebo Blank Message** with the `ApplyJointTorque` command type is used to specify the bus type. The model and joint name are provided by the **Gazebo Select Entity** block, which is linked to the joint associated with the left wheel in the Gazebo world, `left_wheel_hinge`. The torque is applied for the entire step time, 0.01 seconds, specified in nanoseconds since these inputs must be provided as integers. The output of the bus is passed to a **Gazebo Apply Command** block.

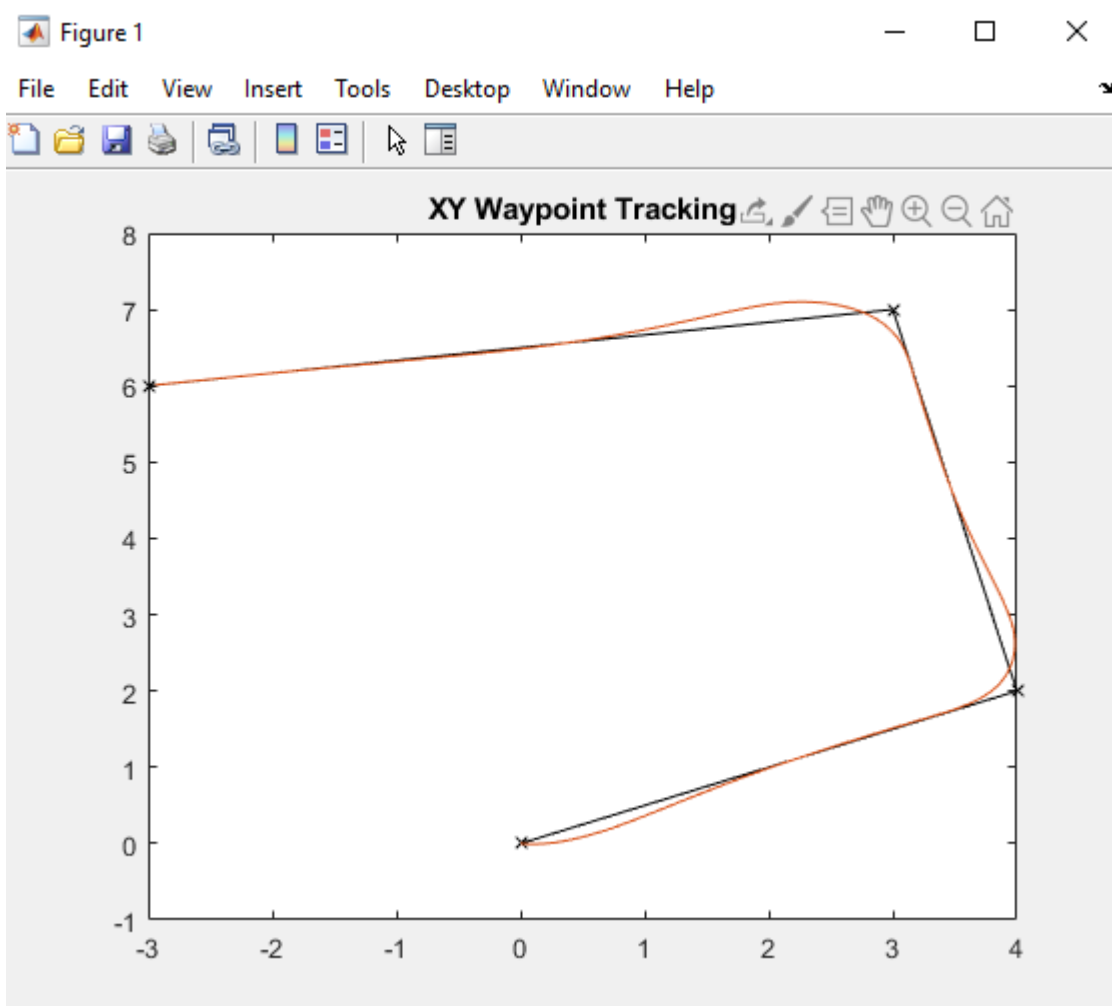
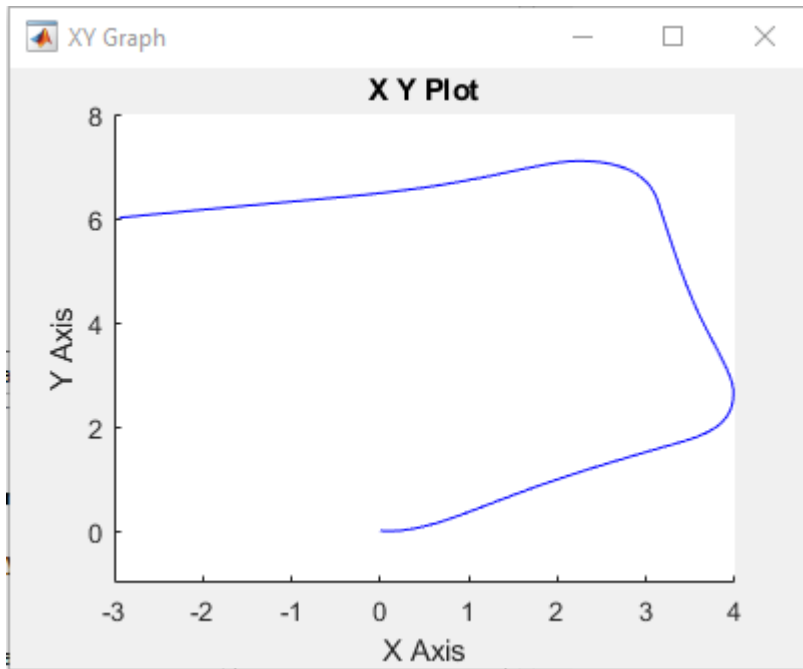
Simulate the robot

To run the model, initialize the waypoints and set the sample time:

```
waypoints = [0 0; 4 2; 3 7; -3 6];  
sampleTime = 0.01;
```

Click **Play** button or use the `sim` command to run the model. During execution, the robot should move in Gazebo, and an **XY Plot** updates the pose observed in Simulink.





The figures plot the set of waypoints and the final executed path of the robot.

Avoid Obstacles using Reinforcement Learning for Mobile Robots

This example uses Deep Deterministic Policy Gradient (DDPG) based reinforcement learning to develop a strategy for a mobile robot to avoid obstacles. For a brief summary of the DDPG algorithm, see “Deep Deterministic Policy Gradient Agents” (Reinforcement Learning Toolbox).

This example scenario trains a mobile robot to avoid obstacles given range sensor readings that detect obstacles in the map. The objective of the reinforcement learning algorithm is to learn what controls (linear and angular velocity), the robot should use to avoid colliding into obstacles. This example uses an occupancy map of a known environment to generate range sensor readings, detect obstacles, and check collisions the robot may make. The range sensor readings are the observations for the DDPG agent, and the linear and angular velocity controls are the action.

Map

Load a map matrix, `simpleMap`, that represents the environment for the robot.

```
load exampleMaps simpleMap
load exampleHelperOfficeAreaMap office_area_map
mapMatrix = simpleMap;
mapScale = 1;
```

Range Sensor Parameters

Next, set up a `rangeSensor` object which simulates a noisy range sensor. The range sensor readings are considered observations by the agent. Define the angular positions of the range readings, the max range, and the noise parameters.

```
scanAngles = [-3*pi/8 : pi/8 :3*pi/8];
maxRange = 12;
lidarNoiseVariance = 0.1^2;
lidarNoiseSeeds = randi(intmax,size(scanAngles));
```

Robot Parameters

The action of the agent is a two-dimensional vector $a = [v, \omega]$ where v and ω are the linear and angular velocities of our robot. The DDPG agent uses normalized inputs for both the angular and linear velocities, meaning the actions of the agent are a scalar between -1 and 1, which is multiplied by the `maxLinSpeed` and `maxAngSpeed` parameters to get the actual control. Specify this maximum linear and angular velocity.

Also, specify the initial position of the robot as `[x y theta]`.

```
% Max speed parameters
maxLinSpeed = 0.3;
maxAngSpeed = 0.3;

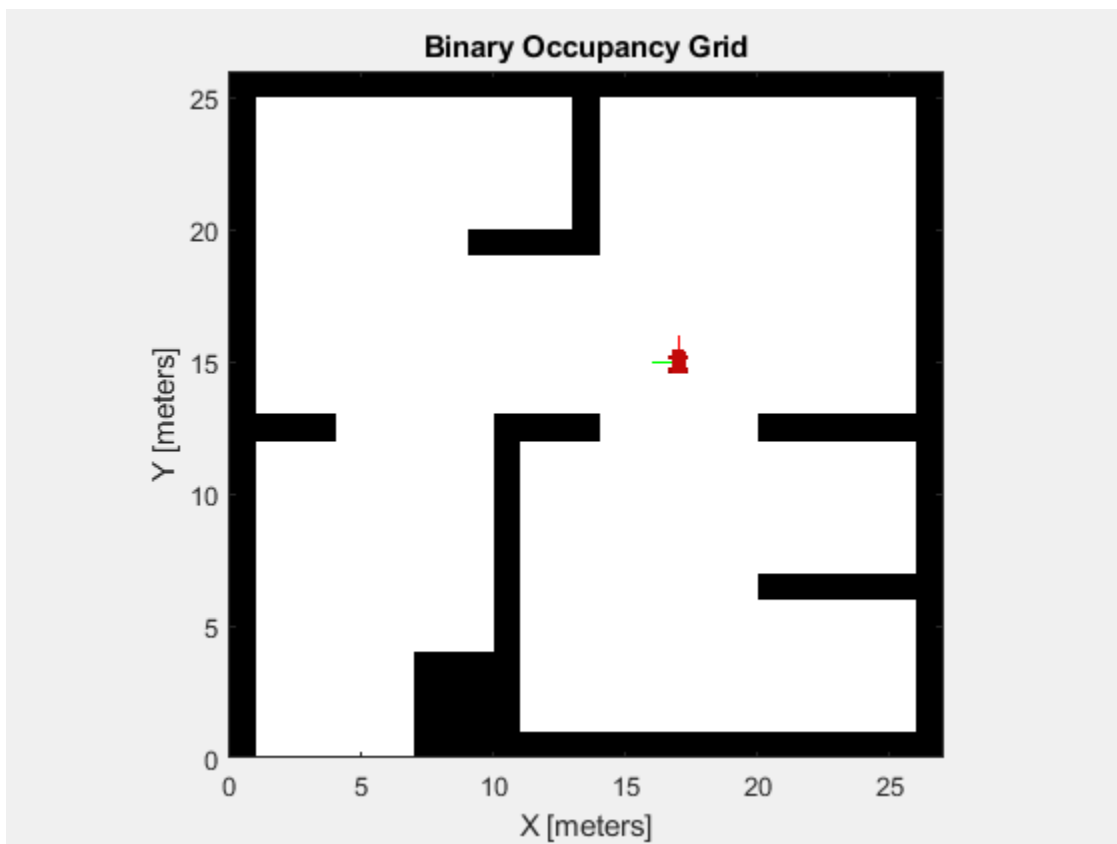
% Initial pose of the robot
initX = 17;
initY = 15;
initTheta = pi/2;
```

Visualization

To visualize the actions of the robot, create a figure. Start by showing the occupancy map and plot the initial position of the robot.

```
fig = figure("Name","simpleMap");
set(fig, "Visible", "on");
ax = axes(fig);

show(binaryOccupancyMap(mapMatrix), "Parent", ax);
hold on
plotTransforms([initX, initY, 0], eul2quat([initTheta, 0, 0]), "MeshFilePath", "groundvehicle.stl", "Parent", ax);
light;
hold off
```



Environment Interface

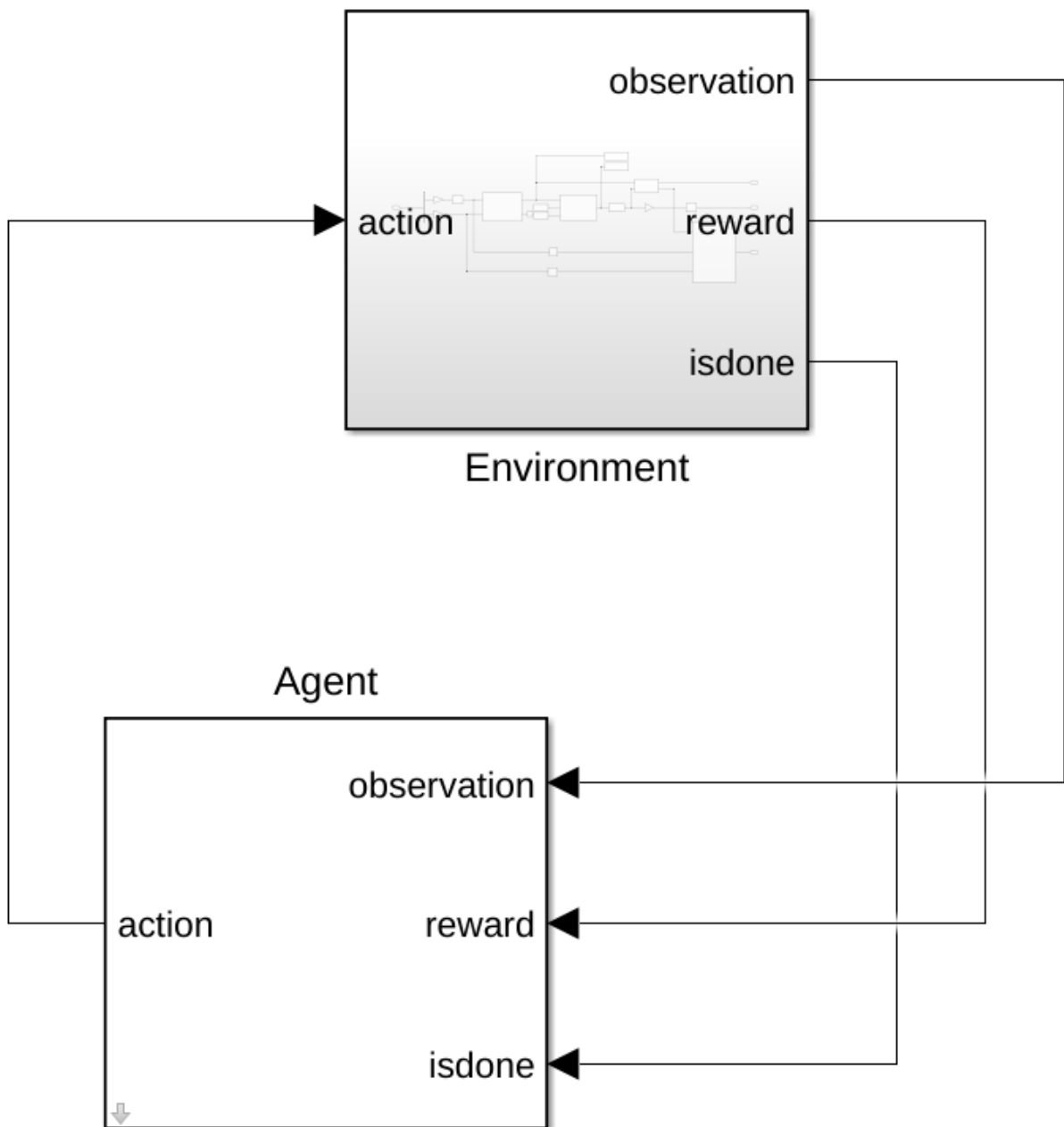
Create an environment model that takes the action, and gives the observation and reward signals. Specify the provided example model name, `exampleHelperAvoidObstaclesMobileRobot`, the simulation time parameters, and the agent block name.

```
mdl = "exampleHelperAvoidObstaclesMobileRobot";
Tfinal = 100;
sampleTime = 0.1;
```

```
agentBlk = mdl + "/Agent";
```

Open the model.

```
open_system mdl
```



The model contains the Environment and Agent blocks. The Agent block is not defined yet.

Inside the Environment Subsystem block, you should see a model for simulating the robot and sensor data. The subsystem takes in the action, generates the observation signal based on the range sensor readings, and calculates the reward based on the distance from obstacles, and the effort of the action commands.

```
open_system mdl + "/Environment")
```

Define observation parameters, `obsInfo`, using the `rlNumericSpec` object and giving the lower and upper limit for the range readings with enough elements for each angular position in the range sensor.

```
obsInfo = rlNumericSpec([numel(scanAngles) 1],...
    "LowerLimit",zeros(numel(scanAngles),1),...
    "UpperLimit",ones(numel(scanAngles),1)*maxRange);
numObservations = obsInfo.Dimension(1);
```

Define action parameters, `actInfo`. The action is the control command vector, $a = [v, \omega]$, normalized to $[-1, 1]$.

```
numActions = 2;
actInfo = rlNumericSpec([numActions 1],...
    "LowerLimit",-1,...
    "UpperLimit",1);
```

Build the environment interface object using `rlSimulinkEnv` (Reinforcement Learning Toolbox). Specify the model, agent block name, observation parameters, and action parameters. Set the reset function for the simulation using `exampleHelperRLAvoidObstaclesResetFcn`. This function restarts the simulation by placing the robot in a new random location to begin avoiding obstacles.

```
env = rlSimulinkEnv mdl,agentBlk,obsInfo,actInfo);
env.ResetFcn = @(in)exampleHelperRLAvoidObstaclesResetFcn(in,scanAngles,maxRange,mapMatrix);
env.UseFastRestart = "Off";
```

For another example that sets up a Simulink® environment for training, see “Create Simulink Environment and Train Agent” (Reinforcement Learning Toolbox).

DDPG Agent

A DDPG agent approximates the long-term reward given observations and actions using a critic value function representation. To create the critic, first create a deep neural network with two inputs, the observation and action, and one output. For more information on creating a deep neural network value function representation, see “Create Policy and Value Function Representations” (Reinforcement Learning Toolbox).

```
statePath = [
    featureInputLayer(numObservations, "Normalization", "none", "Name", "State")
    fullyConnectedLayer(50, "Name", "CriticStateFC1")
    reluLayer("Name", "CriticRelu1")
    fullyConnectedLayer(25, "Name", "CriticStateFC2)];
actionPath = [
    featureInputLayer(numActions, "Normalization", "none", "Name", "Action")
    fullyConnectedLayer(25, "Name", "CriticActionFC1)];
commonPath = [
    additionLayer(2, "Name", "add")
    reluLayer("Name", "CriticCommonRelu")
    fullyConnectedLayer(1, "Name", "CriticOutput)];

criticNetwork = layerGraph();
criticNetwork = addLayers(criticNetwork,statePath);
criticNetwork = addLayers(criticNetwork,actionPath);
criticNetwork = addLayers(criticNetwork,commonPath);
criticNetwork = connectLayers(criticNetwork,"CriticStateFC2","add/in1");
criticNetwork = connectLayers(criticNetwork,"CriticActionFC1","add/in2");
```


Next, specify options for the critic representation using `rlRepresentationOptions` (Reinforcement Learning Toolbox).

Finally, create the critic representation using the specified deep neural network and options. You must also specify the action and observation specifications for the critic, which you obtain from the environment interface. For more information, see `rlQValueRepresentation` (Reinforcement Learning Toolbox).

```
criticOpts = rlRepresentationOptions("LearnRate",1e-3,"L2RegularizationFactor",1e-4,"GradientThreshold",1e-4);
critic = rlQValueRepresentation(criticNetwork,obsInfo,actInfo,"Observation",{ 'State' },"Action",{ 'Action' },{ 'Action' },{ 'Action' });
```

A DDPG agent decides which action to take given observations using an actor representation. To create the actor, first create a deep neural network with one input, the observation, and one output, the action.

Finally, construct the actor in a similar manner as the critic. For more information, see `rlDeterministicActorRepresentation` (Reinforcement Learning Toolbox).

```
actorNetwork = [
    featureInputLayer(numObservations, "Normalization", "none", "Name", "State")
    fullyConnectedLayer(50, "Name", "actorFC1")
    reluLayer("Name","actorReLU1")
    fullyConnectedLayer(50, "Name", "actorFC2")
    reluLayer("Name","actorReLU2")
    fullyConnectedLayer(2, "Name", "actorFC3")
    tanhLayer("Name", "Action")];
```

```
actorOptions = rlRepresentationOptions("LearnRate",1e-4,"L2RegularizationFactor",1e-4,"GradientThreshold",1e-4);
actor = rlDeterministicActorRepresentation(actorNetwork,obsInfo,actInfo,"Observation",{ 'State' },"Action",{ 'Action' },{ 'Action' },{ 'Action' });
```

Create DDPG agent object

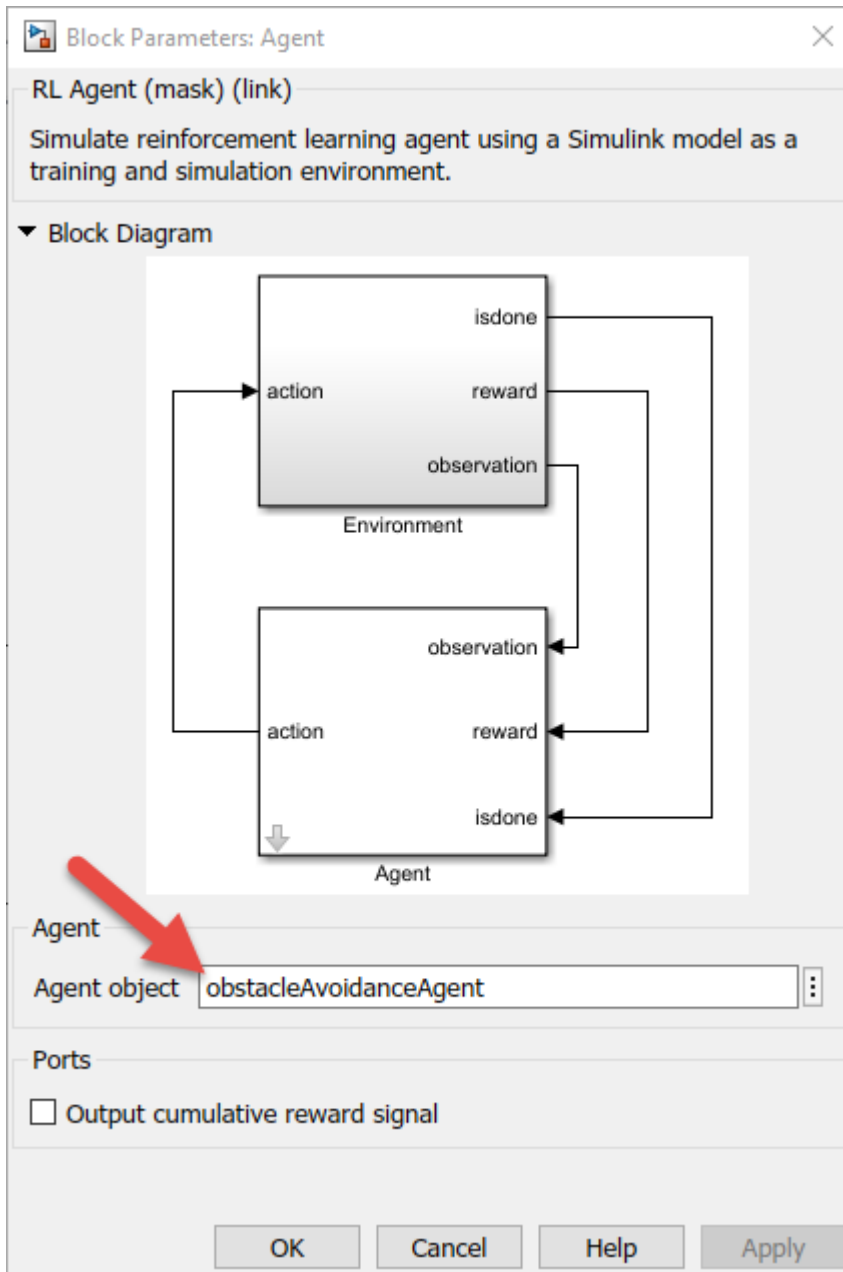
Specify the agent options.

```
agentOpts = rlDDPGAgentOptions(...
    "SampleTime",sampleTime,...
    "TargetSmoothFactor",1e-3,...
    "DiscountFactor",0.995, ...
    "MiniBatchSize",128, ...
    "ExperienceBufferLength",1e6);
```

```
agentOpts.NoiseOptions.Variance = 0.1;
agentOpts.NoiseOptions.VarianceDecayRate = 1e-5;
```

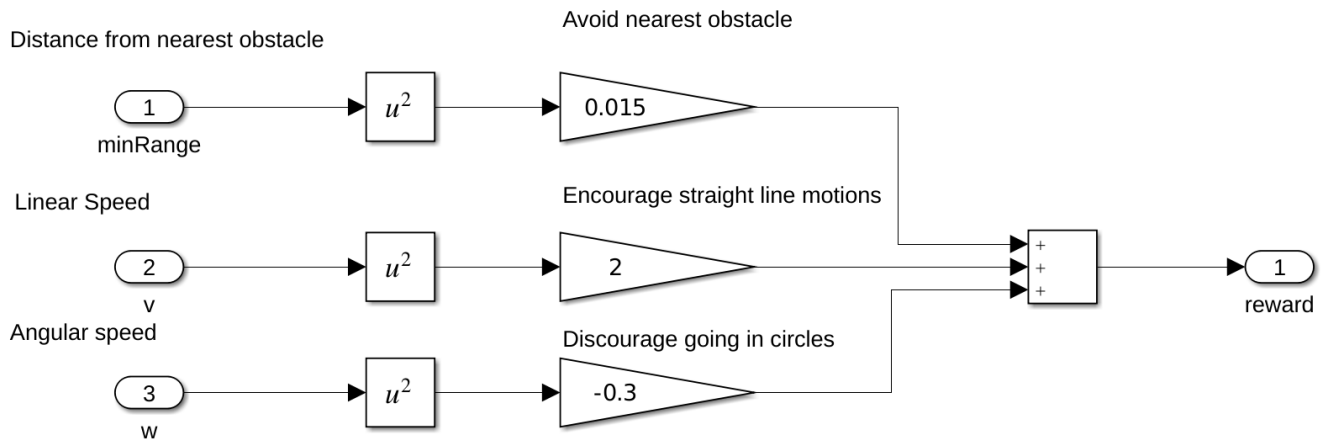
Create the `rlDDPGAgent` object. The `obstacleAvoidanceAgent` variable is used in the model for the Agent block.

```
obstacleAvoidanceAgent = rlDDPGAgent(actor,critic,agentOpts);
open_system mdl + "/Agent")
```



Reward

The reward function for the agent is modeled as shown.



The agent is rewarded to avoid the nearest obstacle, which minimizes the worst-case scenario. Additionally, the agent is given a positive reward for higher linear speeds, and is given a negative reward for higher angular speeds. This rewarding strategy discourages the agent's behavior of going in circles. Tuning your rewards is key to properly training an agent, so your rewards vary depending on your application.

Train Agent

To train the agent, first specify the training options. For this example, use the following options:

- Train for at most 10000 episodes, with each episode lasting at most `maxSteps` time steps.
- Display the training progress in the Episode Manager dialog box (set the `Plots` option) and enable the command line display (set the `Verbose` option to true).
- Stop training when the agent receives an average cumulative reward greater than 400 over fifty consecutive episodes.

For more information, see `rlTrainingOptions` (Reinforcement Learning Toolbox).

```
maxEpisodes = 10000;
maxSteps = ceil(Tfinal/sampleTime);
trainOpts = rlTrainingOptions(...
    "MaxEpisodes",maxEpisodes, ...
    "MaxStepsPerEpisode",maxSteps, ...
    "ScoreAveragingWindowLength",50, ...
    "StopTrainingCriteria","AverageReward", ...
    "StopTrainingValue",400, ...
    "Verbose", true, ...
    "Plots","training-progress");
```

Train the agent using the `train` (Reinforcement Learning Toolbox) function. Training is a computationally-intensive process that takes several minutes to complete. To save time while running this example, load a pretrained agent by setting `doTraining` to `false`. To train the agent yourself, set `doTraining` to `true`.

```
doTraining = false; % Toggle this to true for training.
```

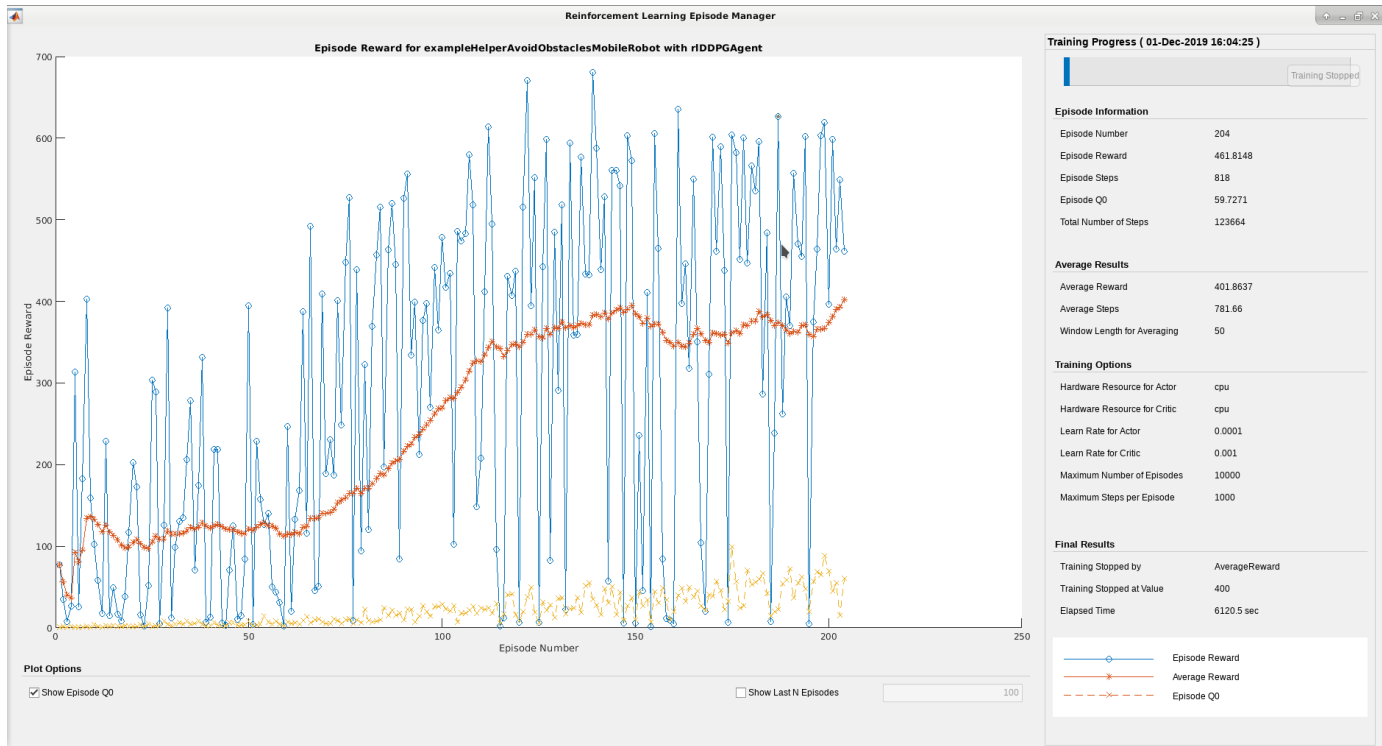
```
if doTraining
```

```

% Train the agent.
trainingStats = train(obstacleAvoidanceAgent,env,trainOpts);
else
% Load pretrained agent for the example.
load exampleHelperAvoidObstaclesAgent obstacleAvoidanceAgent
end

```

The **Reinforcement Learning Episode Manager** can be used to track episode-wise training progress. As the episode number increases, you want to see an increase in the reward value.



Simulate

Use the trained agent to simulate the robot driving in the map and avoiding obstacles.

```
out = sim("exampleHelperAvoidObstaclesMobileRobot.slx");
```

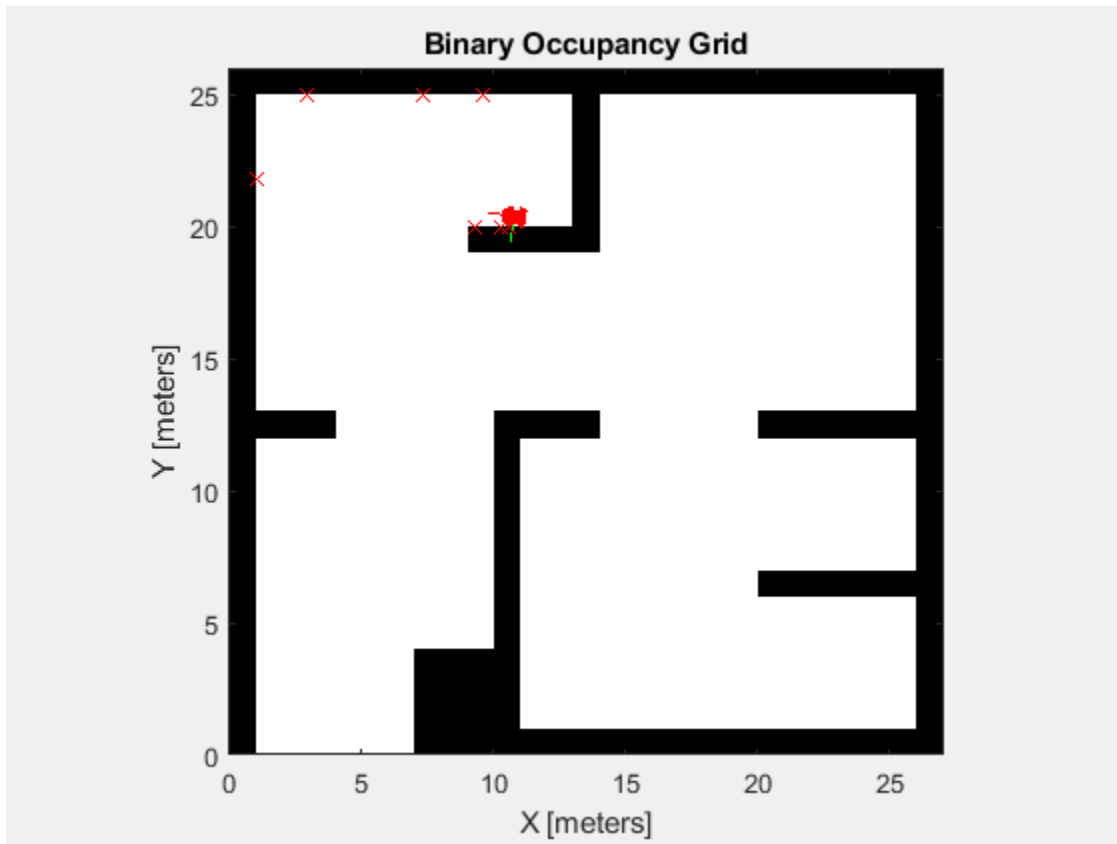
Visualization

To visualize the simulation of the robot driving around the environment with range sensor readings, use the helper, `exampleHelperAvoidObstaclesPosePlot`.

```

for i = 1:5:size(out.range, 3)
    u = out.pose(i, :);
    r = out.range(:, :, i);
    exampleHelperAvoidObstaclesPosePlot(u, mapMatrix, mapScale, r, scanAngles, ax);
end

```

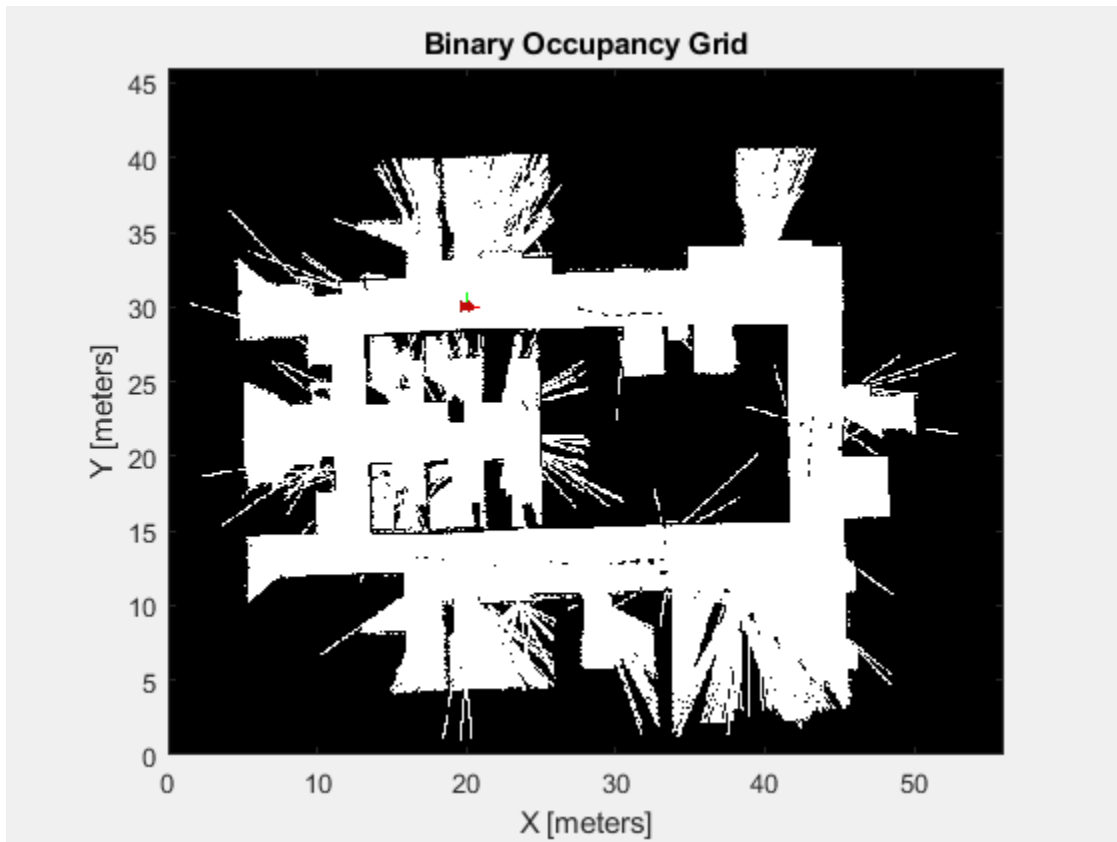


Extensibility

You can now use this agent to simulate driving in a different map. Another map generated from lidar scans of an office environment is used with the same trained model. This map represents a more realistic scenario to apply the trained model after training.

Change the map

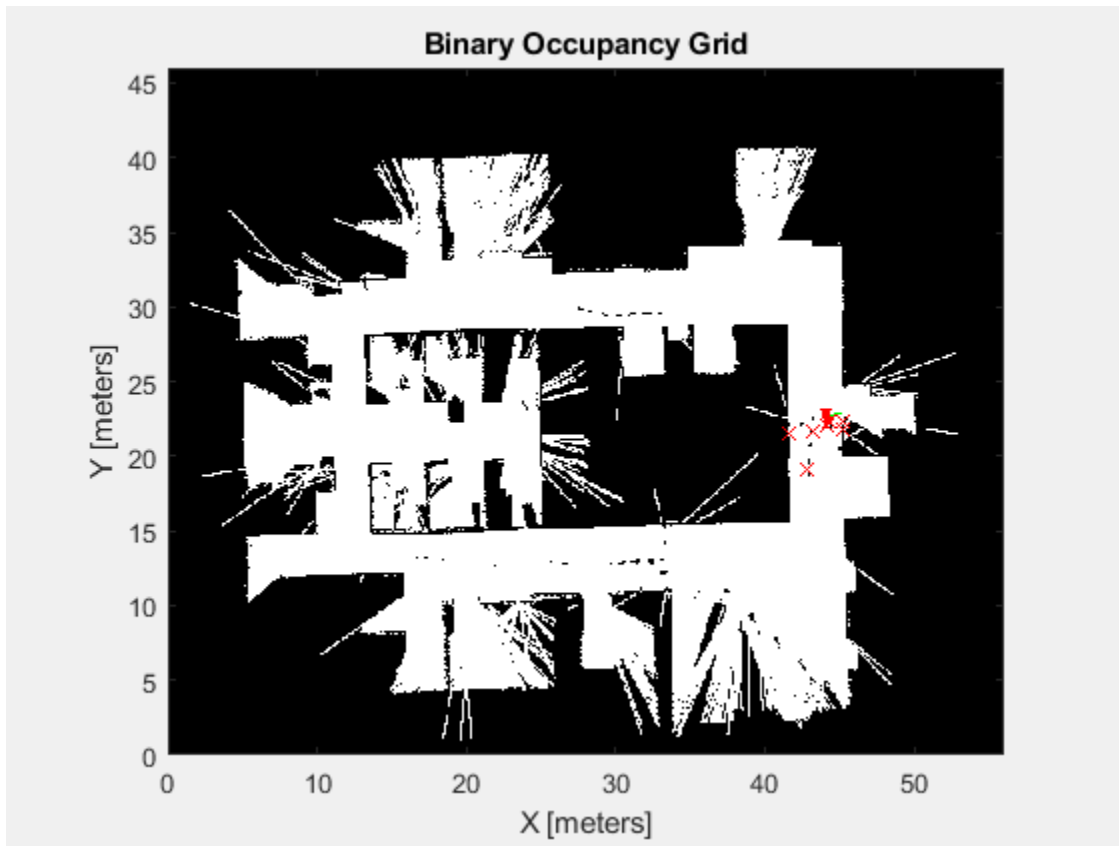
```
mapMatrix = office_area_map.occupancyMatrix > 0.5;
mapScale = 10;
initX = 20;
initY = 30;
initTheta = 0;
fig = figure("Name","office_area_map");
set(fig, "Visible", "on");
ax = axes(fig);
show(binaryOccupancyMap(mapMatrix, mapScale),"Parent",ax);
hold on
plotTransforms([initX, initY, 0], eul2quat([initTheta, 0, 0]), "MeshFilePath","groundvehicle.stl");
light;
hold off
```

**Simulate**

```
out = sim("exampleHelperAvoidObstaclesMobileRobot.slx");
```

Visualize

```
for i = 1:5:size(out.range, 3)
    u = out.pose(i, :);
    r = out.range(:, :, i);
    exampleHelperAvoidObstaclesPosePlot(u, mapMatrix, mapScale, r, scanAngles, ax);
end
```



A* Path Planning and Obstacle Avoidance in a Warehouse

This example is an extension to the “Simulate a Mobile Robot in a Warehouse Using Gazebo” on page 1-53 example. The example shows to change the PRM path planner with an A* planner, and add a vector field histogram (VFH) algorithm to avoid obstacles.

Prerequisites

- Review the “Simulate a Mobile Robot in a Warehouse Using Gazebo” on page 1-53 example to setup the sensing and actuation elements. This example goes over how to download and use a virtual machine (VM) to setup a simulated robot.
- Review the “Execute Tasks for a Warehouse Robot” on page 1-31 example for the workflow of path planning and navigating in a warehouse scenario.

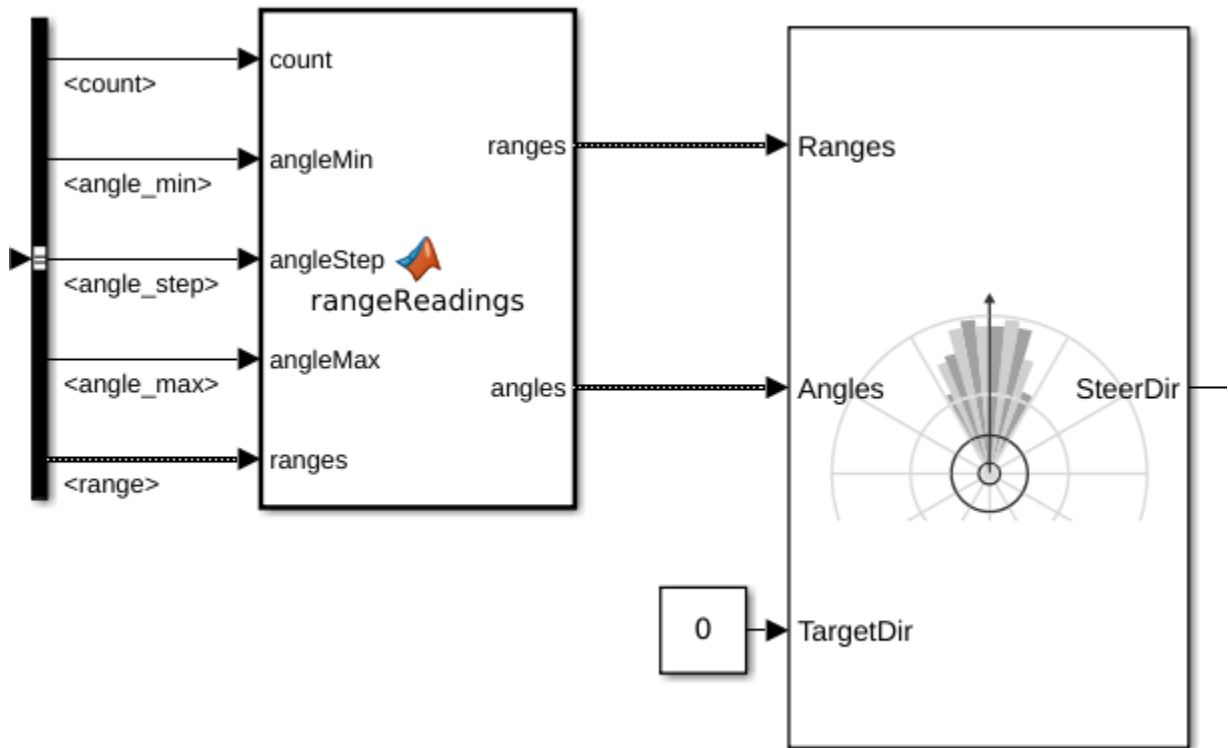
Model Overview

There are two major changes to this model from the “Execute Tasks for a Warehouse Robot” on page 1-31 example. The goal is to replace the path planner algorithm used and add a controller that avoids obstacles in the environment.

The **Planner** MATLAB® Function Block now uses the `plannerAStarGrid` (Navigation Toolbox) object to run the A* path planning algorithm.

The **Obstacle Avoidance** subsystem now uses a **Vector Field Histogram** block as part of the controller. The `rangeReadings` function block outputs the ranges and angles when the data received is not empty. The VFH block then generates a steering direction based on obstacles within the scan range. For close obstacles, the robot should turn to drive around them. Tune the VFH parameters for different obstacle avoidance performance.

```
open_system("aStarPathPlanningAndObstacleAvoidanceInWarehouse.slx");
```

Setup

Warehouse Facility

Load the example map file, `map`, which is a matrix of logical values indicating occupied space in the warehouse. Invert this matrix to indicate free space, and create a `binaryOccupancyMap` object. Specify a resolution of 100 cells per meter.

The map is based off of the `obstacleAvoidanceWorld.world`, which is loaded in the VM. A PNG-file was generated to use as the map matrix with the `collision_map_creator_plugin` plugin. For more information, see [Collision Map Creator Plugin](#).

```
close
figure("Name", "Warehouse Map", "Visible", "on")
load exampleHelperWarehouseRobotWithGazeboBuses.mat
load helperPlanningAndObstacleAvoidanceWarehouseMap.mat map
logicalMap = map.getOccupancy;
mapScalingFactor = 100;
show(map)
```

Assign the `xy`-locations of the charging station, sorting station, and the unloading location near shelves in the warehouse. The values chosen are based on the simulated world in Gazebo.

```
chargingStn = [2, 13];
loadingStn = [15, 5];
unloadingStn = [15, 15];
```

Show the various locations on the map.

```

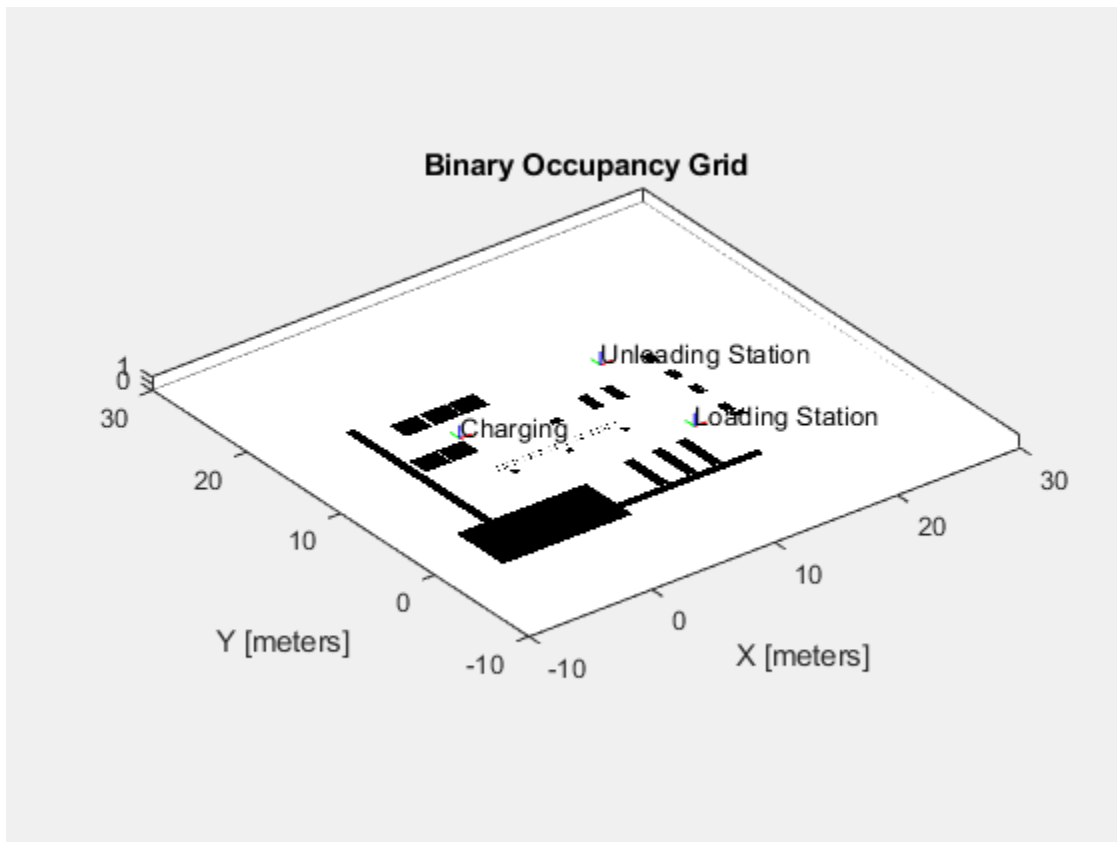
hold on;
localOrigin = map.LocalOriginInWorld;
localTform = trvec2tform([localOrigin 0]);
text(chargingStn(1), chargingStn(2),1,'Charging');
plotTransforms([chargingStn, 0],[1 0 0 0])

text(loadingStn(1), loadingStn(2),1,'Loading Station');
plotTransforms([loadingStn, 0], [1 0 0 0])

text(unloadingStn(1), unloadingStn(2),1,'Unloading Station');
plotTransforms([unloadingStn, 0], [1 0 0 0])

hold off;

```



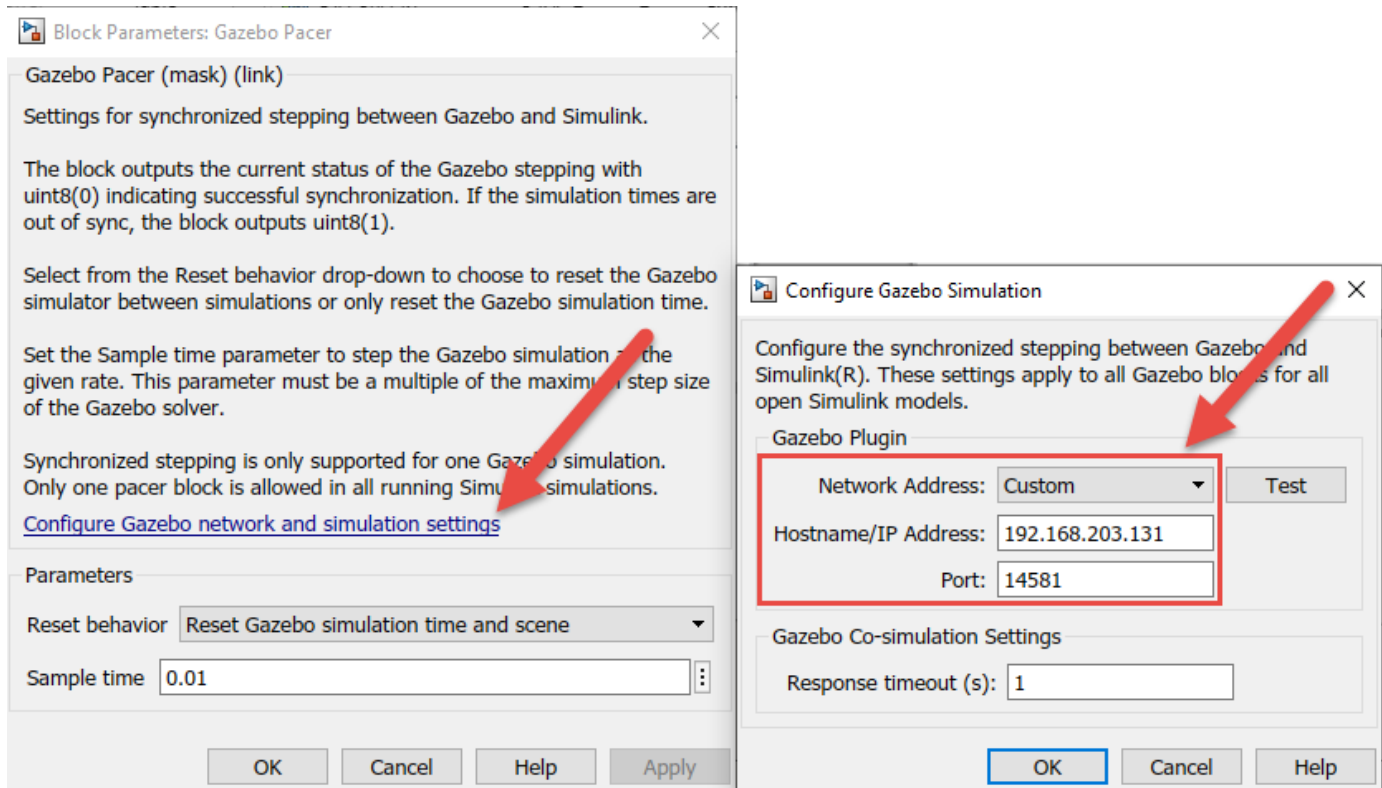
Simulate

To simulate the scenario, set up the connection to Gazebo.

First, run the Gazebo Simulator. In the virtual machine, click the **Gazebo Warehouse Robot with Obstacles** icon.

In Simulink, open the **Gazebo Pacer** block and click **Configure Gazebo network and simulation settings**. Specify the **Network Address** as **Custom**, the **Hostname/IP Address** for your Gazebo simulation, and a **Port** of 14581, which is the default port for Gazebo. The desktop of the VM displays the IP address.

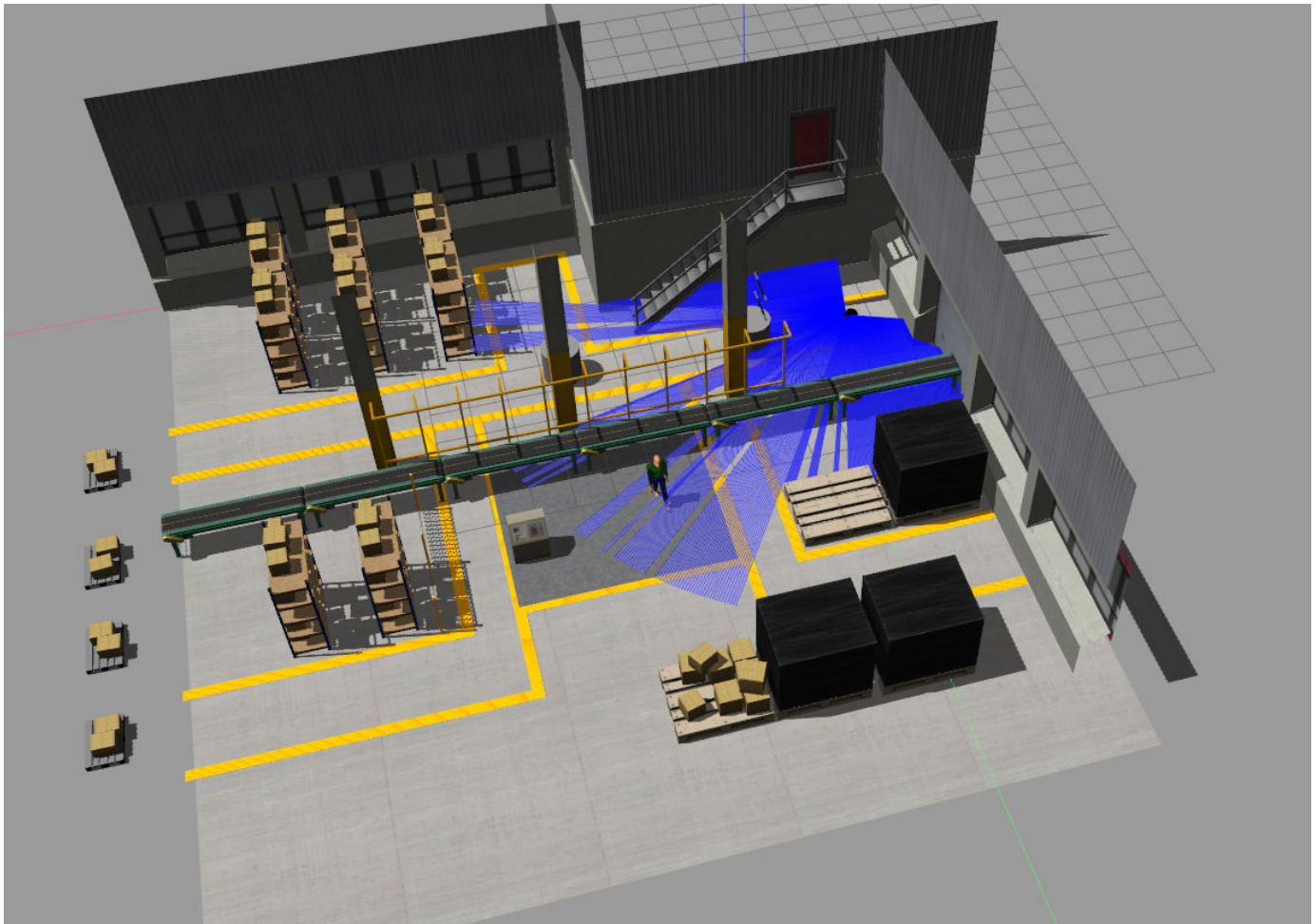
For more information about connecting to Gazebo to enable co-simulation, see “Perform Co-Simulation between Simulink and Gazebo” on page 1-257.



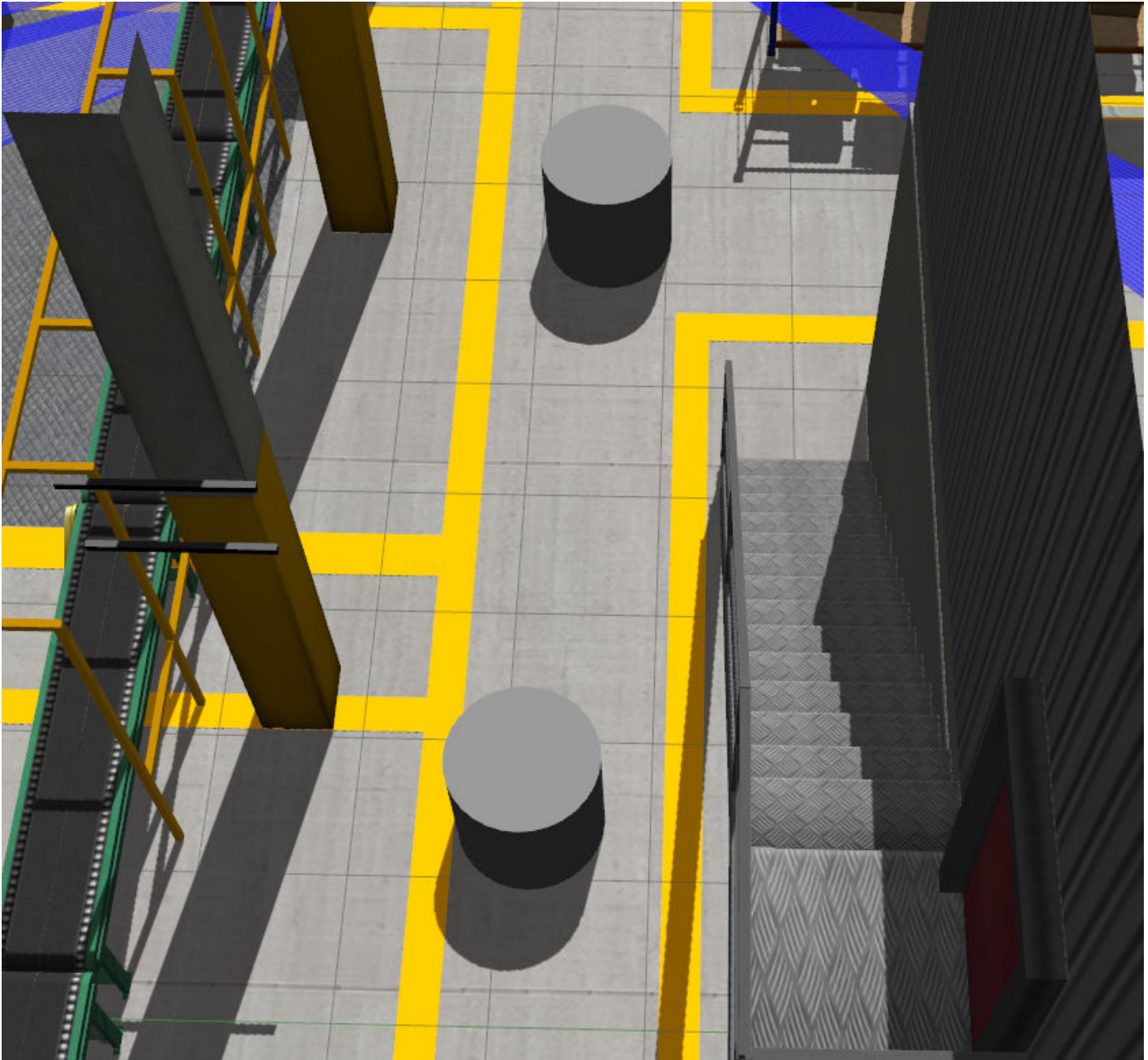
Click the **Initialize Model** button at the top of the model to initialize all the variables declared above.

Run the simulation. The robot drives around the environment and avoids unexpected obstacles.

```
sim("aStarPathPlanningAndObstacleAvoidanceInWarehouse.slx");
```



Notice that there are a two cylindrical obstacles which are not present on the occupancy map. The robot still avoids them when detected using the VFH algorithm.



A green lamp `AvoidingObstacle` lights up when the robot is trying to avoid an obstacle.



Interactively Build a Trajectory For an ABB YuMi Robot

This example shows how to use the `interactiveRigidBodyTree` object to move a robot, design a trajectory, and replay it.

Load Robot Visualization and Build Environment

Load the 'abbYumi' robot model. Initialize the interactive figure using `interactiveRigidBodyTree`. Save the current axes.

```
robot = loadrobot('abbYumi', 'Gravity', [0 0 -9.81]);
iviz = interactiveRigidBodyTree(robot);
ax = gca;
```

Build an environment consisting of a collision boxes that represent a floor, two shelves with objects, and a center table.

```
plane = collisionBox(1.5,1.5,0.05);
plane.Pose = trvec2tform([0.25 0 -0.025]);
show(plane, 'Parent', ax);

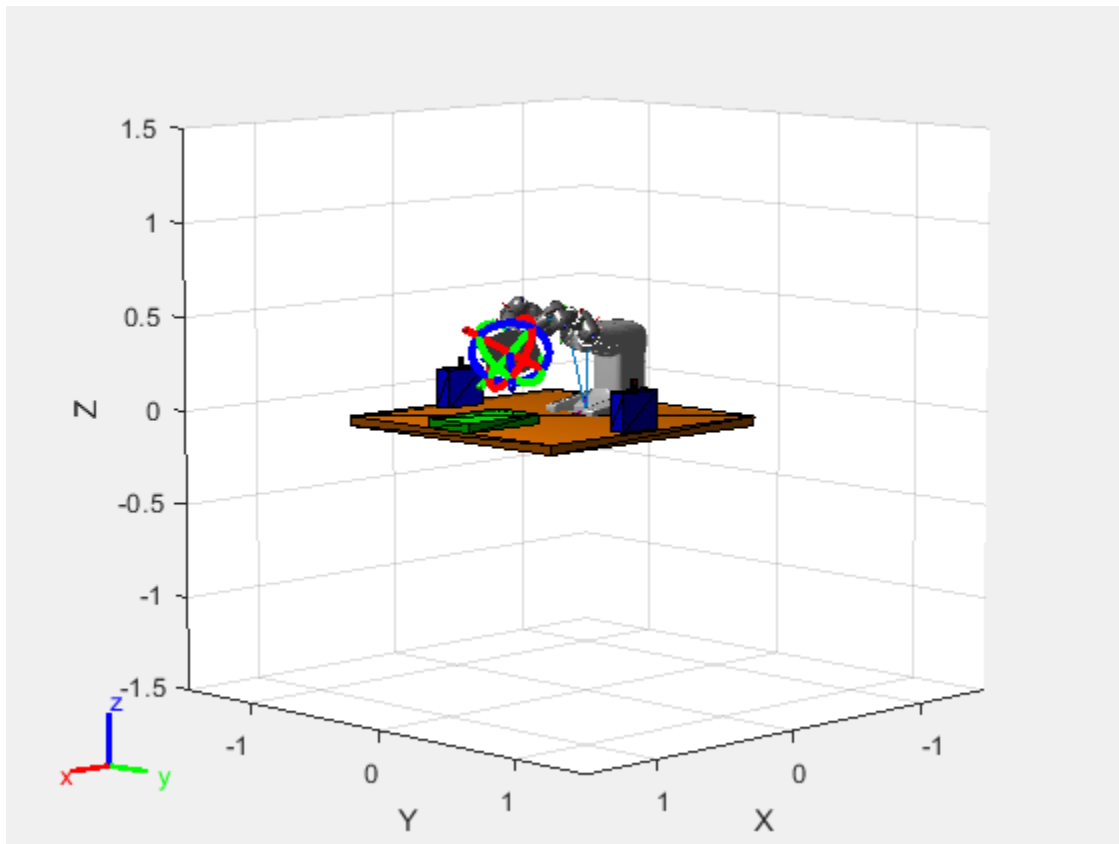
leftShelf = collisionBox(0.25,0.1,0.2);
leftShelf.Pose = trvec2tform([0.3 -.65 0.1]);
[~, patchObj] = show(leftShelf, 'Parent', ax);
patchObj.FaceColor = [0 0 1];

rightShelf = collisionBox(0.25,0.1,0.2);
rightShelf.Pose = trvec2tform([0.3 .65 0.1]);
[~, patchObj] = show(rightShelf, 'Parent', ax);
patchObj.FaceColor = [0 0 1];

leftWidget = collisionCylinder(0.01, 0.07);
leftWidget.Pose = trvec2tform([0.3 -0.65 0.225]);
[~, patchObj] = show(leftWidget, 'Parent', ax);
patchObj.FaceColor = [1 0 0];

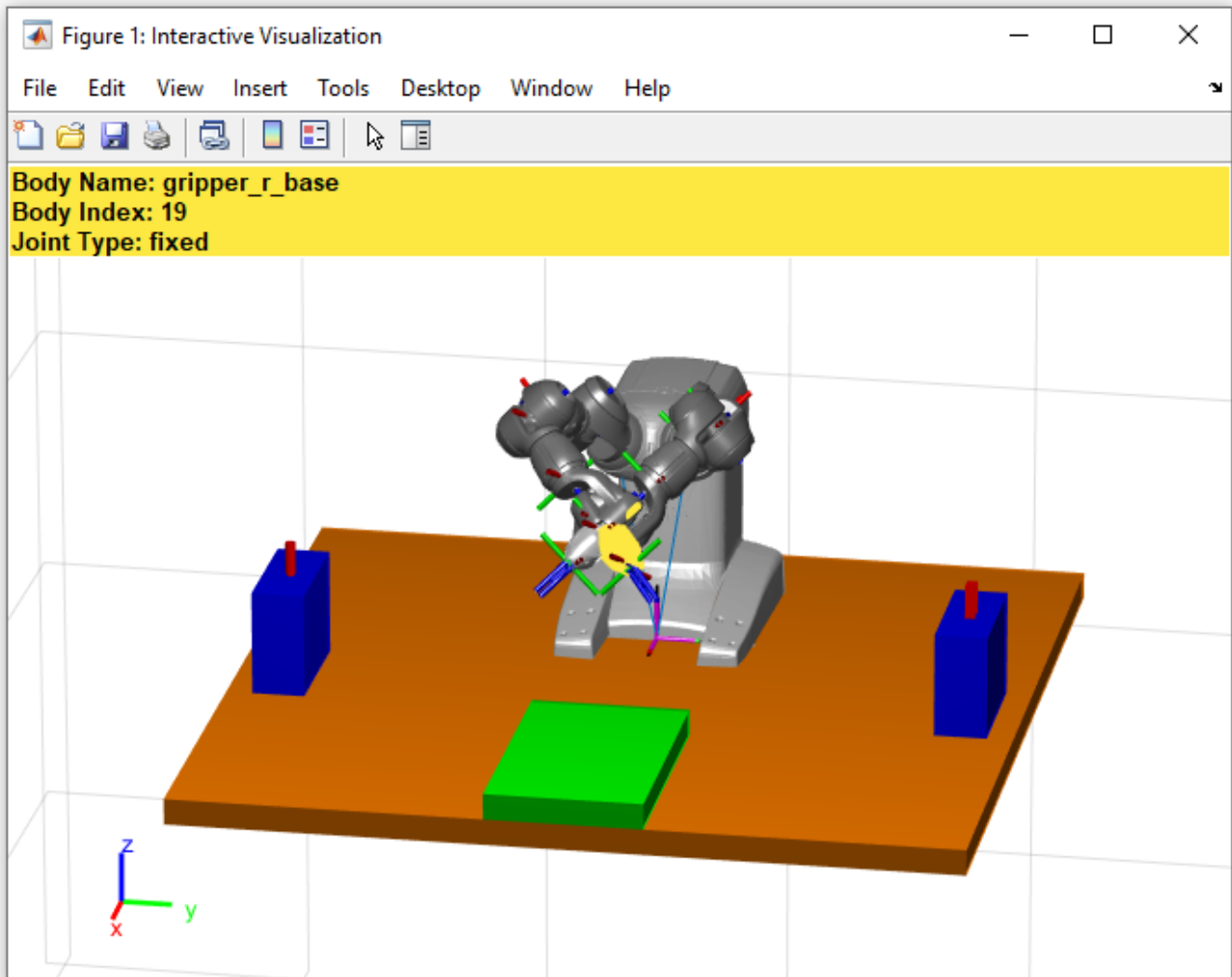
rightWidget = collisionBox(0.03, 0.02, 0.07);
rightWidget.Pose = trvec2tform([0.3 0.65 0.225]);
[~, patchObj] = show(rightWidget, 'Parent', ax);
patchObj.FaceColor = [1 0 0];

centerTable = collisionBox(0.5,0.3,0.05);
centerTable.Pose = trvec2tform([0.75 0 0.025]);
[~, patchObj] = show(centerTable, 'Parent', ax);
patchObj.FaceColor = [0 1 0];
```

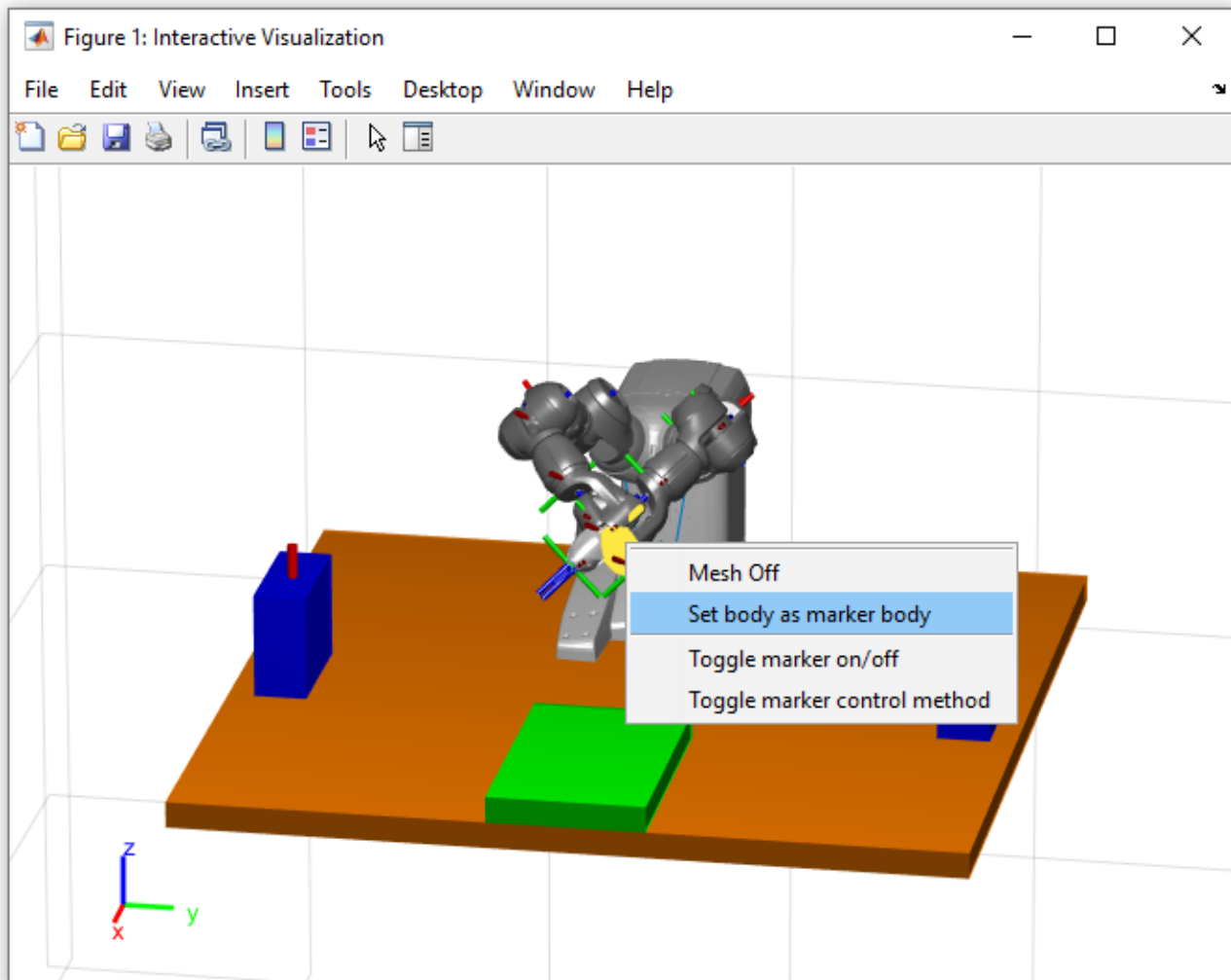


Interactively Generate Configurations

Use the interactive visualization to move the robot around and set configurations. When the figure is initialized, the robot is in its home configuration with the arms crossed. Zoom in and click on an end effector to get more information.



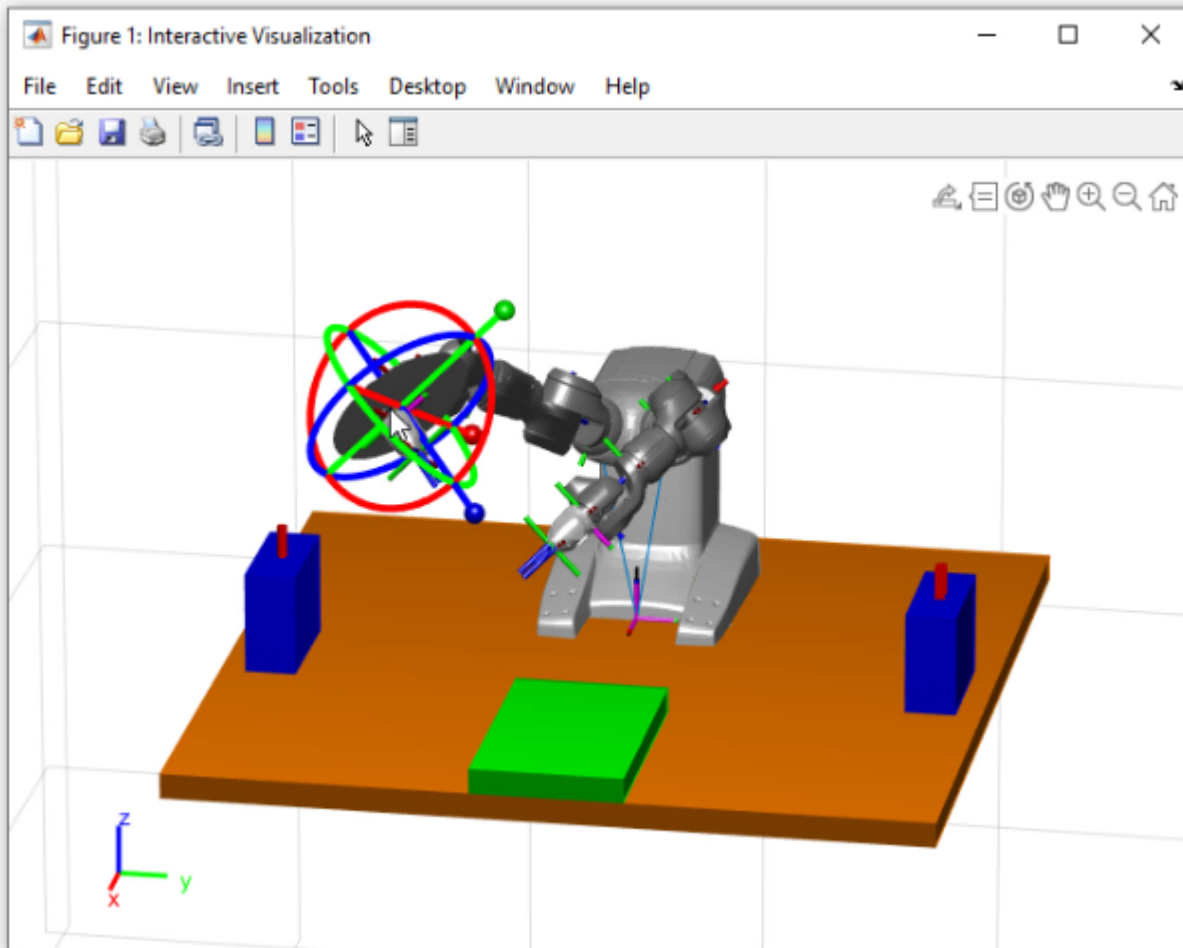
To select the body as the end effector, right-click on the body to select it.



The marker body can also be assigned from the command line:

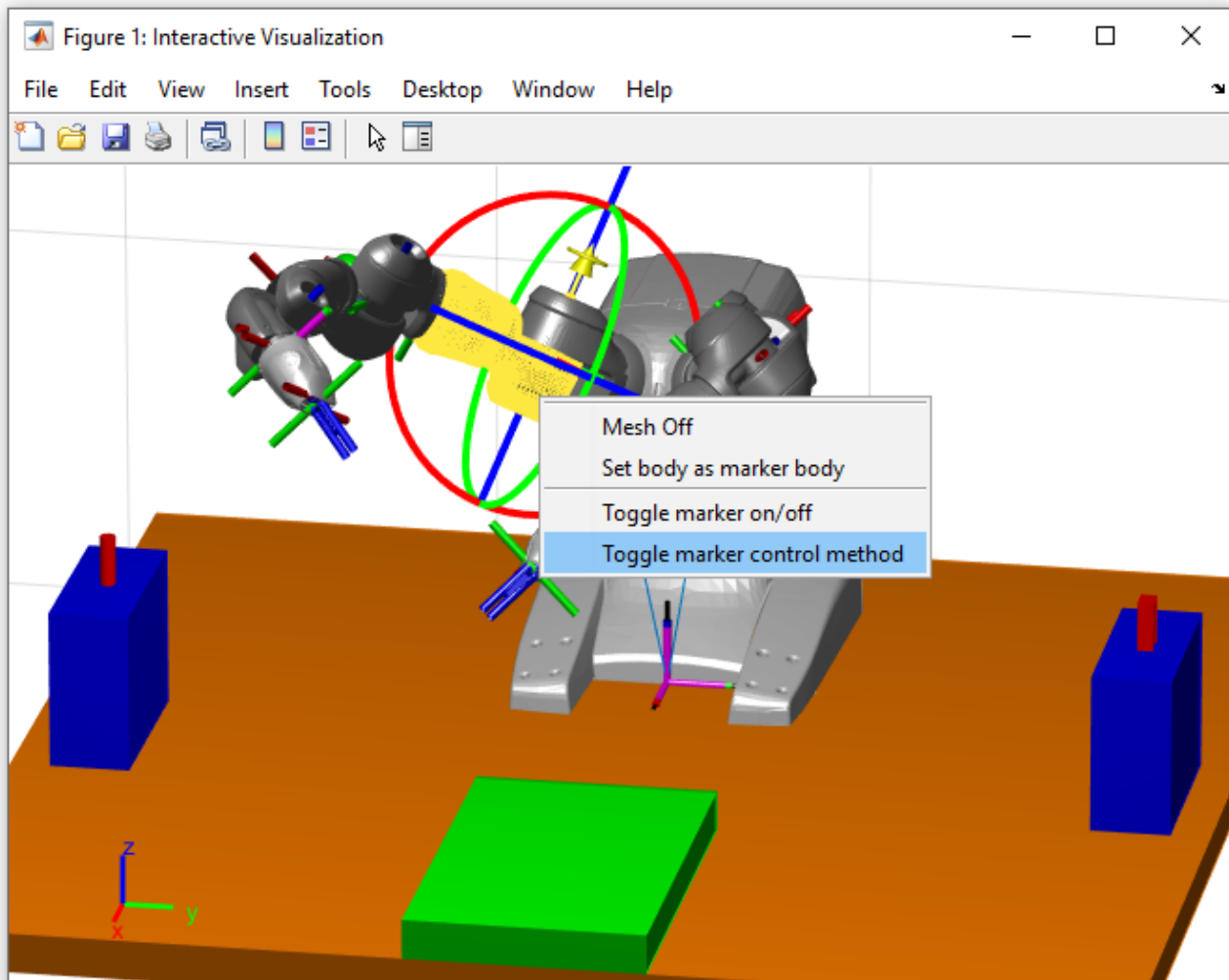
```
iviz.MarkerBodyName = "gripper_r_base";
```

Once the body has been set, use the provided marker elements to move the marker around, and the selected body follows. Dragging the central gray marker moves the marker in Cartesian space. The red, green, and blue axes move the marker along the xyz-axes. The circles rotate the marker about the axes of equivalent color.



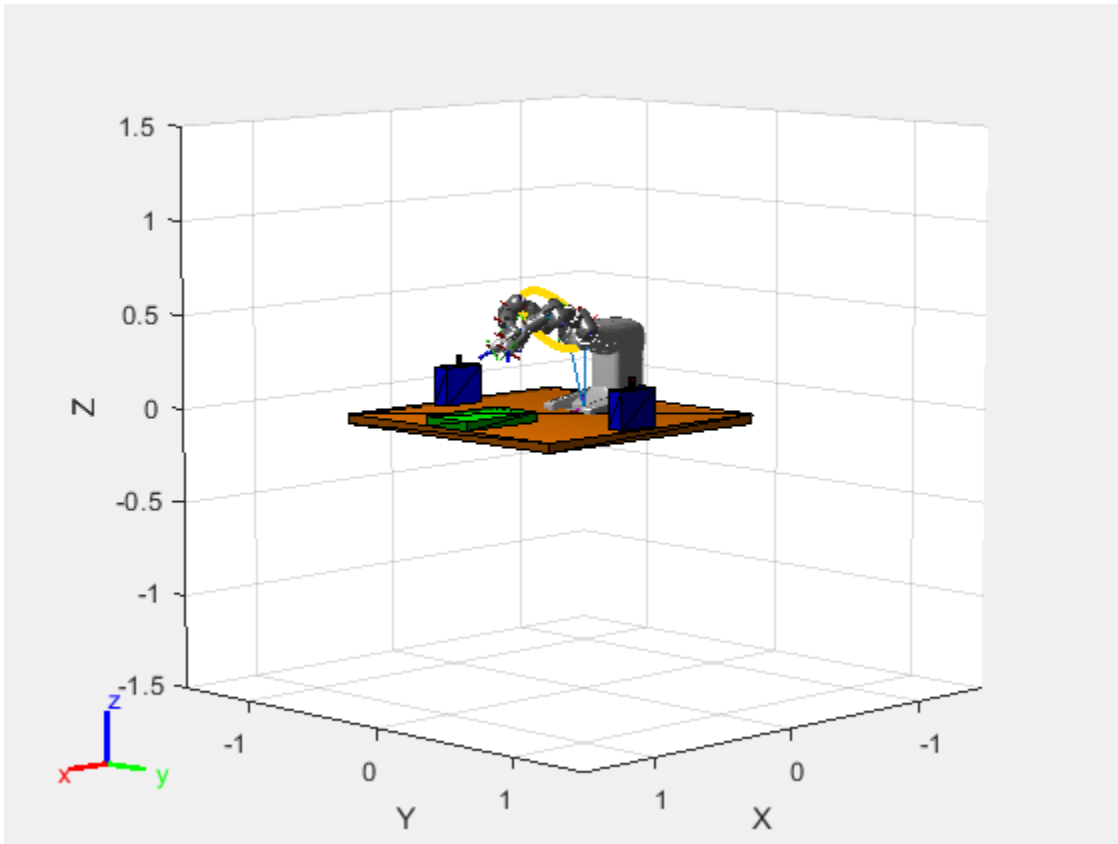
You can also move individual joints by right-clicking the joint and click **Toggle marker control method**.

The `MarkerControlMethod` property of the object is set to "JointControl".

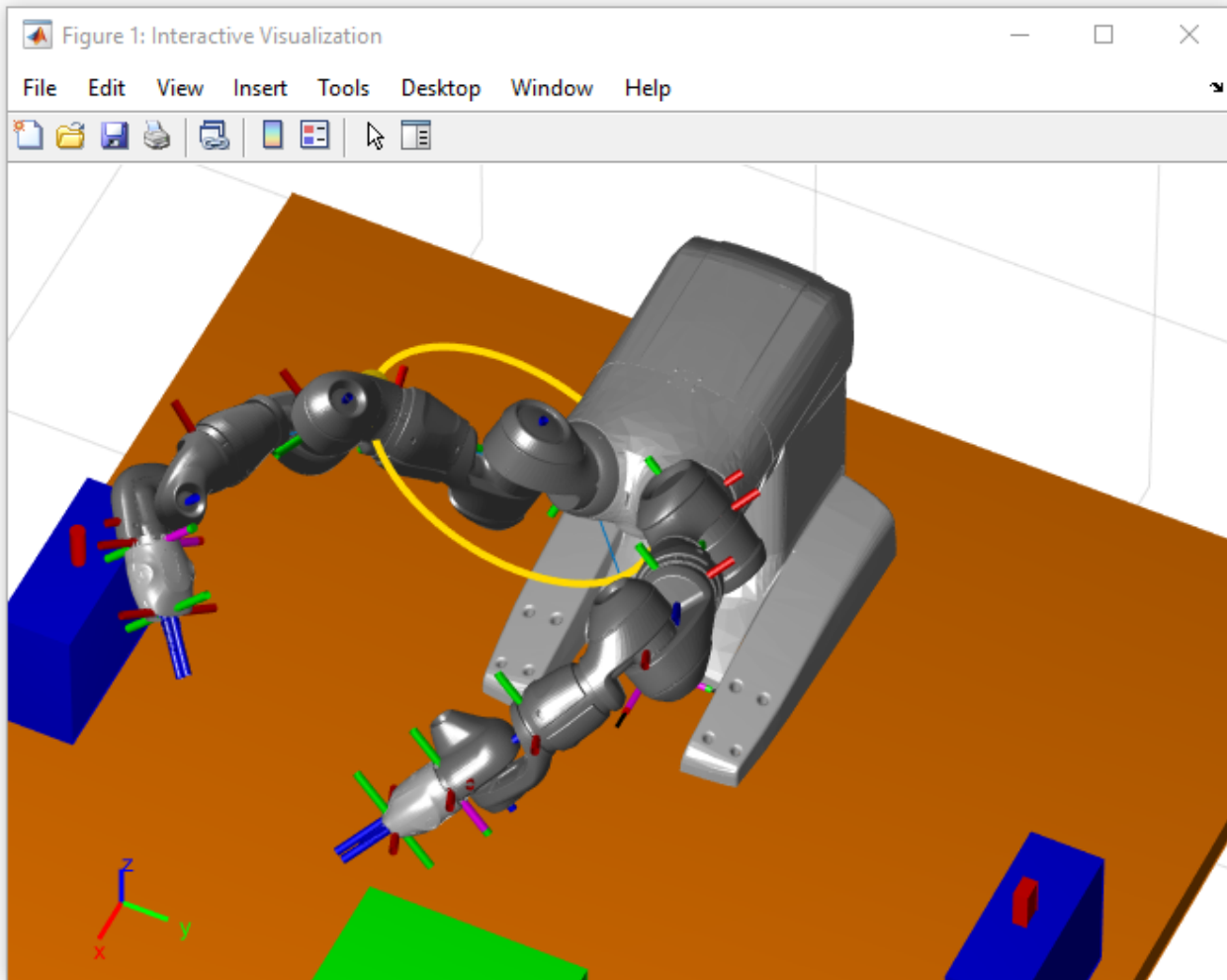


These steps can also be accomplished by changing properties on the object directly.

```
iviz.MarkerBodyName = "yumi_link_2_r";  
iviz.MarkerControlMethod = "JointControl";
```



Changing to joint control produces a yellow marker that allows the joint position to be set directly.



Interactively move the robot around until you have a desired configuration. Save configurations using `addConfiguration`. Each call adds the current configuration to the `StoredConfigurations` property.

```
addConfiguration(iviz)
```

Define Waypoints for a Trajectory

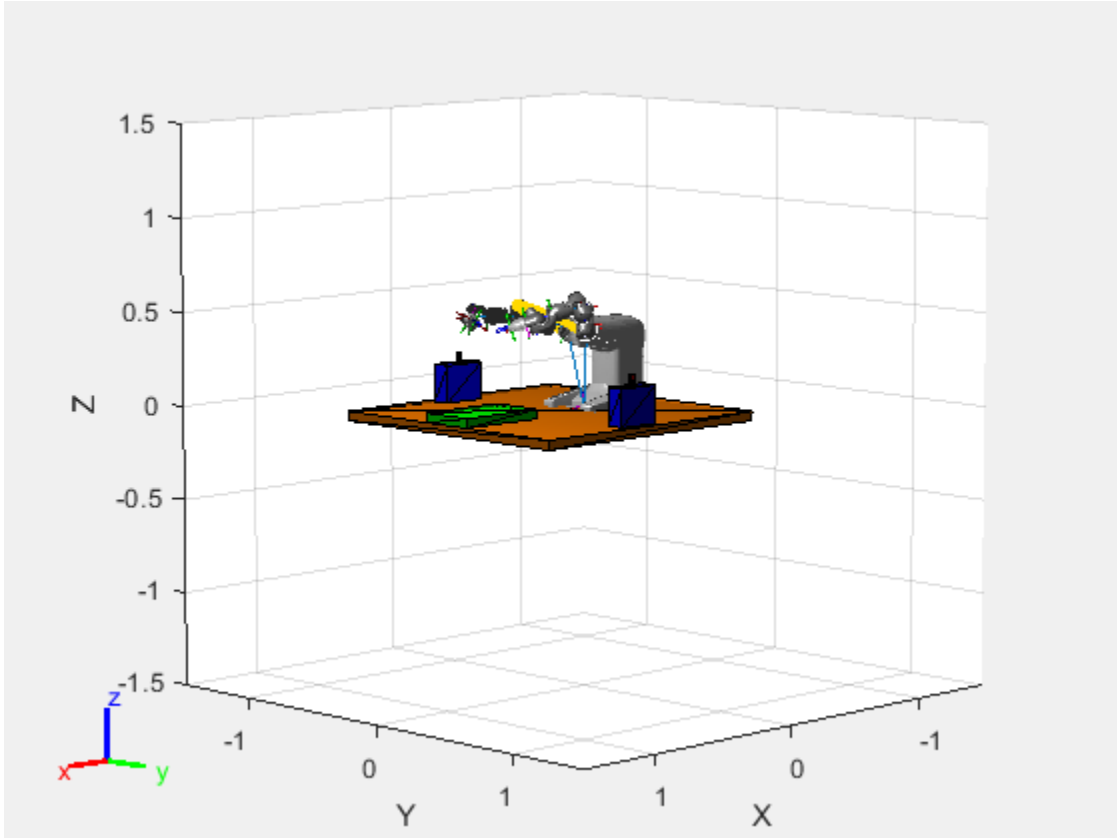
For the purpose of this example, a set of configurations are provided in a `.mat` file.

Load the configurations, and specify them as the set of stored configurations. The first configuration is added by updating the `Configuration` property and calling `addConfiguration`, which you could do interactively, but the rest are simply added by assigning the `StoredConfigurations` property directly.

```
load abbYumiSaveTrajectoryWaypts.mat
```

```
removeConfigurations(iviz) % Clear stored configurations
```

```
% Start at a valid starting configuration
iviz.Configuration = startingConfig;
```



```
addConfiguration(iviz)
```

```
% Specify the entire set of waypoints
iviz.StoredConfigurations = [startingConfig, ...
    graspApproachConfig, ...
    graspPoseConfig, ...
    graspDepartConfig, ...
    placeApproachConfig, ...
    placeConfig, ...
    placeDepartConfig, ...
    startingConfig];
```

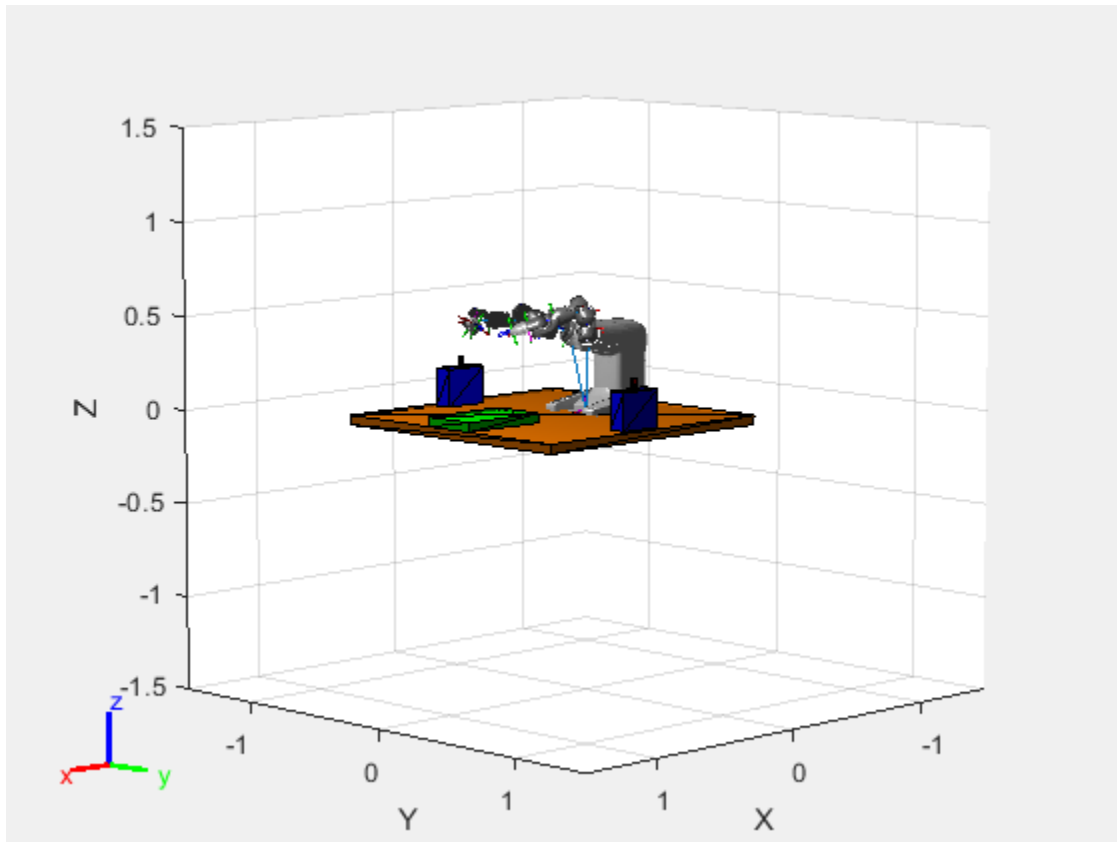
Generate the Trajectory and Play It Back

Once all the waypoints have been stored, construct a trajectory that the robot follows. For this example, a trapezoidal velocity profile is generated using `trapveltraj`. A trapezoidal velocity profile means the robot stops smoothly at each waypoint, but achieves a set max speed while in motion.

```
numSamples = 100*size(iviz.StoredConfigurations, 2) + 1;
[q,~,~, tvec] = trapveltraj(iviz.StoredConfigurations,numSamples,'EndTime',2);
```

Replay the generated trajectory by iterating the generated `q` matrix, which represents a series of joint configurations that move between each waypoint. In this case, a rate control object is used to ensure that the play back speed is reflective of the actual execution speed.

```
iviz.ShowMarker = false;  
showFigure(iviz)  
rateCtrlObj = rateControl(numSamples/(max(tvec) + tvec(2)));  
for i = 1:numSamples  
    iviz.Configuration = q(:,i);  
    waitfor(rateCtrlObj);  
end
```



The figure shows the robot executes a smooth trajectory between all the defined waypoints.

Position A Delta Robot Using Generalized Inverse Kinematics

Model a delta robot using the a `rigidBodyTree` robot model. Specify kinematic constraints for generalized inverse kinematics (GIK) to ensure the proper behavior of the robot. Solve for joint configurations that obey the defined model and constraints.

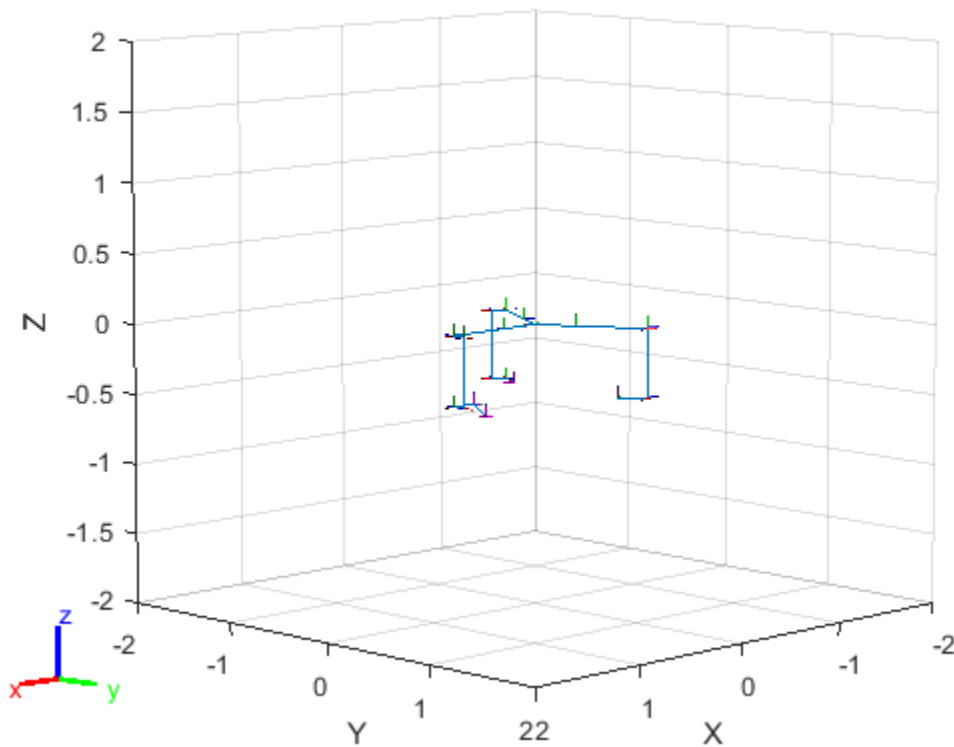
Create Delta Robot

Normally, delta robots contain closed-loop kinematic chains. The `rigidBodyTree` object does not support closed-loop chains. To avoid this, the robot is modeled as a tree, with the arms of the delta robot remaining unconnected. Call the helper function which builds the robot model and outputs the `rigidBodyTree` object.

In a subsequent step, the generalized inverse kinematics solver will apply constraints that force the separate arms of the tree to move together, thereby ensuring that the robot behaves in a kinematically accurate manner.

The robot is fairly complicated, so a helper function is used to create the `rigidBodyTree` object.

```
robot = exampleHelperDeltaRobot;
show(robot);
```



As shown, the robot consists of three arms, but they still need to be connected to match the classic delta robot configuration.

Create Inverse Kinematic Constraints

Create a `generalizedInverseKinematics` object, and specify the robot model. Limit the maximum number of iterations based on performance.

```
gik1 = generalizedInverseKinematics('RigidBodyTree', robot);  
gik1.SolverParameters.MaxIterations = 20;
```

Create an `interactiveRigidBodyTree` object to visualize the robot model and provide interactive markers for moving bodies. This interactivity helps verify your kinematic constraints. Specify the `gik1` solver using name-value pairs. Specify a pose weight vector that only focuses on the xyz-position and not the orientation.

```
viztree = interactiveRigidBodyTree(robot, 'IKSolver', gik1, 'SolverPoseWeights', [0 1]);
```

Using this interactive object, the end effector can be dragged around to show how the robot moves. Currently, the behavior is not as desired for a normal delta robot.

Store the current axes.

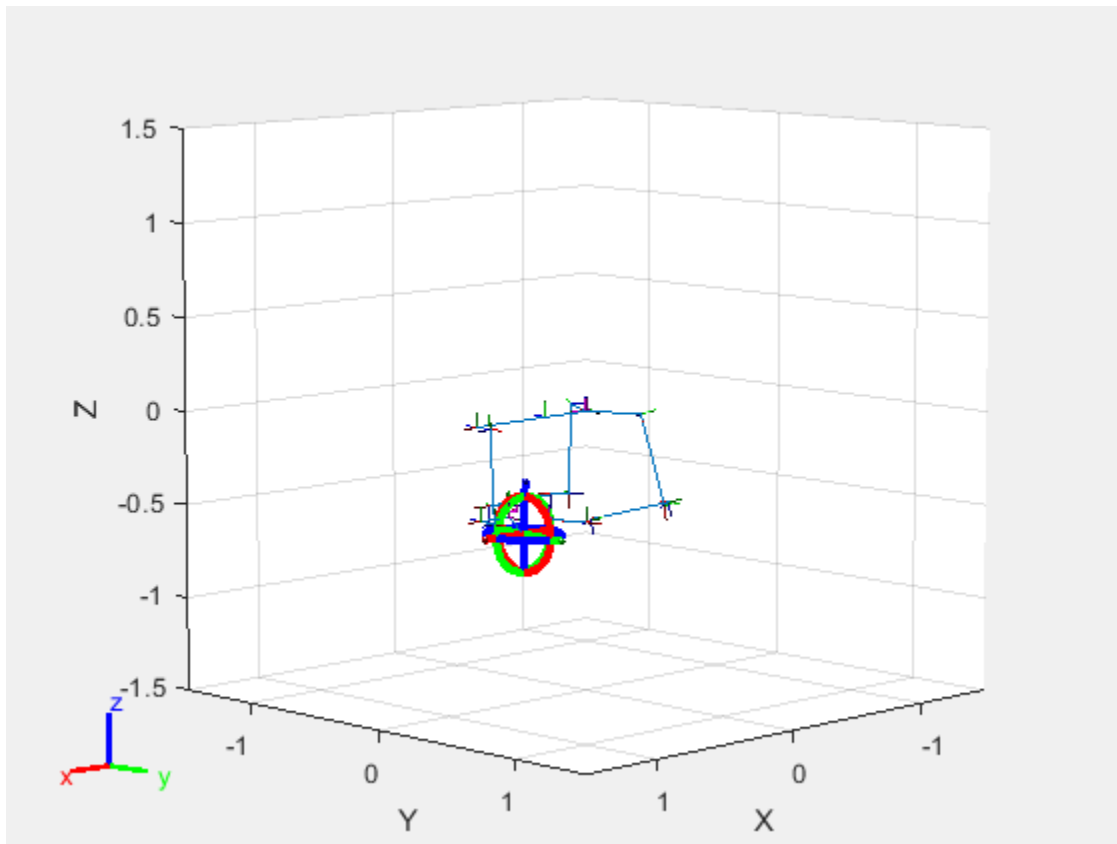
```
ax = gca;
```

Add constraints to the GIK solver to ensure that the arms are connected. Attach the two arms with no end effector to the 6th body of the primary arm which includes the end effector.

```
% Ensure that the body 6 of arm 2 maintains a pose relative to body 6 of arm 1  
poseTgt1 = constraintPoseTarget('arm2_body6');  
poseTgt1.ReferenceBody = 'arm1_body6';  
poseTgt1.TargetTransform = trvec2tform([-sqrt(3)*0.5*0.2, 0.5*0.2, 0]) * eul2tform([2*pi/3, 0, 0]);  
  
% Ensure that the body 6 of arm 3 maintains a pose relative to body 6 of arm 1  
poseTgt2 = constraintPoseTarget('arm3_body6');  
poseTgt2.ReferenceBody = 'arm1_body6';  
poseTgt2.TargetTransform = trvec2tform([-sqrt(3)*0.5*0.2, -0.5*0.2, 0]) * eul2tform([-2*pi/3, 0, 0]);
```

To apply these constraints to the robot, call `addConstraint` to the `vizTree` object.

```
addConstraint(viztree,poseTgt1);  
addConstraint(viztree,poseTgt2);
```



Now when the end effector is moved around, the constraints are respected and the arms stay connected.

Solve Generalized Inverse Kinematics Programmatically

The interactive visualization is useful for validating the solver constraints, but for direct programmatic use, create a separate GIK solver that can be called. This solver can be copied from the `IKSolver` property of the `interactiveRigidBodyTree` object, or created independently.

```
gik2 = generalizedInverseKinematics('RigidBodyTree', robot);
gik2.SolverParameters.MaxIterations = 20;
```

For the GIK solver, an additional constraint is required to define the end effector position, which is normally controlled by the interactive marker. Update the `TargetTransform` to solve for different desired end-effector positions.

```
poseTgt3 = constraintPoseTarget('endEffector');
poseTgt3.ReferenceBody = 'base';
poseTgt3.TargetTransform = trvec2tform([0, 0, -1]);
```

Specify all the constraint types used by the solver.

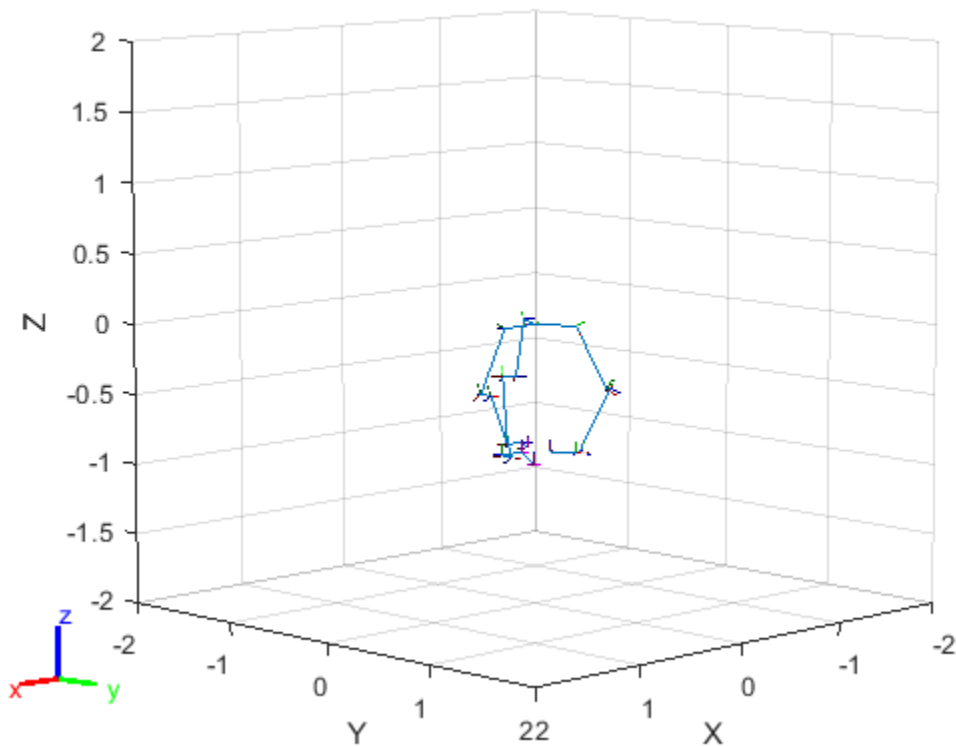
```
gik2.ConstraintInputs = {'pose', 'pose', 'pose'};
```

Call the `gik2` solver with the specified pose target constraint objects. Give an initial guess of the home configuration of the robot. Show the solution.

```
% Provide an initial guess for the solver
q0 = homeConfiguration(robot);

% Solve for a the target pose given to poseTgt3
[q, solutionInfo] = gik2(q0, poseTgt1, poseTgt2, poseTgt3);

% Visualize the results
figure;
show(robot, q);
```



Trajectory Control Modeling With Inverse Kinematics

This example demonstrates how the Inverse Kinematics block can drive a manipulator along a specified trajectory. The desired trajectory is specified as a series of tightly-spaced poses for the end effector of the manipulator. Trajectory generation and waypoint definition represents many robotics applications like pick and place operation, calculating trajectories from spatial acceleration and velocity profiles, or even mimicking external observations of key frames using cameras and computer vision. Once a trajectory is generated, the Inverse Kinematics block is used to translate this to a joint-space trajectory, which can then be used to simulate the dynamics of the manipulator and controller.

Model Overview

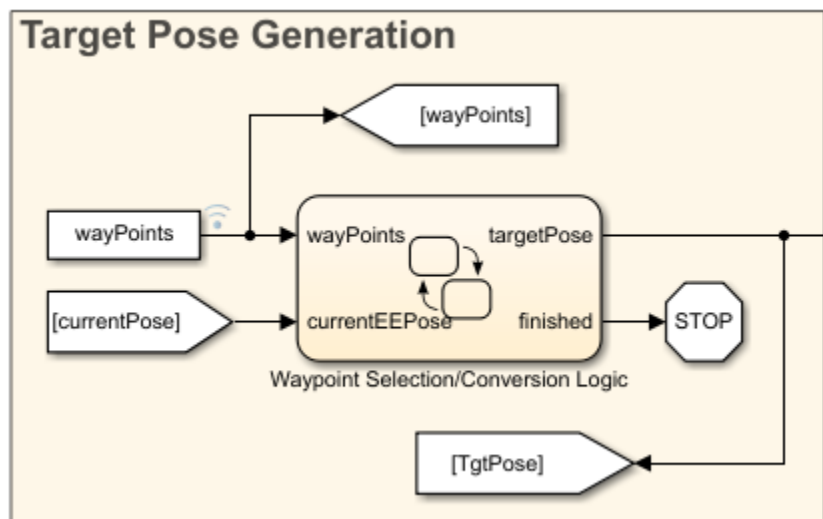
Load the model to see how it is constructed.

```
open_system('IKTrajectoryControlExample.slx');
```

The model is composed of four primary operations:

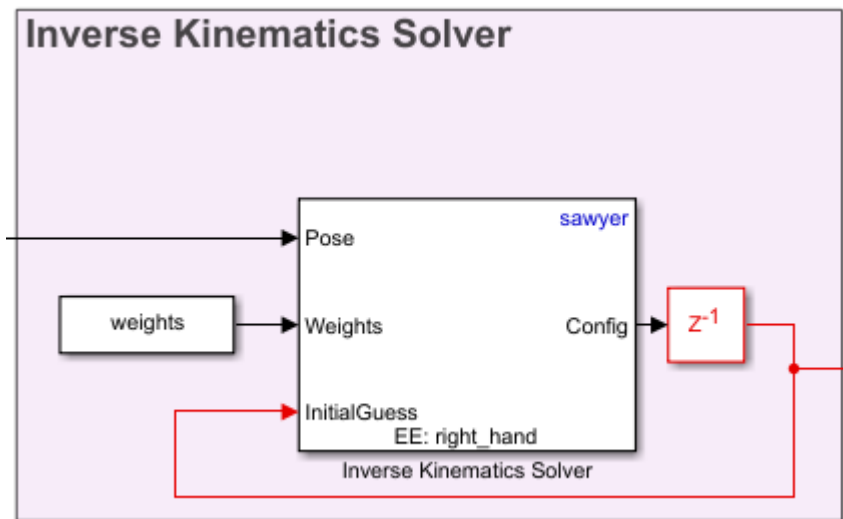
- **Target Pose Generation**
- **Inverse Kinematics**
- **Manipulator Dynamics**
- **Pose Measurement**

Target Pose Generation



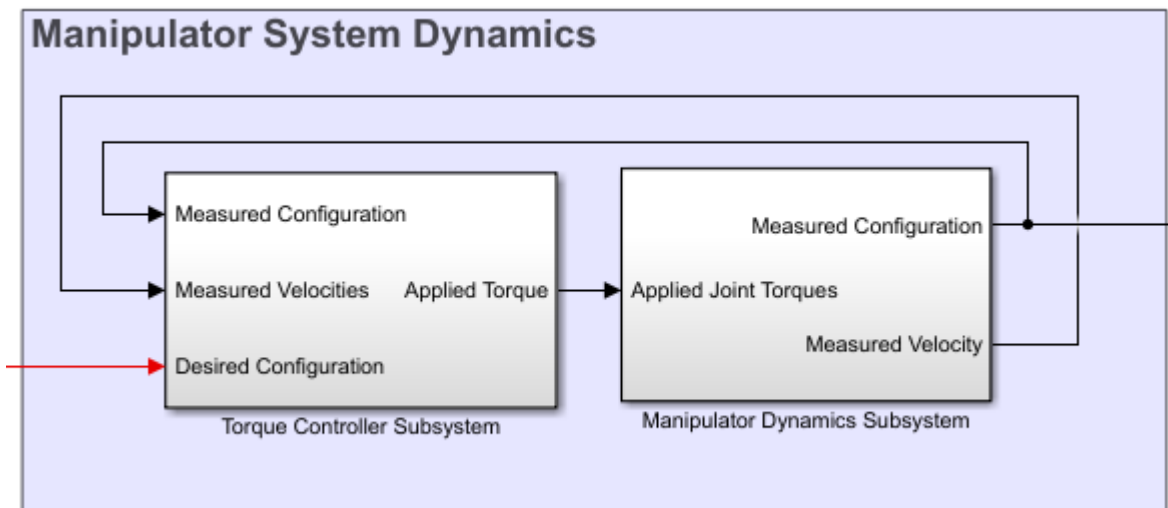
This Stateflow chart selects which waypoint is the current objective for the manipulator. The chart adjusts the target to the next waypoint once the manipulator gets to within a tolerance of the current objective. The chart also converts and assembles the components of the waypoint into a homogenous transformation through the `eu2tform` function. Once there are no more waypoints to select, the chart terminates the simulation.

Inverse Kinematics



Inverse kinematics calculated a set of joint angles to produce a desired pose for an end effector. Use the Inverse Kinematics with a `rigidBodyTree` model and specify the target pose of the end effect as a homogenous transformation. Specify a series of weights for the relative tolerance constraints on the position and orientation of the solution, and give an initial estimate of the joint positions. The block outputs a vector of joint positions that produce the desired pose from the `rigidBodyTree` model specified in the block parameters. To ensure smooth continuity of the solutions, the previous configuration solution is used as the starting position for the solver. This also reduces the redundancy of calculations if the target pose has not updated since the last simulation time step.

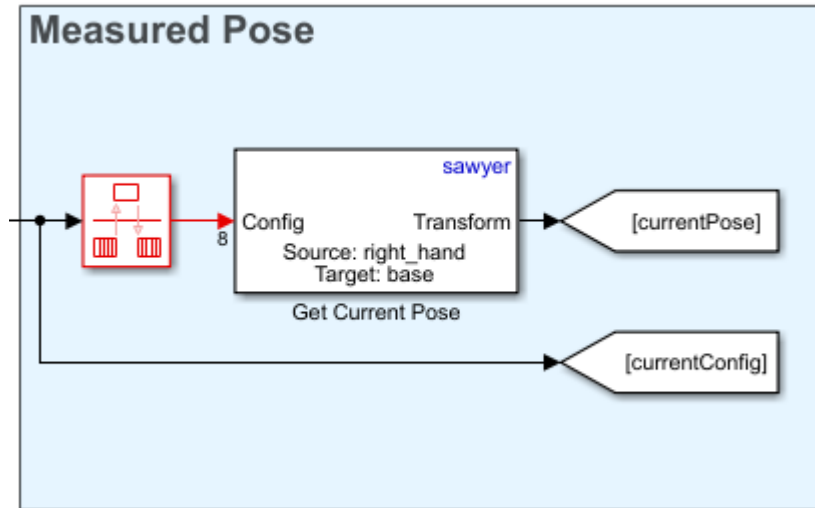
Manipulator Dynamics



The manipulator dynamics consists of two components, a controller to generate torque signals and a dynamics model to model the dynamics of the manipulator given these torque signals. The controller in the example uses a feed-forward component calculated through the inverse dynamics of the manipulator and a feedback PD controller to correct for error. The model of the manipulator uses the Forward Dynamics block that works with a `rigidBodyTree` object. For more sophisticated dynamics

and visualization techniques, consider utilizing tools from the Control Systems Toolbox™ blockset and Simscape Multibody™ to replace the Forward Dynamics block.

Pose Measurement



The pose measurement takes the joint angle readings from the manipulator model and converts them into a homogenous transform matrix to be used as feedback in the **Waypoint Selection** section.

Manipulator Definition

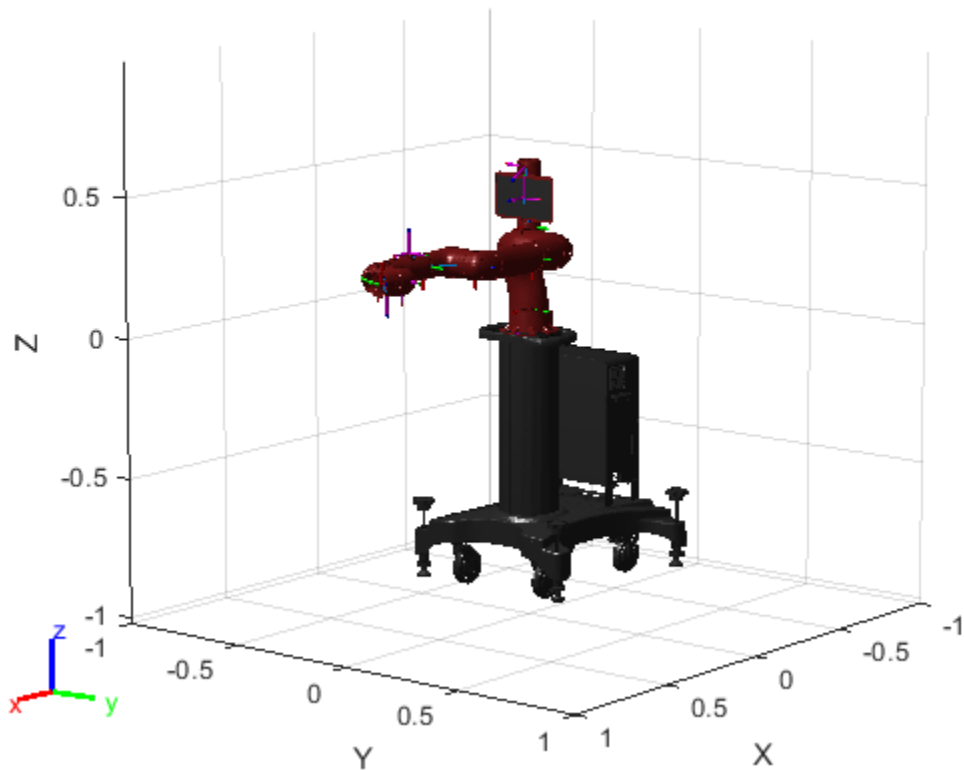
The manipulator used for this example is the Rethink Sawyer™ robot manipulator. The `rigidBodyTree` object that describes the manipulator is imported from a URDF (unified robot description format) file using `importrobot`.

```
% Import the manipulator as a rigidBodyTree Object
sawyer = importrobot('sawyer.urdf');
sawyer.DataFormat = 'column';

% Define end-effector body name
eeName = 'right_hand';

% Define the number of joints in the manipulator
numJoints = 8;

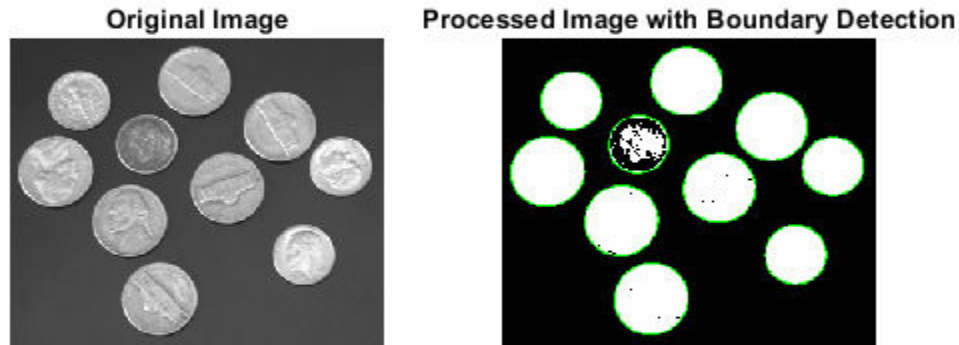
% Visualize the manipulator
show(sawyer);
xlim([-1.00 1.00]);
ylim([-1.00 1.00]);
zlim([-1.02 0.98]);
view([128.88 10.45]);
```



Waypoint Generation

In this example, the goal of the manipulator is to be able to trace out the boundaries of the coins detected in the image, `coins.png`. First, the image is processed to find the boundaries of the coins.

```
I = imread('coins.png');  
bwBoundaries = imread('coinBoundaries.png');  
  
figure  
subplot(1,2,1)  
imshow(I,'Border','tight')  
title('Original Image')  
  
subplot(1,2,2)  
imshow(bwBoundaries,'Border','tight')  
title('Processed Image with Boundary Detection')
```

After the image processing, the edges of the coins are extracted as pixel locations. The data is loaded in from the MAT-file, `boundaryData`. `boundaries` is a cell array where each cell contains an array describing the pixel coordinates for a single detected boundary. A more comprehensive view of how to generate this data can be found in the example, "Boundary Tracing in Images" (requires Image Processing Toolbox).

```
load boundaryData.mat boundaries
whos boundaries
```

Name	Size	Bytes	Class	Attributes
boundaries	10x1	25376	cell	

To map this data to the world frame, we need to define where the image is located and the scaling between pixel coordinates and spatial coordinates.

```
% Image origin coordinates
imageOrigin = [0.4,0.2,0.08];

% Scale factor to convert from pixels to physical distance
scale = 0.0015;
```

The Euler angles for the desired end effector orientation at each point must also be defined.

```
eeOrientation = [0, pi, 0];
```

In this example the orientation is chosen such that the end effector is always perpendicular to the plane of the image.

Once this information is defined each set of desired coordinates and Euler angles can be compiled into a waypoint. Each waypoint is represented as a six-element vector whose first three elements correspond to the desired xyz-positions of the manipulator in the world frame. The last three elements correspond to the ZYX Euler angles of the desired orientation.

$$\text{Waypoint} = [X \ Y \ Z \ \phi_z \ \phi_y \ \phi_x]$$

The waypoints are concatenated to form an n -by-6 array, where n is the total number of poses in the trajectory. Each row in the array corresponds to a waypoint in the trajectory.

```
% Clear previous waypoints and begin building wayPoint array
clear waypoints

% Start just above image origin
waypt0 = [imageOrigin + [0 0 .2],ee0orientation];

% Touch the origin of the image
waypt1 = [imageOrigin,ee0orientation];

% Interpolate each element for smooth motion to the origin of the image
for i = 1:6

    interp = linspace(waypt0(i),waypt1(i),100);
    waypoints(:,i) = interp';

end
```

In total, there are 10 coins. For simplicity and speed, a smaller subset of coins can be traced by limiting the total number passed to the waypoints. Below, numTraces = 3 coins are traced in the image.

```
% Define the number of coins to trace
numTraces = 3;

% Assemble the waypoints for boundary tracing
for i = 1:min(numTraces, size(boundaries,1))

    %Select a boundary and map to physical size
    segment = boundaries{i}*scale;

    % Pad data for approach waypoint and lift waypoint between boundaries
    segment = [segment(1,:); segment(:,,:); segment(end,:)];

    % Z-offset for moving between boundaries
    segment(1,3) = .02;
    segment(end,3) = .02;

    % Translate to origin of image
    cartesianCoord = imageOrigin + segment;

    % Repeat desired orientation to match the number of waypoints being added
    eulerAngles = repmat(ee0orientation,size(segment,1),1);

    % Append data to end of previous waypoints
    waypoints = [waypoints;
                 cartesianCoord, eulerAngles];

end
```

This array is the primary input to the model.

Model Setup

Several parameters must be initialized before the model can be run.

```
% Initialize size of q0, the robot joint configuration at t=0. This will
% later be replaced by the first waypoint.
q0 = zeros(numJoints,1);

% Define a sampling rate for the simulation.
Ts = .01;

% Define a [1x6] vector of relative weights on the orientation and
% position error for the inverse kinematics solver.
weights = ones(1,6);

% Transform the first waypoint to a Homogenous Transform Matrix for initialization
initTargetPose = eul2tform(wayPoints(1,4:6));
initTargetPose(1:3,end) = wayPoints(1,1:3)';

% Solve for q0 such that the manipulator begins at the first waypoint
ik = inverseKinematics('RigidBodyTree',sawyer);
[q0,solInfo] = ik(eeName,initTargetPose,weights,q0);
```

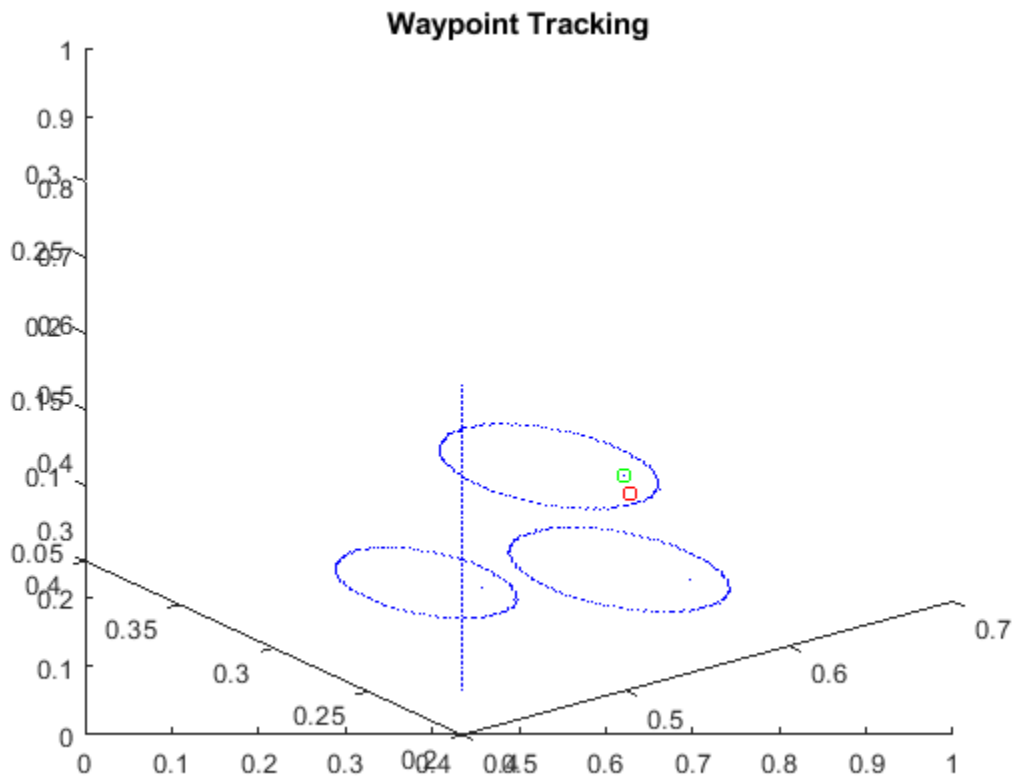
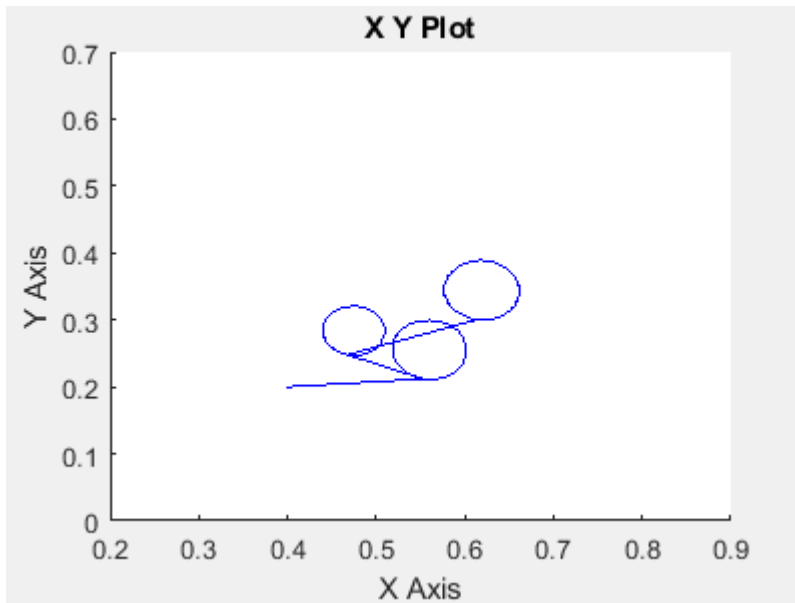
Simulate the Manipulator Motion

To simulate the model, use the `sim` command. The model generates the output dataset, `jointData` and shows the progress in two plots:

- The **X Y Plot** shows a top-down view of the tracing motions of the manipulator. The lines between the circles occur as the manipulator transitions from one coin outline to the next.
- The **Waypoint Tracking** plot visualizes the progress in 3D. The green dot indicates the target position. The red dot indicates the actual end-effector position achieved by the end effector using feedback control.

```
% Close currently open figures
close all

% Open & simulate the model
open_system('IKTrajectoryControlExample.slx');
sim('IKTrajectoryControlExample.slx');
```



Visualize the Results

The model outputs two datasets that can be used for visualization after simulation. The joint configurations are provided as `jointData`. The robot end-effector poses are output as `poseData`.

```
% Remove unnecessary meshes for faster visualization
clearMeshes(sawyer);

% Data for mapping image
[m,n] = size(I);

[X,Y] = meshgrid(0:m,0:n);
X = imageOrigin(1) + X*scale;
Y = imageOrigin(2) + Y*scale;

Z = zeros(size(X));
Z = Z + imageOrigin(3);

% Close all open figures
close all

% Initialize a new figure window
figure;
set(gcf, 'Visible', 'on');

% Plot the initial robot position
show(sawyer, jointData(1,:)');
hold on

% Initialize end effector plot position
p = plot3(0,0,0, '.');
warp(X,Y,Z,I');

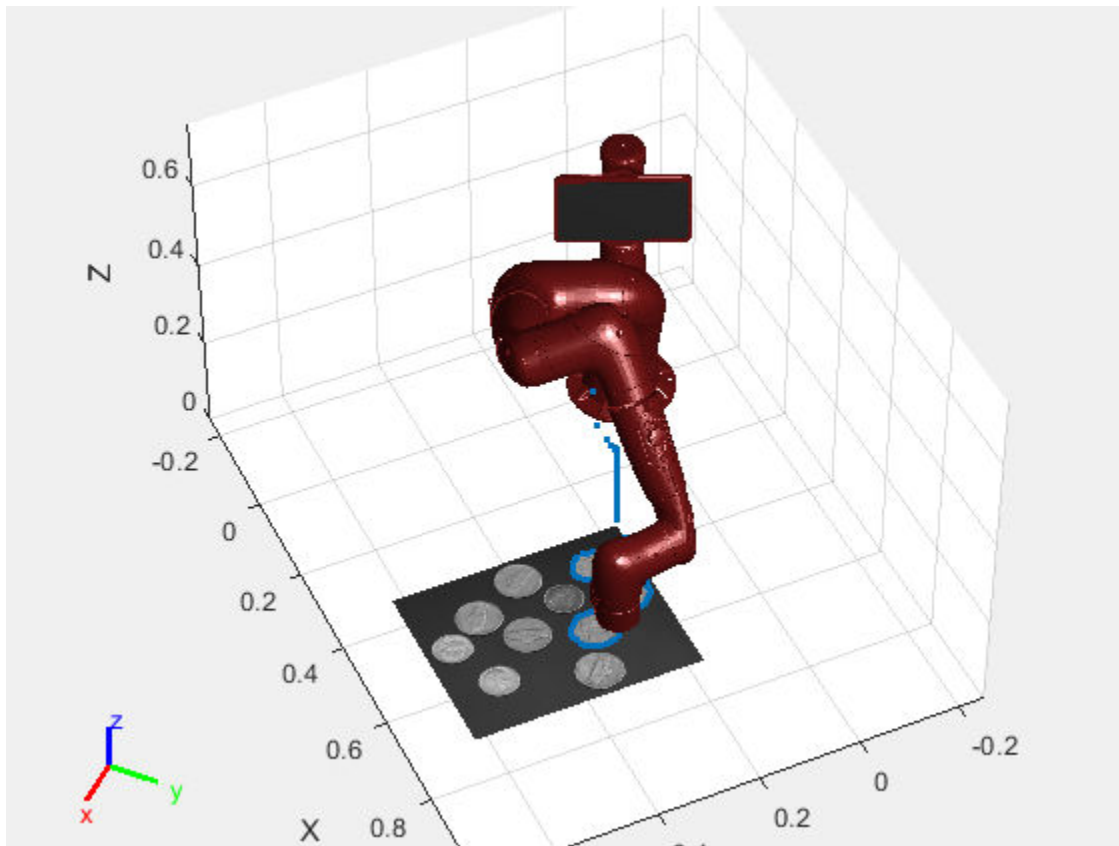
% Change view angle and axis
view(65,45)
axis([-0.25 1 -0.25 0.75 0 0.75])

% Iterate through the outputs at 10-sample intervals to visualize the results
for j = 1:10:length(jointData)
    % Display manipulator model
    show(sawyer, jointData(j,:)'), 'Frames', 'off', 'PreservePlot', false);

    % Get end effector position from homogeneous transform output
    pos = poseData(1:3,4,j);

    % Update end effector position for plot
    p.XData = [p.XData pos(1)];
    p.YData = [p.YData pos(2)];
    p.ZData = [p.ZData pos(3)];

    % Update figure
    drawnow
end
```

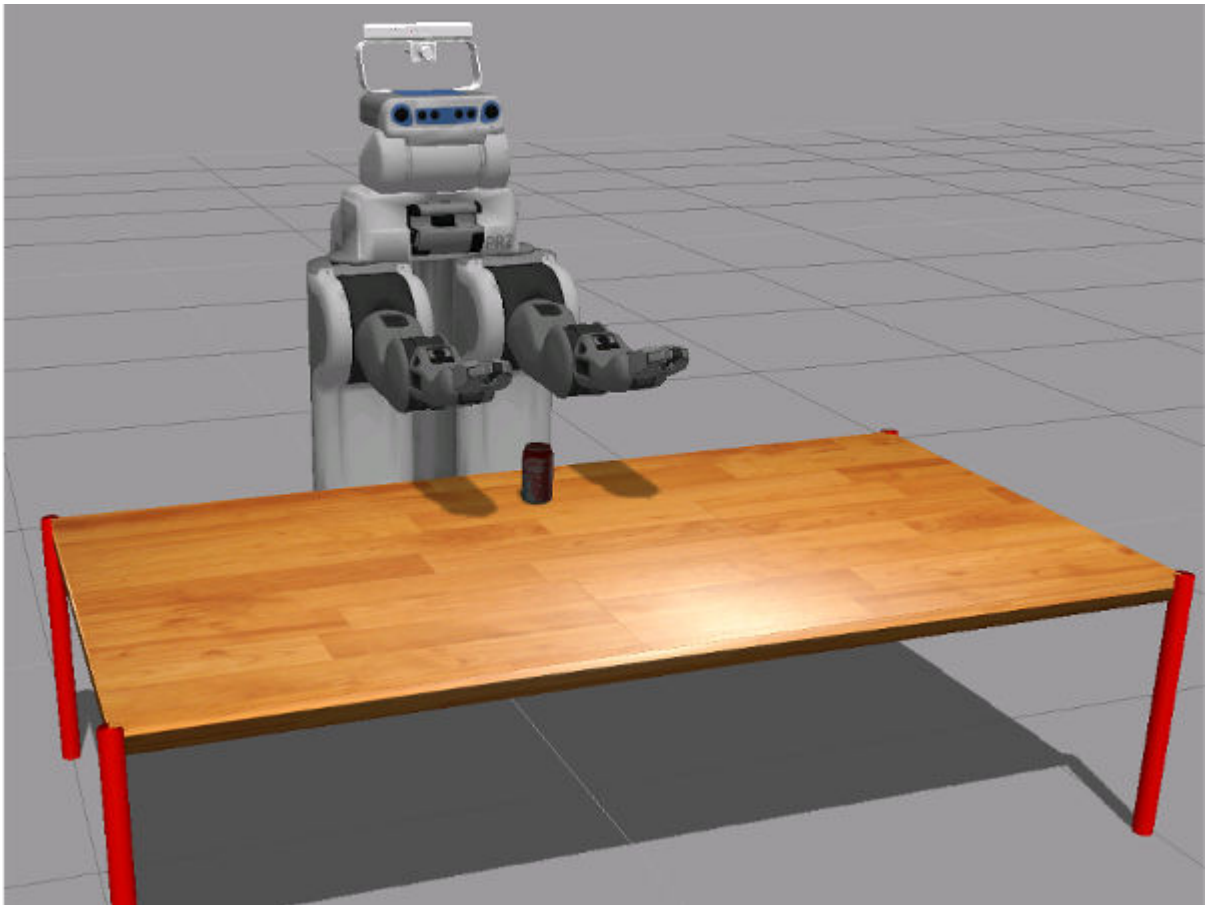


Control PR2 Arm Movements Using ROS Actions and Inverse Kinematics

This example shows how to send commands to robotic manipulators in MATLAB®. Joint position commands are sent via a ROS action client over a ROS network. This example also shows how to calculate joint positions for a desired end-effector position. A rigid body tree defines the robot geometry and joint constraints, which is used with inverse kinematics to get the robot joint positions. You can then send these joint positions as a trajectory to command the robot to move.

Bring up PR2 Gazebo Simulation

Spawn PR2 in a simple environment (only with a table and a coke can) in Gazebo Simulator. Follow steps in the “Get Started with Gazebo and a Simulated TurtleBot” (ROS Toolbox) to launch the Gazebo PR2 Simulator from the Ubuntu® virtual machine desktop.



Connect to ROS Network from MATLAB®

In your MATLAB instance on the host computer, run the following commands to initialize ROS global node in MATLAB and connect to the ROS master in the virtual machine through its IP address `ipaddress`. Replace '192.168.233.133' with the IP address of your virtual machine. Specify the port if needed.

```
ipaddress = '192.168.233.133';  
rosinit(ipaddress,11311);
```

```
Initializing global node /matlab_global_node_59258 with NodeURI http://192.168.233.1:57169/
```

Create Action Clients for Robot Arms and Send Commands

In this task, you send joint trajectories to the PR2 arms. The arms can be controlled via ROS actions. Joint trajectories are manually specified for each arm and sent as separate goal messages via separate action clients.

Create a ROS simple action client to send goal messages to move the right arm of the robot. `rosactionclient` (ROS Toolbox) object and goal message are returned. Wait for the client to connect to the ROS action server.

```
[rArm, rGoalMsg] = rosactionclient('r_arm_controller/joint_trajectory_action');  
waitForServer(rArm);
```

The goal message is a `trajectory_msgs/JointTrajectoryPoint` message. Each trajectory point should specify positions and velocities of the joints.

```
disp(rGoalMsg)
```

```
ROS JointTrajectoryGoal message with properties:
```

```
  MessageType: 'pr2_controllers_msgs/JointTrajectoryGoal'  
  Trajectory: [1x1 JointTrajectory]
```

```
Use showdetails to show the contents of the message
```

```
disp(rGoalMsg.Trajectory)
```

```
ROS JointTrajectory message with properties:
```

```
  MessageType: 'trajectory_msgs/JointTrajectory'  
  Header: [1x1 Header]  
  JointNames: {0x1 cell}  
  Points: [0x1 JointTrajectoryPoint]
```

```
Use showdetails to show the contents of the message
```

Set the joint names to match the PR2 robot joint names. Note that there are 7 joints to control. To find what joints are in PR2 right arm, type this command in the virtual machine terminal:

```
rosparam get /r_arm_controller/joints
```

```
rGoalMsg.Trajectory.JointNames = {'r_shoulder_pan_joint', ...  
    'r_shoulder_lift_joint', ...  
    'r_upper_arm_roll_joint', ...  
    'r_elbow_flex_joint', ...  
    'r_forearm_roll_joint', ...  
    'r_wrist_flex_joint', ...  
    'r_wrist_roll_joint'};
```

Create setpoints in the arm joint trajectory by creating ROS `trajectory_msgs/JointTrajectoryPoint` messages and specifying the position and velocity of all 7 joints as a vector. Specify a time from the start as a ROS duration object.

```
% Point 1  
tjPoint1 = rosmesssage('trajectory_msgs/JointTrajectoryPoint');  
tjPoint1.Positions = zeros(1,7);
```



```
tjPoint1.Velocities = zeros(1,7);
tjPoint1.TimeFromStart = rosduration(1.0);
```

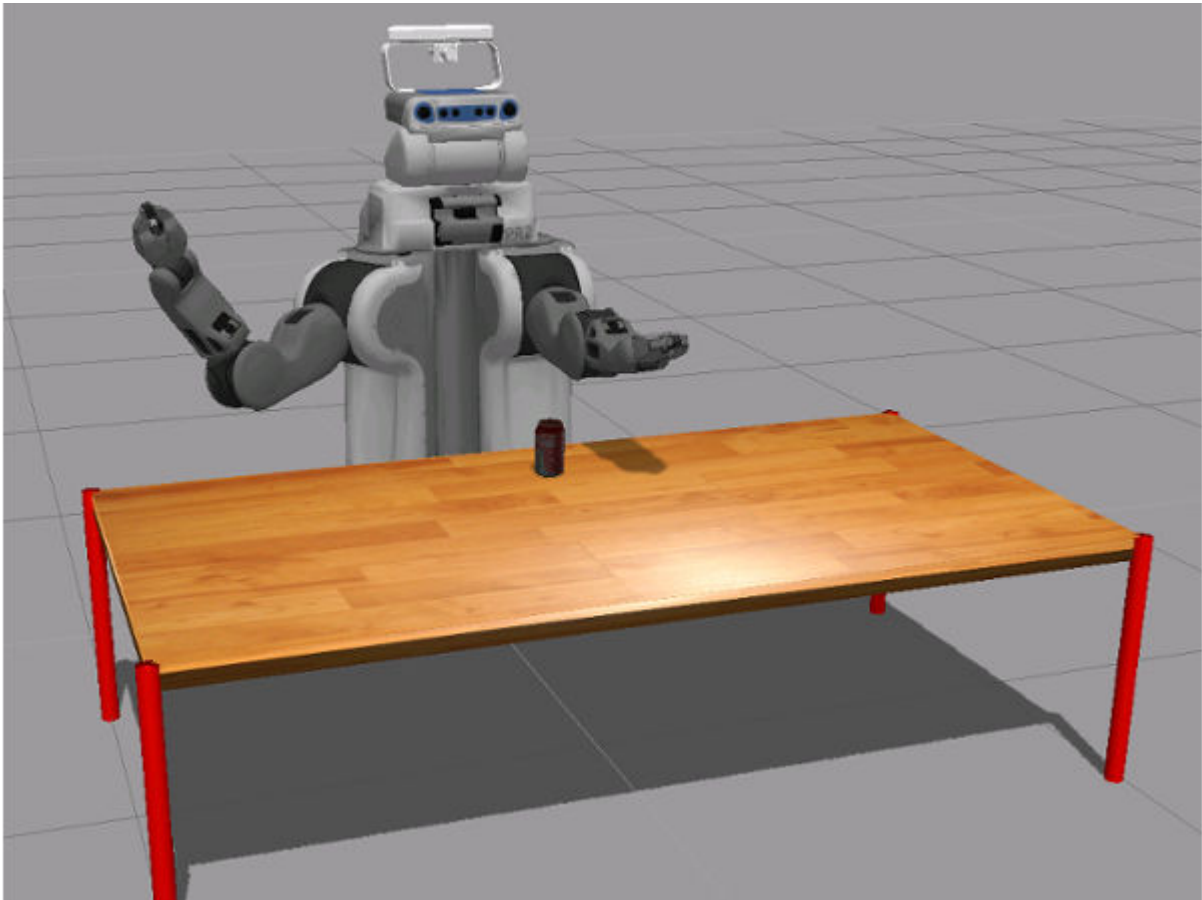
```
% Point 2
```

```
tjPoint2 = rosmesssage('trajectory_msgs/JointTrajectoryPoint');
tjPoint2.Positions = [-1.0 0.2 0.1 -1.2 -1.5 -0.3 -0.5];
tjPoint2.Velocities = zeros(1,7);
tjPoint2.TimeFromStart = rosduration(2.0);
```

Create an object array with the points in the trajectory and assign it to the goal message. Send the goal using the action client. The `sendGoalAndWait` (ROS Toolbox) function will block execution until the PR2 arm finishes executing the trajectory

```
rGoalMsg.Trajectory.Points = [tjPoint1,tjPoint2];
```

```
sendGoalAndWait(rArm,rGoalMsg);
```



Create another action client to send commands to the left arm. Specify the joint names of the PR2 robot.

```
[lArm, lGoalMsg] = rosmesssage('l_arm_controller/joint_trajectory_action');
waitForServer(lArm);
```

```
lGoalMsg.Trajectory.JointNames = {'l_shoulder_pan_joint', ...
                                   'l_shoulder_lift_joint', ...
```

```

'l_upper_arm_roll_joint', ...
'l_elbow_flex_joint',...
'l_forearm_roll_joint',...
'l_wrist_flex_joint',...
'l_wrist_roll_joint'};

```

Set a trajectory point for the left arm. Assign it to the goal message and send the goal.

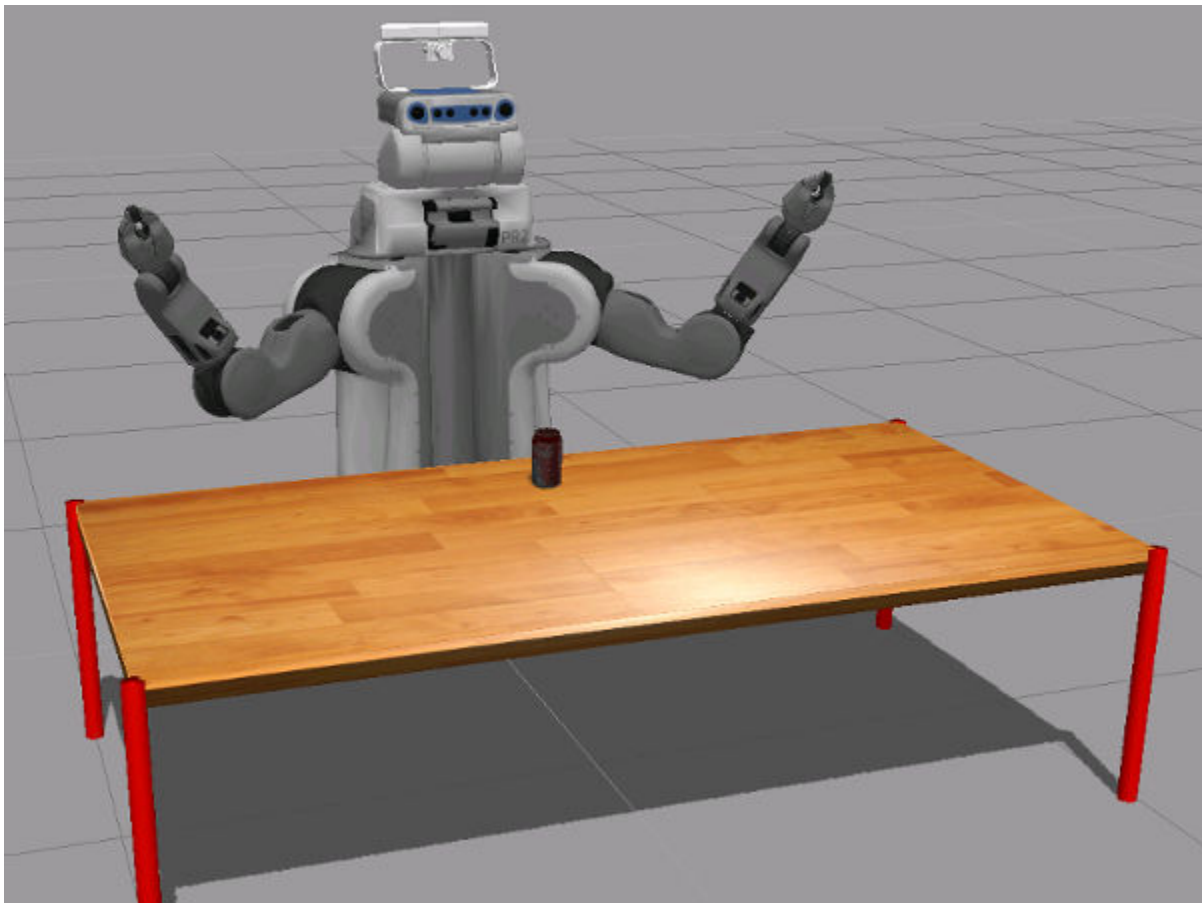
```

tjPoint3 = rosmesssage('trajectory_msgs/JointTrajectoryPoint');
tjPoint3.Positions = [1.0 0.2 -0.1 -1.2 1.5 -0.3 0.5];
tjPoint3.Velocities = zeros(1,7);
tjPoint3.TimeFromStart = rosduration(2.0);

lGoalMsg.Trajectory.Points = tjPoint3;

sendGoalAndWait(lArm,lGoalMsg);

```



Calculate Inverse Kinematics for an End-Effector Position

In this section, you calculate a trajectory for joints based on the desired end-effector (PR2 right gripper) positions. The `inverseKinematics` class calculates all the required joint positions, which can be sent as a trajectory goal message via the action client. A `rigidBodyTree` object is used to define the robot parameters, generate configurations, and visualize the robot in MATLAB®.

Perform The following steps:

- Get the current state of the PR2 robot from the ROS network and assign it to a `rigidBodyTree` object to work with the robot in MATLAB®.
- Define an end-effector goal pose.
- Visualize the robot configuration using these joint positions to ensure a proper solution.
- Use inverse kinematics to calculate joint positions from goal end-effector poses.
- Send the trajectory of joint positions to the ROS action server to command the actual PR2 robot.

Create a Rigid Body Tree in MATLAB®

Load a PR2 robot as a `rigidBodyTree` object. This object defines all the kinematic parameters (including joint limits) of the robot.

```
pr2 = exampleHelperWGPR2Kinect;
```

Get the Current Robot State

Create a subscriber to get joint states from the robot.

```
jointSub = rossubscriber('joint_states');
```

Get the current joint state message.

```
jntState = receive(jointSub);
```

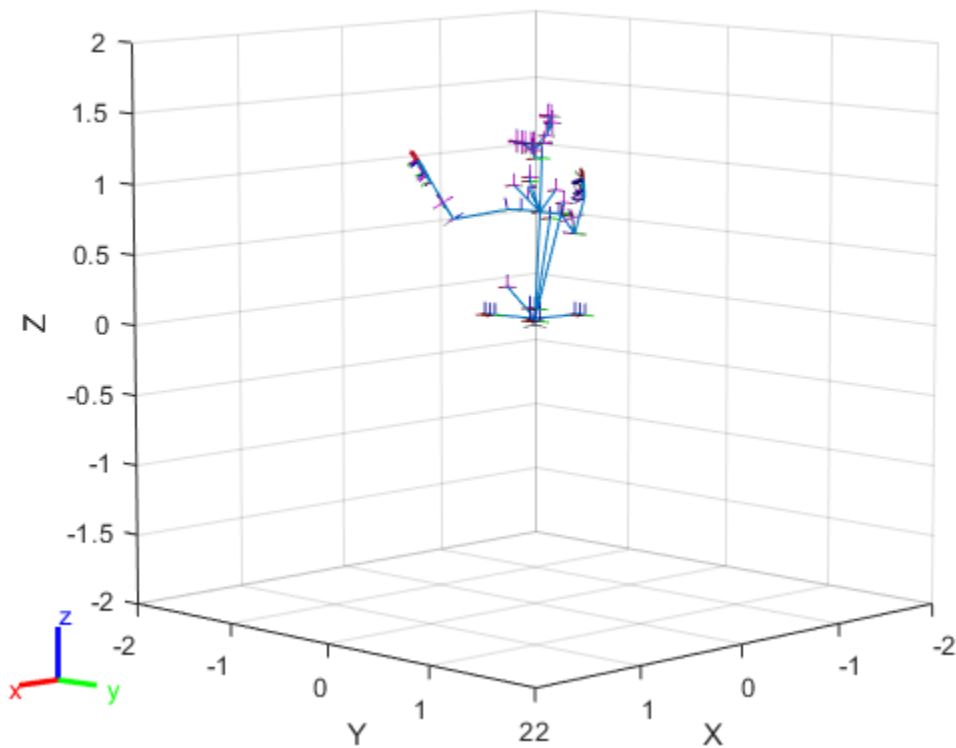
Assign the joint positions from the joint states message to the fields of a configuration struct that the `pr2` object understands.

```
jntPos = exampleHelperJointMsgToStruct(pr2, jntState);
```

Visualize the Current Robot Configuration

Use `show` to visualize the robot with the given joint position vector. This should match the current state of the robot.

```
show(pr2, jntPos)
```



```
ans =
  Axes (Primary) with properties:

    XLim: [-2 2]
    YLim: [-2 2]
    XScale: 'linear'
    YScale: 'linear'
    GridLineStyle: '-'
    Position: [0.1300 0.1100 0.7750 0.8150]
    Units: 'normalized'
```

Show all properties

Create an `inverseKinematics` object from the `pr2` robot object. The goal of inverse kinematics is to calculate the joint angles for the PR2 arm that places the gripper (i.e. the end-effector) in a desired pose. A sequence of end-effector poses over a period of time is called a trajectory.

In this example, we will only be controlling the robot's arms. Therefore, we place tight limits on the torso-lift joint during planning.

```
torsoJoint = pr2.getBody('torso_lift_link').Joint;
idx = strcmp({jntPos.JointName}, torsoJoint.Name);
torsoJoint.HomePosition = jntPos(idx).JointPosition;
torsoJoint.PositionLimits = jntPos(idx).JointPosition + [-1e-3,1e-3];
```

Create the `inverseKinematics` object.

```
ik = inverseKinematics('RigidBodyTree', pr2);
```

Disable random restart to ensure consistent IK solutions.

```
ik.SolverParameters.AllowRandomRestart = false;
```

Specify weights for the tolerances on each component of the goal pose.

```
weights = [0.25 0.25 0.25 1 1 1];
initialGuess = jntPos; % current jnt pos as initial guess
```

Specify end-effector poses related to the task. In this example, PR2 will reach to the can on the table, grasp the can, move it to a different location and set it down again. We will use the `inverseKinematics` object to plan motions that smoothly transition from one end-effector pose to another.

Specify the name of the end effector.

```
endEffectorName = 'r_gripper_tool_frame';
```

Specify the can's initial (current) pose and the desired final pose.

```
TCanInitial = trvec2tform([0.7, 0.0, 0.55]);
TCanFinal = trvec2tform([0.6, -0.5, 0.55]);
```

Define the desired relative transform between the end-effector and the can when grasping.

```
TGraspToCan = trvec2tform([0,0,0.08])*eul2tform([pi/8,0,-pi]);
```

Define the key waypoints of a desired Cartesian trajectory. The can should move along this trajectory. The trajectory can be broken up as follows:

- Open the gripper
- Move the end-effector from current pose to T1 so that the robot will feel comfortable to initiate the grasp
- Move the end-effector from T1 to TGrasp (ready to grasp)
- Close the gripper and grab the can
- Move the end-effector from TGrasp to T2 (lift can in the air)
- Move the end-effector from T2 to T3 (move can levelly)
- Move the end-effector from T3 to TRelease (lower can to table surface and ready to release)
- Open the gripper and let go of the can
- Move the end-effector from TRelease to T4 (retract arm)

```
TGrasp = TCanInitial*TGraspToCan; % The desired end-effector pose when grasping the can
T1 = TGrasp*trvec2tform([0.,0,-0.1]);
T2 = TGrasp*trvec2tform([0,0,-0.2]);
T3 = TCanFinal*TGraspToCan*trvec2tform([0,0,-0.2]);
TRelease = TCanFinal*TGraspToCan; % The desired end-effector pose when releasing the can
T4 = T3*trvec2tform([-0.1,0,0]);
```

The actual motion will be specified by `numWaypoints` joint positions in a sequence and sent to the robot through the ROS simple action client. These configurations will be chosen using the `inverseKinematics` object such that the end effector pose is interpolated from the initial pose to the final pose.

Execute the Motion

Specify the sequence of motions.

```
motionTask = {'Release', T1, TGrasp, 'Grasp', T2, T3, TRelease, 'Release', T4};
```

Execute each task specified in motionTask one by one. Send commands using the specified helper functions.

```
for i = 1: length(motionTask)

    if strcmp(motionTask{i}, 'Grasp')
        exampleHelperSendPR2GripperCommand('right',0.0,1000,true);
        continue
    end

    if strcmp(motionTask{i}, 'Release')
        exampleHelperSendPR2GripperCommand('right',0.1,-1,true);
        continue
    end

    Tf = motionTask{i};
    % Get current joint state
    jntState = receive(jointSub);
    jntPos = exampleHelperJointMsgToStruct(pr2, jntState);

    T0 = getTransform(pr2, jntPos, endEffectorName);

    % Interpolating between key waypoints
    numWaypoints = 10;
    TWaypoints = exampleHelperSE3Trajectory(T0, Tf, numWaypoints); % end-effector pose waypoints
    jntPosWaypoints = repmat(initialGuess, numWaypoints, 1); % joint position waypoints

    rArmJointNames = rGoalMsg.Trajectory.JointNames;
    rArmJntPosWaypoints = zeros(numWaypoints, numel(rArmJointNames));

    % Calculate joint position for each end-effector pose waypoint using IK
    for k = 1:numWaypoints
        jntPos = ik(endEffectorName, TWaypoints(:,:,k), weights, initialGuess);
        jntPosWaypoints(k, :) = jntPos;
        initialGuess = jntPos;

        % Extract right arm joint positions from jntPos
        rArmJointPos = zeros(size(rArmJointNames));
        for n = 1:length(rArmJointNames)
            rn = rArmJointNames{n};
            idx = strcmp({jntPos.JointName}, rn);
            rArmJointPos(n) = jntPos(idx).JointPosition;
        end
        rArmJntPosWaypoints(k,:) = rArmJointPos';
    end

    % Time points corresponding to each waypoint
    timePoints = linspace(0,3,numWaypoints);

    % Estimate joint velocity trajectory numerically
    h = diff(timePoints); h = h(1);
    jntTrajectoryPoints = arrayfun(@(~) rosmesssage('trajectory_msgs/JointTrajectoryPoint'), zeros
```

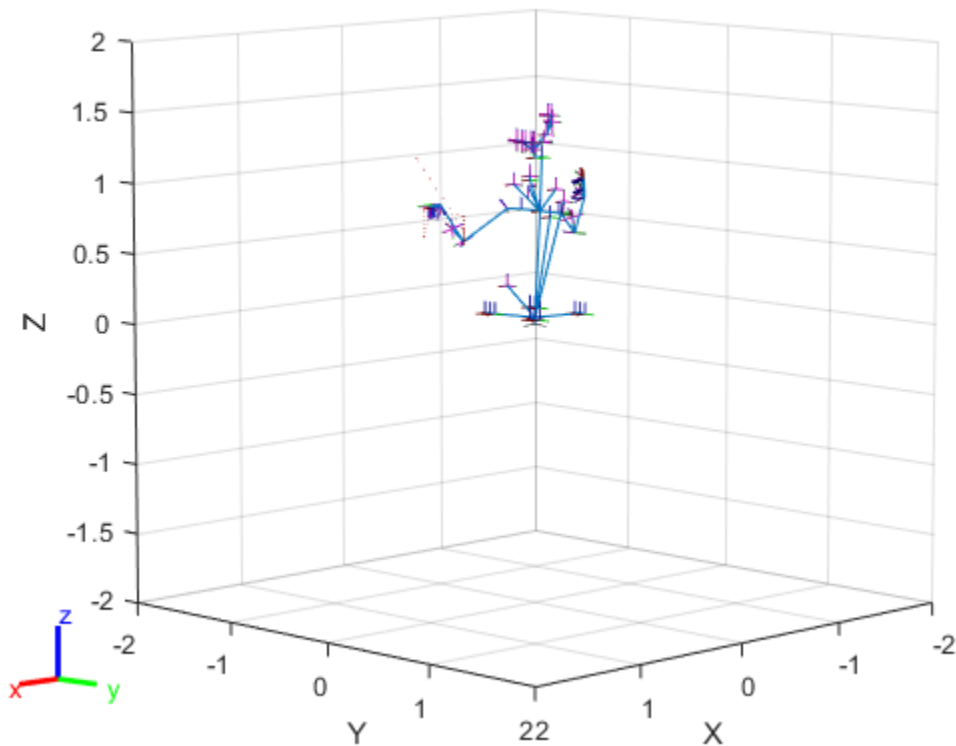
```

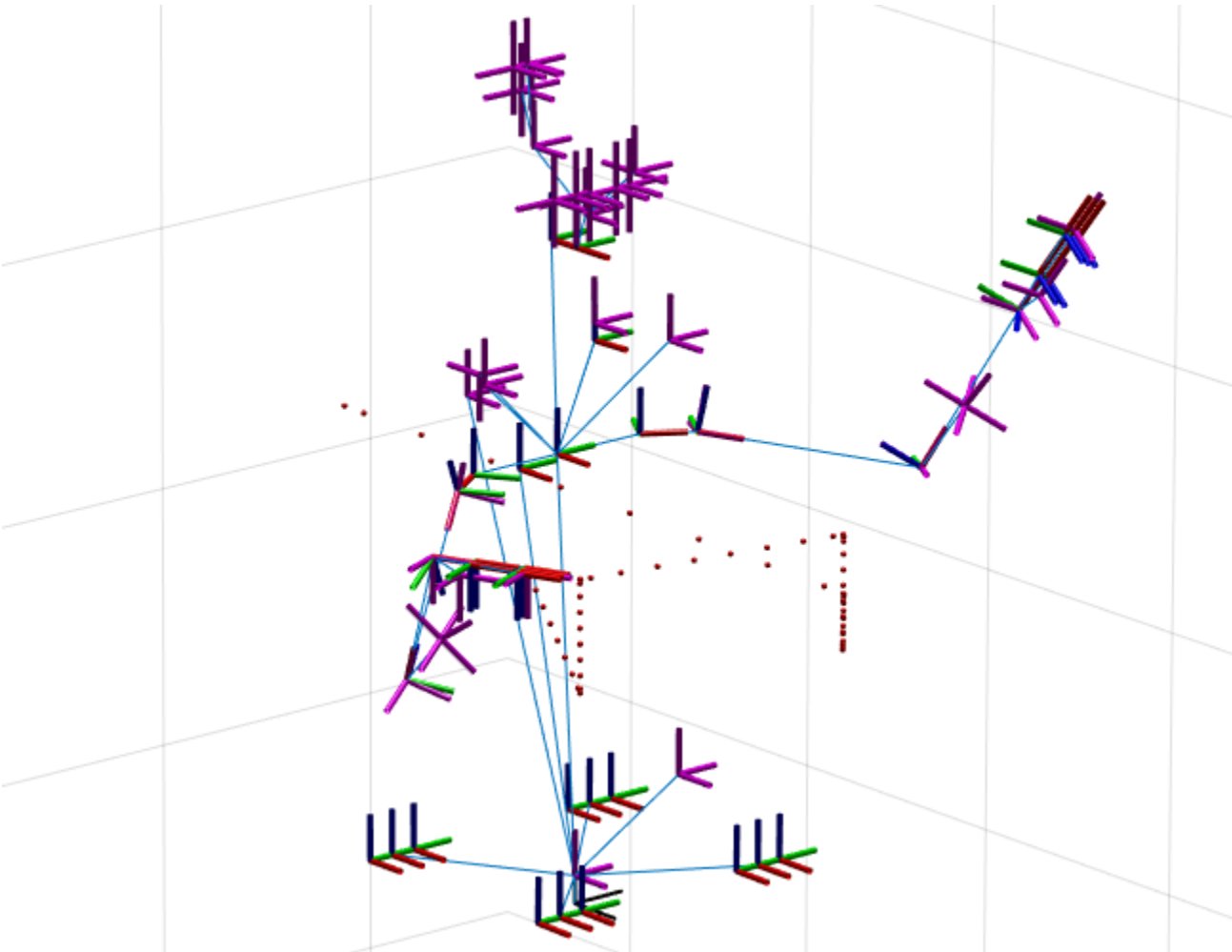
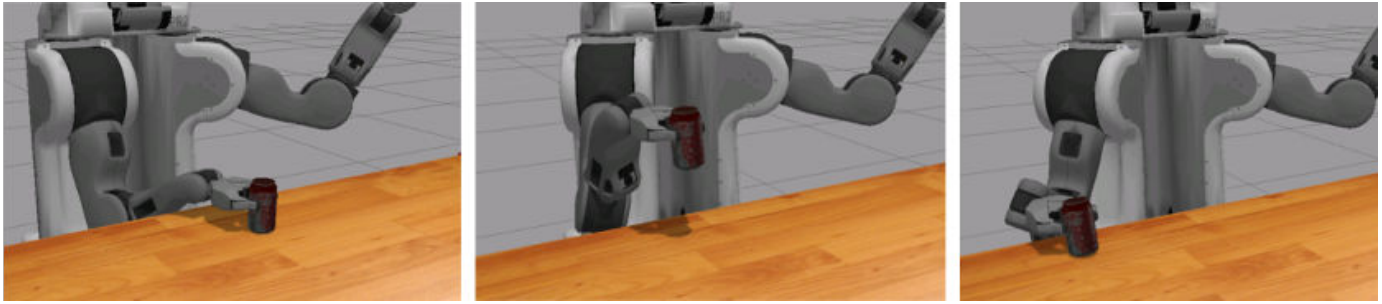
[~, rArmJntVelWaypoints] = gradient(rArmJntPosWaypoints, h);
for m = 1:numWaypoints
    jntTrajectoryPoints(m).Positions = rArmJntPosWaypoints(m,:);
    jntTrajectoryPoints(m).Velocities = rArmJntVelWaypoints(m,:);
    jntTrajectoryPoints(m).TimeFromStart = rosduration(timePoints(m));
end

% Visualize robot motion and end-effector trajectory in MATLAB(R)
hold on
for j = 1:numWaypoints
    show(pr2, jntPosWaypoints(j,:), 'PreservePlot', false);
    exampleHelperShowEndEffectorPos(TWaypoints(:, :, j));
    drawnow;
    pause(0.1);
end

% Send the right arm trajectory to the robot
rGoalMsg.Trajectory.Points = jntTrajectoryPoints;
sendGoalAndWait(rArm, rGoalMsg);
end

```





Wrap Up

Move arm back to starting position.

```
exampleHelperSendPR2GripperCommand('r',0.0,-1)  
rGoalMsg.Trajectory.Points = tjPoint2;  
sendGoal(rArm, rGoalMsg);
```

Call `roshutdown` to shutdown ROS network and disconnect from the robot.

```
roshutdown
```


Shutting down global node /matlab_global_node_59258 with NodeURI http://192.168.233.1:57169/

Plan a Reaching Trajectory With Multiple Kinematic Constraints

This example shows how to use generalized inverse kinematics to plan a joint-space trajectory for a robotic manipulator. It combines multiple constraints to generate a trajectory that guides the gripper to a cup resting on a table. These constraints ensure that the gripper approaches the cup in a straight line and that the gripper remains at a safe distance from the table, without requiring the poses of the gripper to be determined in advance.

Set Up the Robot Model

This example uses a model of the KUKA LBR iiwa, a 7 degree-of-freedom robot manipulator. `importrobot` generates a `rigidBodyTree` model from a description stored in a Unified Robot Description Format (URDF) file.

```
lbr = importrobot('iiwa14.urdf'); % 14 kg payload version
lbr.DataFormat = 'row';
gripper = 'iiwa_link_ee_kuka';
```

Define dimensions for the cup.

```
cupHeight = 0.2;
cupRadius = 0.05;
cupPosition = [-0.5, 0.5, cupHeight/2];
```

Add a fixed body to the robot model representing the center of the cup.

```
body = rigidBody('cupFrame');
setFixedTransform(body.Joint, trvec2tform(cupPosition))
addBody(lbr, body, lbr.BaseName);
```

Define the Planning Problem

The goal of this example is to generate a sequence of robot configurations that satisfy the following criteria:

- Start in the home configuration
- No abrupt changes in robot configuration
- Keep the gripper at least 5 cm above the "table" ($z = 0$)
- The gripper should be aligned with the cup as it approaches
- Finish with the gripper 5 cm from the center of the cup

This example utilizes constraint objects to generate robot configurations that satisfy these criteria. The generated trajectory consists of five configuration waypoints. The first waypoint, `q0`, is set as the home configuration. Pre-allocate the rest of the configurations in `qWaypoints` using `repmat`.

```
numWaypoints = 5;
q0 = homeConfiguration(lbr);
qWaypoints = repmat(q0, numWaypoints, 1);
```

Create a `generalizedInverseKinematics` solver that accepts the following constraint inputs:

- Cartesian bounds - Limits the height of the gripper
- A position target - Specifies the position of the cup relative to the gripper.

- An aiming constraint - Aligns the gripper with the cup axis
- An orientation target - Maintains a fixed orientation for the gripper while approaching the cup
- Joint position bounds - Limits the change in joint positions between waypoints.

```
gik = generalizedInverseKinematics('RigidBodyTree', lbr, ...
    'ConstraintInputs', {'cartesian', 'position', 'aiming', 'orientation', 'joint'})
```

```
gik =
    generalizedInverseKinematics with properties:
```

```
    NumConstraints: 5
    ConstraintInputs: {1x5 cell}
    RigidBodyTree: [1x1 rigidBodyTree]
    SolverAlgorithm: 'BFGSGradientProjection'
    SolverParameters: [1x1 struct]
```

Create Constraint Objects

Create the constraint objects that are passed as inputs to the solver. These object contain the parameters needed for each constraint. Modify these parameters between calls to the solver as necessary.

Create a Cartesian bounds constraint that requires the gripper to be at least 5 cm above the table (negative z direction). All other values are given as `inf` or `-inf`.

```
heightAboveTable = constraintCartesianBounds(gripper);
heightAboveTable.Bounds = [-inf, inf; ...
    -inf, inf; ...
    0.05, inf]
```

```
heightAboveTable =
    constraintCartesianBounds with properties:
```

```
    EndEffector: 'iiwa_link_ee_kuka'
    ReferenceBody: ''
    TargetTransform: [4x4 double]
    Bounds: [3x2 double]
    Weights: [1 1 1]
```

Create a constraint on the position of the cup relative to the gripper, with a tolerance of 5 mm.

```
distanceFromCup = constraintPositionTarget('cupFrame');
distanceFromCup.ReferenceBody = gripper;
distanceFromCup.PositionTolerance = 0.005
```

```
distanceFromCup =
    constraintPositionTarget with properties:
```

```
    EndEffector: 'cupFrame'
    ReferenceBody: 'iiwa_link_ee_kuka'
    TargetPosition: [0 0 0]
    PositionTolerance: 0.0050
    Weights: 1
```

Create an aiming constraint that requires the z-axis of the `iiwa_link_ee` frame to be approximately vertical, by placing the target far above the robot. The `iiwa_link_ee` frame is oriented such that this constraint aligns the gripper with the axis of the cup.

```
alignWithCup = constraintAiming('iiwa_link_ee');  
alignWithCup.TargetPoint = [0, 0, 100]
```

```
alignWithCup =  
  constraintAiming with properties:  
  
    EndEffector: 'iiwa_link_ee'  
  ReferenceBody: ''  
    TargetPoint: [0 0 100]  
  AngularTolerance: 0  
        Weights: 1
```

Create a joint position bounds constraint. Set the `Bounds` property of this constraint based on the previous configuration to limit the change in joint positions.

```
limitJointChange = constraintJointBounds(lbr)
```

```
limitJointChange =  
  constraintJointBounds with properties:  
  
    Bounds: [7x2 double]  
  Weights: [1 1 1 1 1 1 1]
```

Create an orientation constraint for the gripper with a tolerance of one degree. This constraint requires the orientation of the gripper to match the value specified by the `TargetOrientation` property. Use this constraint to fix the orientation of the gripper during the final approach to the cup.

```
fixOrientation = constraintOrientationTarget(gripper);  
fixOrientation.OrientationTolerance = deg2rad(1)
```

```
fixOrientation =  
  constraintOrientationTarget with properties:  
  
    EndEffector: 'iiwa_link_ee_kuka'  
  ReferenceBody: ''  
  TargetOrientation: [1 0 0 0]  
  OrientationTolerance: 0.0175  
        Weights: 1
```

Find a Configuration That Points at the Cup

This configuration should place the gripper at a distance from the cup, so that the final approach can be made with the gripper properly aligned.

```
intermediateDistance = 0.3;
```

Constraint objects have a `Weights` property which determines how the solver treats conflicting constraints. Setting the weights of a constraint to zero disables the constraint. For this configuration, disable the joint position bounds and orientation constraint.

```
limitJointChange.Weights = zeros(size(limitJointChange.Weights));  
fixOrientation.Weights = 0;
```

Set the target position for the cup in the gripper frame. The cup should lie on the z-axis of the gripper at the specified distance.

```
distanceFromCup.TargetPosition = [0,0,intermediateDistance];
```

Solve for the robot configuration that satisfies the input constraints using the `gik` solver. You must specify all the input constraints. Set that configuration as the second waypoint.

```
[qWaypoints(2,:),solutionInfo] = gik(q0, heightAboveTable, ...
    distanceFromCup, alignWithCup, fixOrientation, ...
    limitJointChange);
```

Find Configurations That Move Gripper to the Cup Along a Straight Line

Re-enable the joint position bound and orientation constraints.

```
limitJointChange.Weights = ones(size(limitJointChange.Weights));
fixOrientation.Weights = 1;
```

Disable the align-with-cup constraint, as the orientation constraint makes it redundant.

```
alignWithCup.Weights = 0;
```

Set the orientation constraint to hold the orientation based on the previous configuration (`qWaypoints(2,:)`). Get the transformation from the gripper to the base of the robot model. Convert the homogeneous transformation to a quaternion.

```
fixOrientation.TargetOrientation = ...
    tform2quat(getTransform(lbr,qWaypoints(2,:),gripper));
```

Define the distance between the cup and gripper for each waypoint

```
finalDistanceFromCup = 0.05;
distanceFromCupValues = linspace(intermediateDistance, finalDistanceFromCup, numWaypoints-1);
```

Define the maximum allowed change in joint positions between each waypoint.

```
maxJointChange = deg2rad(10);
```

Call the solver for each remaining waypoint.

```
for k = 3:numWaypoints
    % Update the target position.
    distanceFromCup.TargetPosition(3) = distanceFromCupValues(k-1);
    % Restrict the joint positions to lie close to their previous values.
    limitJointChange.Bounds = [qWaypoints(k-1,:) - maxJointChange, ...
        qWaypoints(k-1,:) + maxJointChange];
    % Solve for a configuration and add it to the waypoints array.
    [qWaypoints(k,:),solutionInfo] = gik(qWaypoints(k-1,:), ...
        heightAboveTable, ...
        distanceFromCup, alignWithCup, ...
        fixOrientation, limitJointChange);
end
```

Visualize the Generated Trajectory

Interpolate between the waypoints to generate a smooth trajectory. Use `pchip` to avoid overshoots, which might violate the joint limits of the robot.

```

framerate = 15;
r = rateControl(framerate);
tFinal = 10;
tWaypoints = [0, linspace(tFinal/2, tFinal, size(qWaypoints,1)-1)];
numFrames = tFinal*framerate;
qInterp = pchip(tWaypoints, qWaypoints', linspace(0, tFinal, numFrames))';

```

Compute the gripper position for each interpolated configuration.

```

gripperPosition = zeros(numFrames,3);
for k = 1:numFrames
    gripperPosition(k,:) = tform2trvec(getTransform(lbr, qInterp(k,:), ...
                                                    gripper));
end

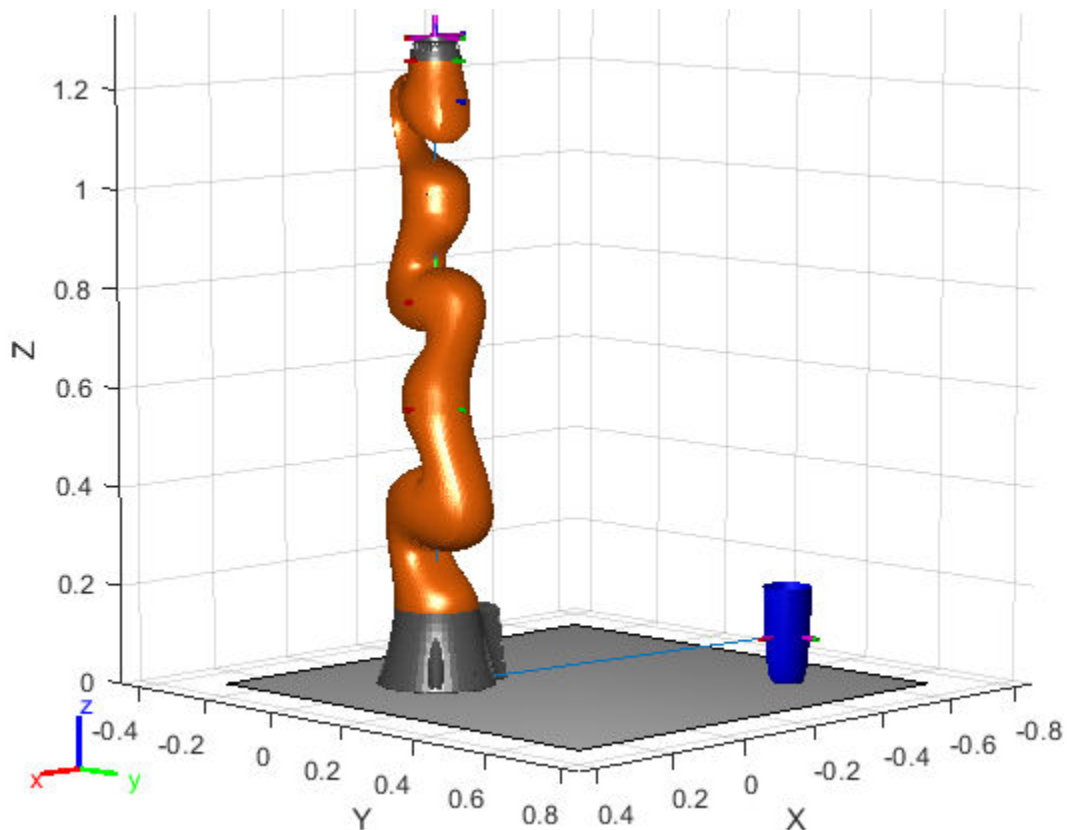
```

Show the robot in its initial configuration along with the table and cup

```

figure;
show(lbr, qWaypoints(1,:), 'PreservePlot', false);
hold on
exampleHelperPlotCupAndTable(cupHeight, cupRadius, cupPosition);
p = plot3(gripperPosition(1,1), gripperPosition(1,2), gripperPosition(1,3));

```



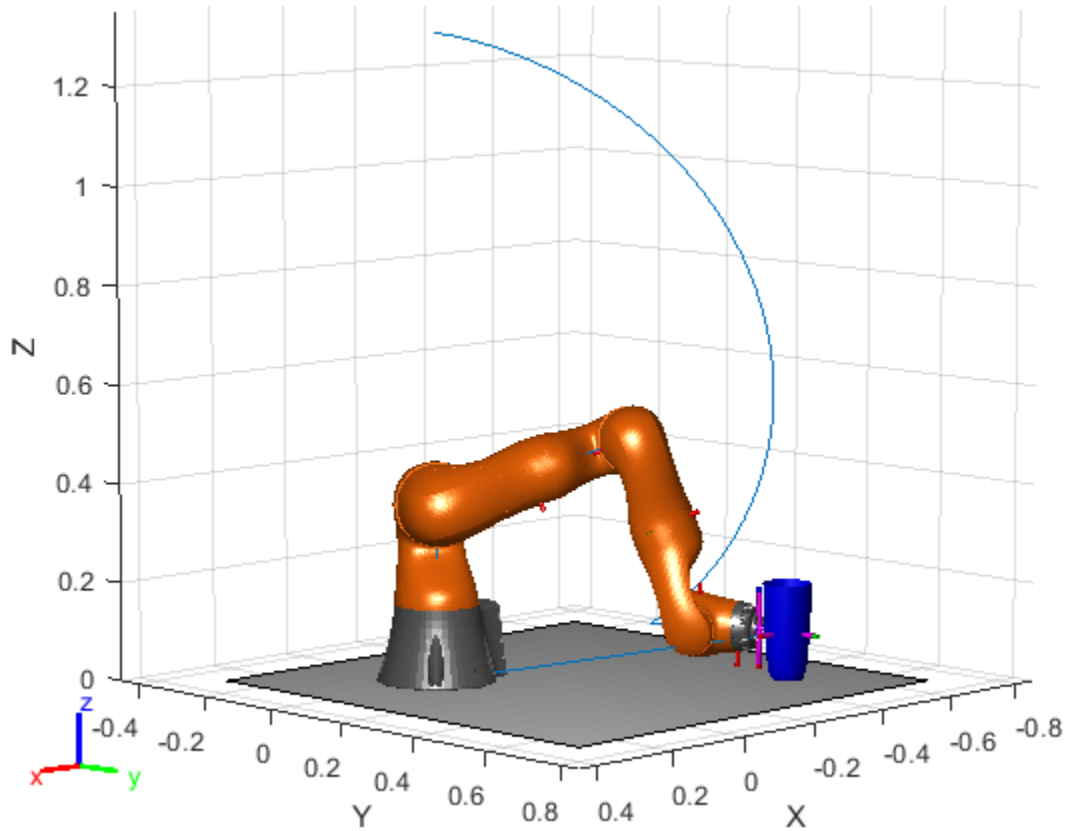
Animate the manipulator and plot the gripper position.

```

hold on
for k = 1:size(qInterp,1)
    show(lbr, qInterp(k,:), 'PreservePlot', false);
end

```

```
p.XData(k) = gripperPosition(k,1);  
p.YData(k) = gripperPosition(k,2);  
p.ZData(k) = gripperPosition(k,3);  
waitfor(r);  
end  
hold off
```



If you want to save the generated configurations to a MAT-file for later use, execute the following:

```
>> save('lbr_trajectory.mat', 'tWaypoints', 'qWaypoints');
```

Create Collision Objects for Manipulator Collision Checking

This example shows the three different ways to create collision objects for manipulator collision checking. To see more in-depth examples that check for self-collisions or environment collision detection, try the following examples:

- “Check for Manipulator Self Collisions using Collision Meshes” on page 1-144
- “Check for Environmental Collisions with Manipulators” on page 1-148
- “Plan and Execute Collision-Free Trajectories using KINOVA Gen3 Manipulator” on page 1-187
- “Pick-and-Place Workflow using Stateflow for MATLAB” on page 1-211

Overview of Collision Checking for Manipulators

The `checkCollisions` function is generic to any application or specific mesh configuration. This means:

- To check for collisions, you need to represent each collision object as a primitive or mesh, and specify the pose.
- For manipulators, the poses can be obtained from the rigid body tree, but the poses must be assigned to the collision object.

This example shows two example helpers that automate this process for building a cell array for storing the collision objects and their poses. The options are:

- Rigid body collision array: cell array of 1x2 cells, where each cell has the collision primitive corresponding to the i th body in the vector `[base robot.Bodies]` and the transform that relates that collision object's origin to the associated rigid body joint.
- World collision array: cell array of world collision objects.

There are three suggested ways to initialize the rigid body collision array:

- 1 Using meshes imported from a known directory.
- 2 Extracting the meshes from a `rigidBodyTree` object.
- 3 Using collision primitives to represent your geometry.

Method 1: Use Meshes in a Known Directory

Many robots come with collision meshes specified in their Unified Robot Definition Format (URDF) file.

The IIWA robot comes with a set of collision meshes, which are simplified versions of the visualization meshes. Call `importrobot` to generate a `rigidBodyTree` object from the URDF file. Set the output format for configurations to "column".

```
iiwa = importrobot('iiwa14.urdf');  
iiwa.DataFormat = 'column';
```

Create Collision-Checking Tools using Collision Meshes

Once the rigid body tree has been created, generate a set of collision meshes for each link of the rigid body tree. This will be achieved by generating an cell array of $n+1$ for the n bodies in the `rigidBodyTree` object. The extra element stores the collision object for the base.


```
collisionArrayFromMesh = cell(iiwa.NumBodies+1, 2);
```

Create a `rigidBodyTree` object and specify the path of the folder containing the collision meshes. This syntax associated the rigid body objects with the STL mesh files based on their specified name.

```
% Create a rigid body tree using the collision mesh path to associate rigid
% bodies with collision mesh STL files
collisionMeshPath = fullfile(matlabroot, 'toolbox', 'robotics', ...
    'robotexamples', 'robotmanip', 'data', 'iiwa_description', ...
    'meshes', 'iiwa14', 'collision');
iiwaCollision = importrobot('iiwa14.urdf', 'MeshPath', collisionMeshPath);
iiwaCollision.DataFormat = 'column';
```

Create the collision mesh definitions for each rigid body from the source directory:

- Convert each STL file to faces and vertices by reading the STL: `stldata = stlread(file.STL)`
- Create a `collisionMesh` from the vertices: `mesh = collisionMesh(stldata.Points);`
- Assign the mesh to the *i*th body by placing it in the (*i*+1)th element of the `collisionArray` cell array. The base mesh occupies the first element of the cell array.

```
% For each body, read the corresponding STL file
robotBodies = [{iiwaCollision.Base} iiwaCollision.Bodies];
for i = 1:numel(robotBodies)
    if ~isempty(robotBodies{i}.Visuals)
        % Assumes the first Visuals element is the correct one.
        visualDetails = robotBodies{i}.Visuals{1};

        % Extract the part of the visual that actually specifies the STL name
        visualParts = strsplit(visualDetails, ':');
        stlFileName = visualParts{2};

        % Read the STL file
        stldata = stlread(fullfile(collisionMeshPath, stlFileName));

        % Create a collisionMesh object from the vertices
        collisionArrayFromMesh{i,1} = collisionMesh(stldata.Points);

        % Transform is always identity
        collisionArrayFromMesh{i,2} = eye(4);
    end
end
```

Check for Self-Collisions at a Specified Configuration

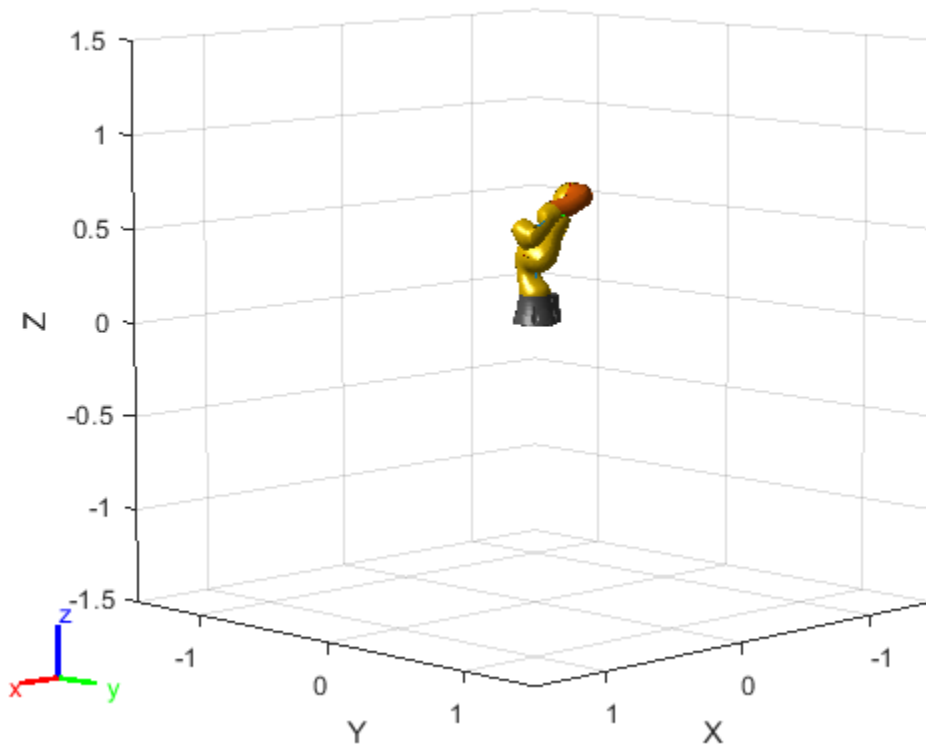
Given an array of collision meshes, the provided `exampleHelperManipCheckCollisions` function iterates through all the bodies to check for collisions and returns the index of the colliding pair.

```
config = [0 -pi/4 pi 0.9*pi 0 -pi/2 0]';
[isCollision, selfCollisionPairIdx] = exampleHelperManipCheckCollisions(iiwaCollision, collisionArrayFromMesh, config);
disp(isCollision)
```

```
1
```

Visualize the robot configuration and highlight colliding bodies using `exampleHelperHighlightCollisionBodies`.

```
show(iiwa, config);
exampleHelperHighlightCollisionBodies(iiwaCollision, selfCollisionPairIdx, gca);
```



Method 2: Extract the Meshes from the Rigid Body Tree

Given a rigid body tree with combined visual and collision meshes, create meshes from the `Visuals` property of each rigid body in the tree. Use `createCollisionArray` from the `exampleHelperManipCollisionsFromVisuals` class. The helper function makes the assumption that in cases of multiple visuals, the first one should be used. If there is no visual for a specific body, the associated cell array is left empty.

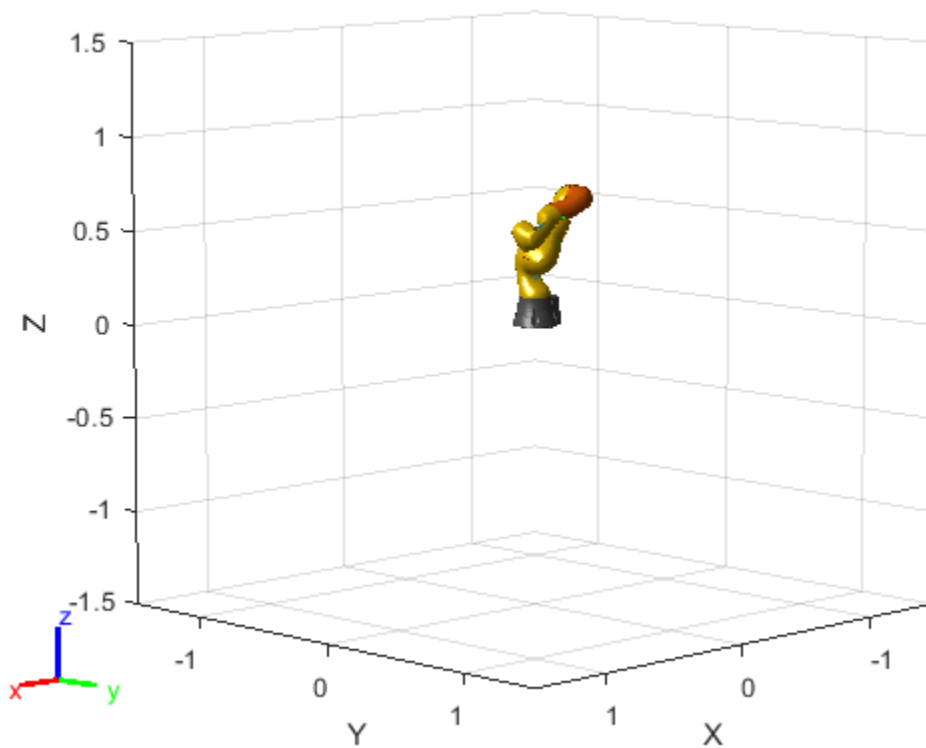
```
collisionArrayFromVisuals = exampleHelperManipCollisionsFromVisuals(iiwa);

config = [0 -pi/4 pi 0.9*pi 0 -pi/2 0]';
[isCollision, selfCollisionPairIdx] = exampleHelperManipCheckCollisions(iiwa, collisionArrayFromVisuals);
disp(isCollision)

1
```

Visualize the robot and highlight the objects in collision.

```
show(iiwa, config);
exampleHelperHighlightCollisionBodies(iiwa, selfCollisionPairIdx, gca);
```



Method 3: Define Collision Primitives

Create collision primitives that use simplified geometry. Manually specify the dimensions. This method is generally less accurate than using higher fidelity mesh definitions.

For this example, use `collisionCylinder` objects, which have a height and radius. Specify each rigid body size as an array.

```
dimensionArray = [...
    .1 0; ... % Base
    .15, 0.1575; ... % iiwa_link_0
    .12, 0.3; ... % iiwa_link_1
    .13, 0.3; ... % iiwa_link_2
    .1, 0.3; ... % iiwa_link_3
    .1, 0.25; ... % iiwa_link_4
    .1, 0.2155; ... % iiwa_link_5
    .08, 0.17; ... % iiwa_link_6
    .05, 0.06; ... % iiwa_link_7
    .01, 0; ... % iiwa_link_ee_kuka
    .01, 0;]; % iiwa_link_ee
```

Build the collision array from the given dimensions. Create a `collisionCylinder` object and specify the transformation between each based on their geometries.

```
primitiveCollisionArray = { ...
    [] eye(4); ... %Base (world)
    collisionCylinder(dimensionArray(2,1), dimensionArray(2,2)) trvec2tform([0 0 dimensionArray(2,3)
```

```

collisionCylinder(dimensionArray(3,1), dimensionArray(3,2)) trvec2tform([0 0 dimensionArray(
collisionCylinder(dimensionArray(4,1), dimensionArray(4,2)) axang2tform([1 0 0 -pi/2])*trvec
collisionCylinder(dimensionArray(5,1), dimensionArray(5,2)) trvec2tform([0 .025 dimensionArra
collisionCylinder(dimensionArray(6,1), dimensionArray(6,2)) axang2tform([1 0 0 -pi/2])*trvec
collisionCylinder(dimensionArray(7,1), dimensionArray(7,2)) trvec2tform([0 0 dimensionArray(
collisionCylinder(dimensionArray(8,1), dimensionArray(8,2)) axang2tform([1 0 0 -pi/2]); ... %
collisionCylinder(dimensionArray(9,1), dimensionArray(9,2)) trvec2tform([0 0 dimensionArray(
[] eye(4); ... % iiwa_link_ee_kuka
[] eye(4); ... % iiwa_link_ee
});

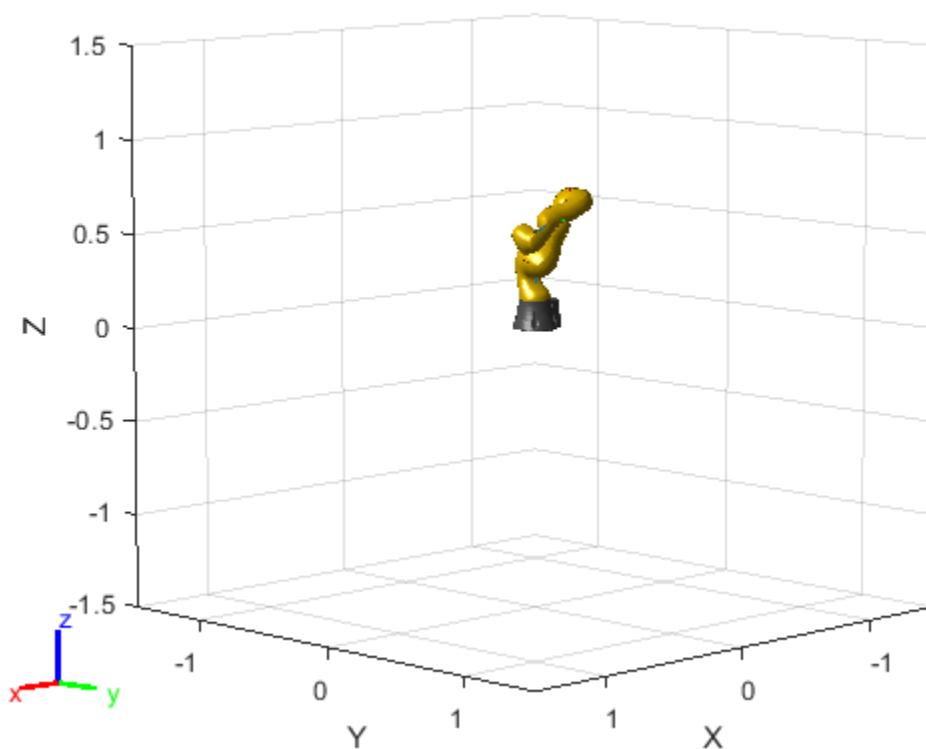
```

Check for collisions. Since these are less precise, collision-checking returns more collisions in this instance.

```

config = [0 -pi/4 pi 0.9*pi 0 -pi/2 0]';
show(iiwa, config);
[isCollision, selfCollisionPairIdx] = exampleHelperManipCheckCollisions(iiwa, primitiveCollisionArray, config);
exampleHelperHighlightCollisionBodies(iiwa, selfCollisionPairIdx, gca);

```

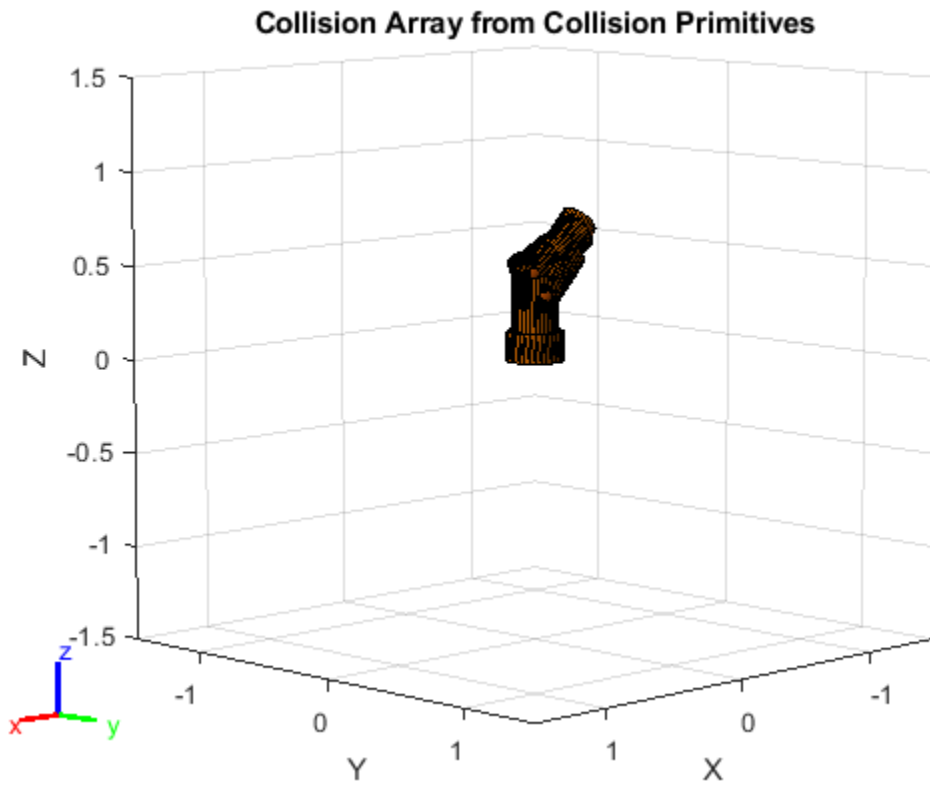


Visualize the collision primitives to show they are less accurate.

```

exampleHelperShowCollisionTree(iiwa, primitiveCollisionArray, config);
title('Collision Array from Collision Primitives')

```



Check for Manipulator Self Collisions using Collision Meshes

This example shows how to check for manipulator self collisions using the collision meshes in the URDF source folder. The following related examples show how to define collision meshes in other ways, and how to check for environmental collisions:

- “Create Collision Objects for Manipulator Collision Checking” on page 1-138
- “Check for Environmental Collisions with Manipulators” on page 1-148

Create KUKA IIWA Robot Representation

Create a `rigidBodyTree` object for the KUKA® IIWA-14 serial manipulator.

```
iiwa = importrobot('iiwa14.urdf');
iiwa.DataFormat = 'column';
```

Create Collision Meshes for the Rigid Body Tree

Generate an array of collision meshes for each link of the rigid body tree. These links will be stored in a cell array with $n+1$ rows, for the base and n bodies in the rigid body tree. Each row will have two elements: the collision object, and a transform indicating the relationship of the object to the associated rigid body tree origin.

```
collisionArray = cell(iiwa.NumBodies+1,2);
```

There are several ways to fill this array. “Create Collision Objects for Manipulator Collision Checking” on page 1-138 covers three different ways to generate collision objects for the links in a rigid body tree. Since the IIWA manipulator provides specific collision meshes in the URDF directory, this example creates collision meshes from the information in the mesh path.

Create a `rigidBodyTree` object and specify the path of the folder containing the collision meshes. This syntax associated the rigid body objects with the STL mesh files based on their specified name.

```
collisionMeshPath = fullfile(matlabroot,'toolbox','robotics',...
    'robotexamples','robotmanip','data','iiwa_description',...
    'meshes','iiwa14','collision');
iiwaCollision = importrobot('iiwa14.urdf','MeshPath',collisionMeshPath);
iiwaCollision.DataFormat = 'column';
```

Create the collision mesh definitions for each rigid body from the source directory:

- Convert each STL file to faces and vertices by reading the STL: `stldata = stlread(file.STL)`
- Create a `collisionMesh` from the vertices: `mesh = collisionMesh(stldata.Points);`
- Assign the mesh to the i th body by placing it in the $(i+1)$ th element of the `collisionArray` cell array. The base mesh occupies the first element of the cell array.

```
% For each body, read the corresponding STL file
robotBodies = [{iiwaCollision.Base} iiwaCollision.Bodies];
for i = 1:numel(robotBodies)
    if ~isempty(robotBodies{i}.Visuals)
        % As a simplifying assumption, assume that the first visual is the
        % only associated collision mesh.
        visualDetails = robotBodies{i}.Visuals{1};
```

```

% Extract the part of the visual that actually specifies the STL name
visualParts = strsplit(visualDetails, ':');
stlFileName = visualParts{2};

% Read the STL file
stlData = stlread(fullfile(collisionMeshPath, stlFileName));

% Create a collisionMesh object from the vertices
collisionArray{i,1} = collisionMesh(stlData.Points);

% For imported meshes, the origin of the imported mesh and the
% rigid body origin are the same
collisionArray{i,2} = eye(4);
end
end

```

Generate Trajectory and Check for Collisions

Specify a start and end configuration and find a joint space trajectory that connects them:

```

% Define collision-free start & goal configurations
startConfig = [0 -pi/4 pi 3*pi/2 0 -pi/2 pi/8]';
goalConfig = [0 -pi/4 pi 3*pi/4 0 -pi/2 pi/8]';

% Define a trapezoidal velocity trajectory between the two configurations
q = trapveltraj([startConfig goalConfig], 100, 'EndTime', 3);

```

To verify this output trajectory doesn't contain self-collisions, iterate over the output samples and see if any points are in collision. Collision checking is performed using an example helper that uses two for loops to verify every body against every other body. The following specific assumptions are considered here:

- Bodies are not checked against neighboring bodies, since they are always in contact at the joint. It is assumed that joint limits would be set to prevent bodies from colliding with their immediate neighbors
- All bodies are checked against each other only once (i.e. body 1 is checked for collision with body 5, but not vice versa).

When the robot has self collisions and an m -by-2 matrix of the pairs of collisions, `collisionPairIdx`, the example outputs a flag, `isInCollision`, as true. The elements of this matrix are indices that map the collisions to the bodies in the associated `collisionArray` cell array of collision meshes.

```

isConfigInCollision = false(100,1);
configCollisionPairs = cell(100,1);
for i = 1:length(q)
    [isConfigInCollision(i), configCollisionPairs{i}] = exampleHelperManipCheckSelfCollisions(iiw);
end

```

The planned trajectory goes through a series of collisions. Visualize the configuration where the first collision occurs and highlight the bodies.

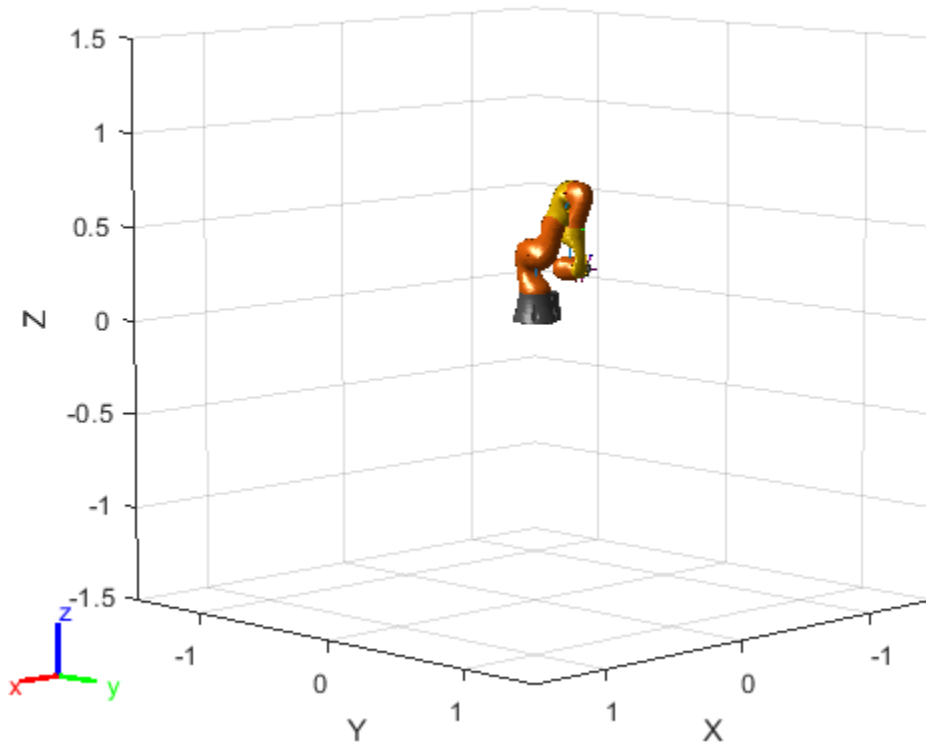
```
any(isConfigInCollision)
```

```
ans = logical
     1
```

```

firstCollisionIdx = find(isConfigInCollision,1);
% Visualize the first configuration that causes problems
figure;
show(iiwaCollision,q(:,firstCollisionIdx));
exampleHelperHighlightCollisionBodies(iiwaCollision,configCollisionPairs{firstCollisionIdx},gca)

```



Generate a Collision-Free Trajectory

This first collision actually occurs at the starting configuration because a joint position is specified past its limits. Call `wrapToPi` to limit the starting positions of the joints.

Generate a new trajectory and check for collisions again. To visualize parts of the trajectory, uncomment the `show` function call.

```

newStartConfig = wrapToPi(startConfig);
q = trapveltraj([newStartConfig goalConfig],100,'EndTime',3);

isConfigInCollision = false(100,1);
configCollisionPairs = cell(100,1);
for i = 1:length(q)
    [isConfigInCollision(i),configCollisionPairs{i}] = exampleHelperManipCheckSelfCollisions(iiw
%     if rem(i,10) == 0
%         show(iiwaCollision,q(:,i));
%         drawnow
%     end
end

```


After checking the whole trajectory, no collisions are found.

```
any(isConfigInCollision)
```

```
ans = logical  
     0
```

Check for Environmental Collisions with Manipulators

Generate a collision-free trajectory in a constrained workspace.

Define an environment

You can create a simple environment using collision primitives. For example, suppose the robot is in a workspace where the aim is to move objects from one table to another while avoiding a circular light fixture. These objects can be modeled as two boxes and a sphere. More complex environments can be created using `collisionMesh` objects.

```
% Create two platforms
```

```
platform1 = collisionBox(0.5,0.5,0.25);  
platform1.Pose = trvec2tform([-0.5 0.4 0.2]);
```

```
platform2 = collisionBox(0.5,0.5,0.25);  
platform2.Pose = trvec2tform([0.5 0.2 0.2]);
```

```
% Add a light fixture, modeled as a sphere
```

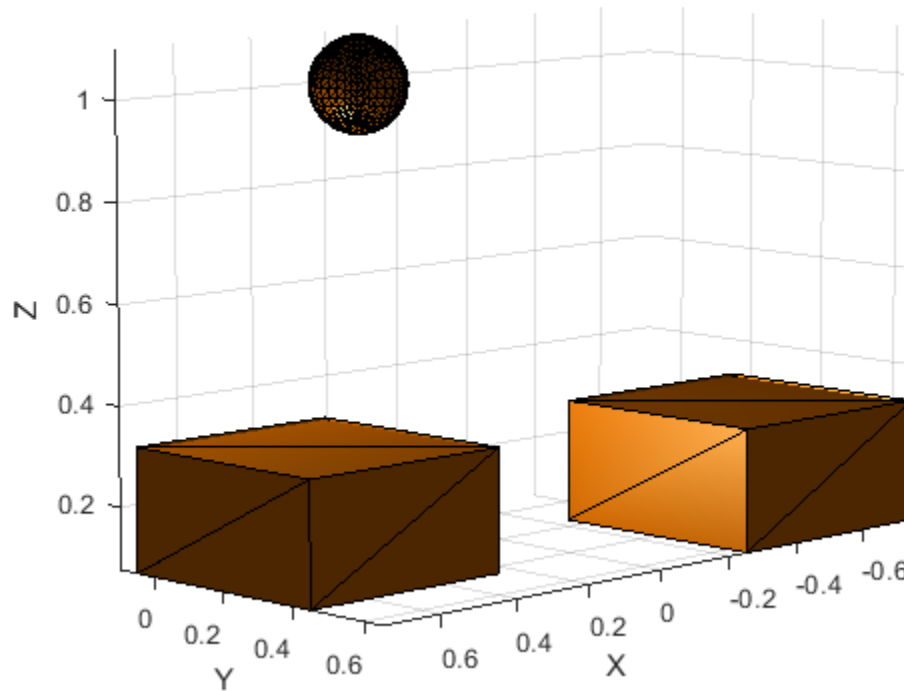
```
lightFixture = collisionSphere(0.1);  
lightFixture.Pose = trvec2tform([.2 0 1]);
```

```
% Store in a cell array for collision-checking
```

```
worldCollisionArray = {platform1 platform2 lightFixture};
```

Visualize the environment using a helper function that iterates through the collision array.

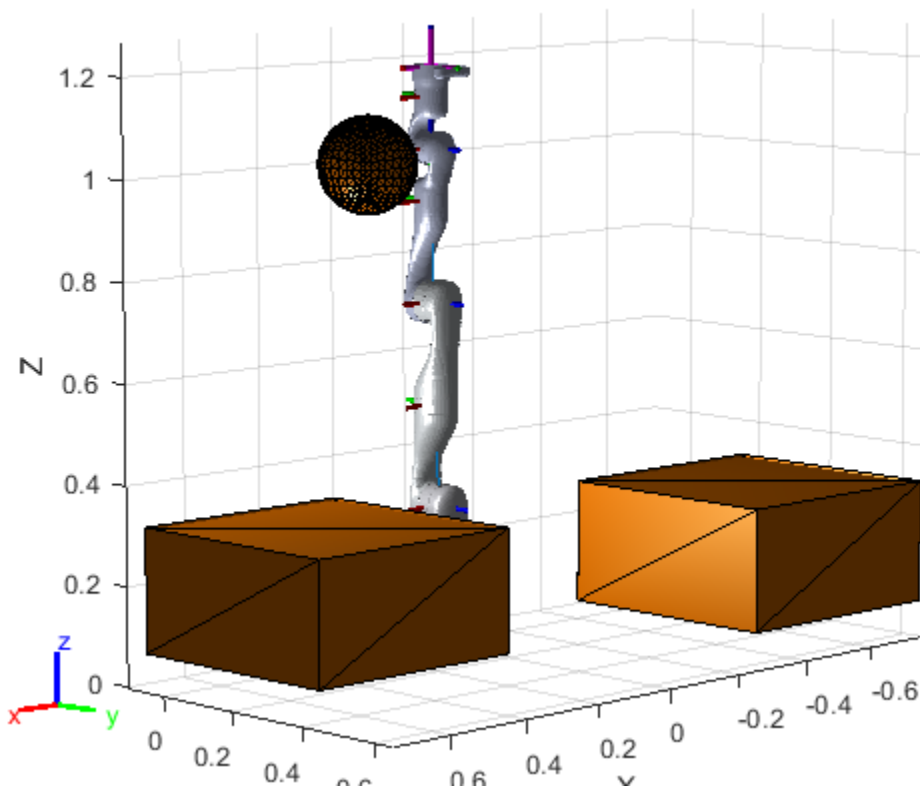
```
exampleHelperVisualizeCollisionEnvironment(worldCollisionArray);
```



Add a manipulator robot

Add a Kinova manipulator to the environment at the origin. Load the provided robot model. Visualize the obstacles and show the robot in the same figure.

```
robot = loadrobot("kinovaGen3","DataFormat","column","Gravity",[0 0 -9.81]);  
ax = exampleHelperVisualizeCollisionEnvironment(worldCollisionArray);  
show(robot,homeConfiguration(robot),"Parent",ax);
```



Model the manipulator as an array of collision objects

Create an array of collision objects from the `rigidBodyTree` object. This approach uses an example helper, `exampleHelperManipCollisionsFromVisuals`, that extracts the meshes from the first visual in each `rigidBody` object. For an overview of other approaches, refer to “Create Collision Objects for Manipulator Collision Checking” on page 1-138.

```
% Generate an array of collision objects from the visuals of the associated tree
collisionArray = exampleHelperManipCollisionsFromVisuals(robot);
```

Generate a trajectory and check for collisions

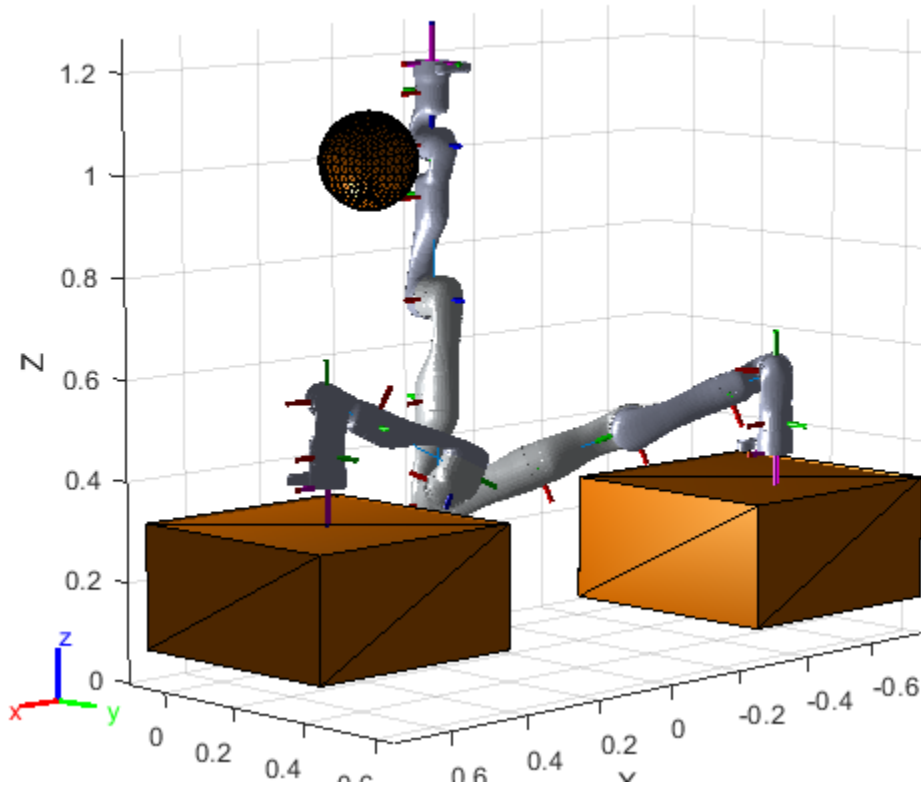
Define a start and end pose as position and orientation. Use `inverseKinematics` to solve for the joint positions based on the desired poses. Inspect manually to verify that the configurations are valid.

```
startPose = trvec2tform([-0.5,0.5,0.4])*axang2tform([1 0 0 pi]);
endPose = trvec2tform([0.5,0.2,0.4])*axang2tform([1 0 0 pi]);

% Use a fixed random seed to ensure repeatable results
rng(0);
ik = inverseKinematics("RigidBodyTree",robot);
weights = ones(1,6);
startConfig = ik("EndEffector_Link",startPose,weights,robot.homeConfiguration);
endConfig = ik("EndEffector_Link",endPose,weights,robot.homeConfiguration);

% Show initial and final positions
```

```
show(robot,startConfig);
show(robot,endConfig);
```



Use a trapezoidal velocity profile to generate a smooth trajectory from the home position to the start position, and then to the end position. Use collision checking to see whether this results in any collisions.

```
q = trapveltraj([homeConfiguration(robot),startConfig,endConfig],200,"EndTime",2);
```

```
%Initialize outputs
```

```
isCollision = false(length(q),1); % Check whether each pose is in collision
```

```
selfCollisionPairIdx = cell(length(q),1); % Provide the bodies that are in collision
```

```
worldCollisionPairIdx = cell(length(q),1); % Provide the bodies that are in collision
```

```
for i = 1:length(q)
```

```
    [isCollision(i),selfCollisionPairIdx{i},worldCollisionPairIdx{i}] = exampleHelperManipCheckC
```

```
end
```

```
isTrajectoryInCollision = any(isCollision)
```

```
isTrajectoryInCollision = logical
```

```
    1
```

Inspect the Problem Cases

By inspecting the collisions, there are 2 collisions occurring. Visualize these configurations to investigate further.

```

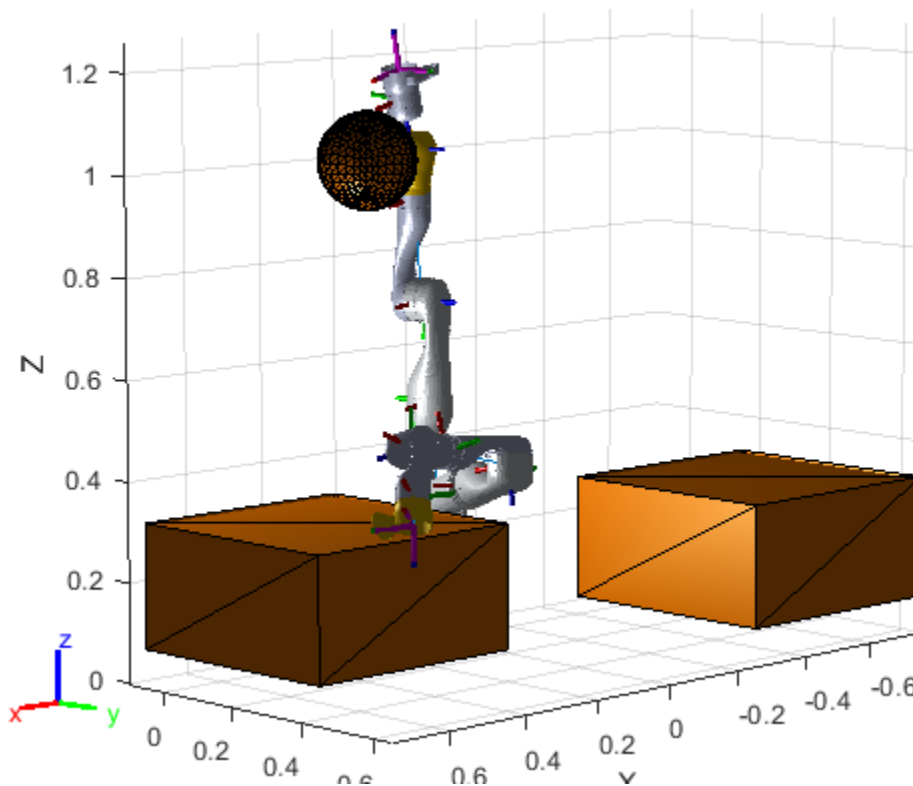
problemIdx1 = find(isCollision,1);
problemIdx2 = find(isCollision,1,"last");

% Identify the problem rigid bodies
problemBodies1 = [selfCollisionPairIdx{problemIdx1} worldCollisionPairIdx{problemIdx1}*[1 0]'];
problemBodies2 = [selfCollisionPairIdx{problemIdx2} worldCollisionPairIdx{problemIdx2}*[1 0]'];

% Visualize the environment
ax = exampleHelperVisualizeCollisionEnvironment(worldCollisionArray);

% Add the robots & highlight the problem bodies
show(robot,q(:,problemIdx1),"Parent",ax,"PreservePlot",false);
exampleHelperHighlightCollisionBodies(robot,problemBodies1,ax);
show(robot,q(:,problemIdx2),"Parent",ax);
exampleHelperHighlightCollisionBodies(robot,problemBodies2,ax);

```



Generate a Collision-Free Trajectory using Intermediate Waypoints

To avoid these collisions, add intermediate waypoints to ensure the robot navigates around the obstacle.

```

intermediatePose1 = trvec2tform([-0.3 -0.2 0.6])*axang2tform([0 1 0 -pi/4]); % Out and around the s
intermediatePose2 = trvec2tform([0.2,0.2,0.6])*axang2tform([1 0 0 pi]); % Come in from above

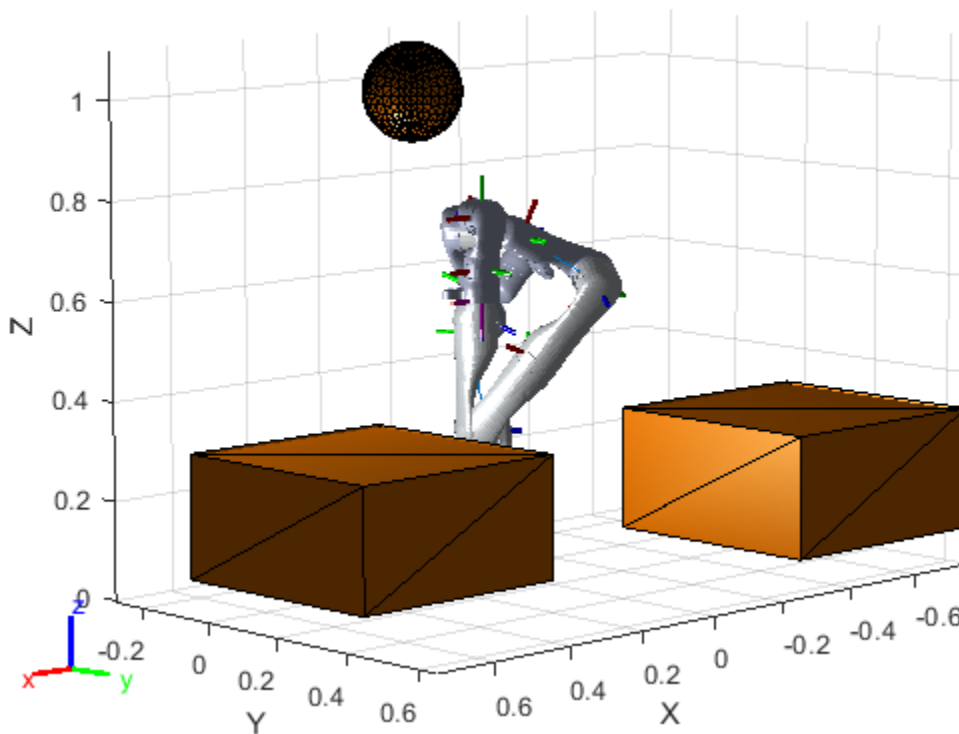
intermediateConfig1 = ik("EndEffector_Link",intermediatePose1,weights,q(:,problemIdx1));
intermediateConfig2 = ik("EndEffector_Link",intermediatePose2,weights,q(:,problemIdx2));

```

```

% Show the new intermediate poses
ax = exampleHelperVisualizeCollisionEnvironment(worldCollisionArray);
show(robot,intermediateConfig1,"Parent",ax,"PreservePlot",false);
show(robot,intermediateConfig2,"Parent",ax);

```



Generate a new trajectory.

```
[q,qd,qdd,t] = trapveltraj([homeConfiguration(robot),intermediateConfig1,startConfig,intermediateConfig2]);
```

Verify that it is collision-free.

```

%Initialize outputs
isCollision = false(length(q),1); % Check whether each pose is in collision
collisionPairIdx = cell(length(q),1); % Provide the bodies that are in collision
for i = 1:length(q)
    [isCollision(i),collisionPairIdx{i}] = exampleHelperManipCheckCollisions(robot,collisionArray);
end
isTrajectoryInCollision = any(isCollision)

isTrajectoryInCollision = logical
0

```

Visualize the Generated Trajectory

Animate the result.

```

% Plot the environment
ax2 = exampleHelperVisualizeCollisionEnvironment(worldCollisionArray);

```

```

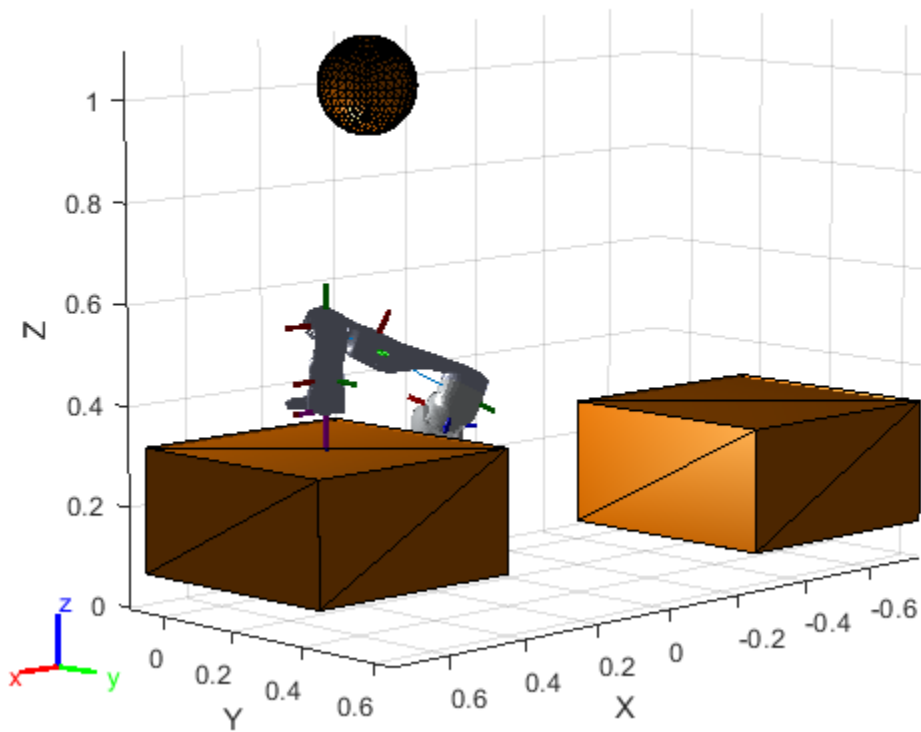
% Visualize the robot in its home configuration
show(robot,startConfig,"Parent",ax2);

% Update the axis size
axis equal

% Loop through the other positions
for i = 1:length(q)
    show(robot,q(:,i),"Parent",ax2,"PreservePlot",false);

    % Update the figure
    drawnow
end

```

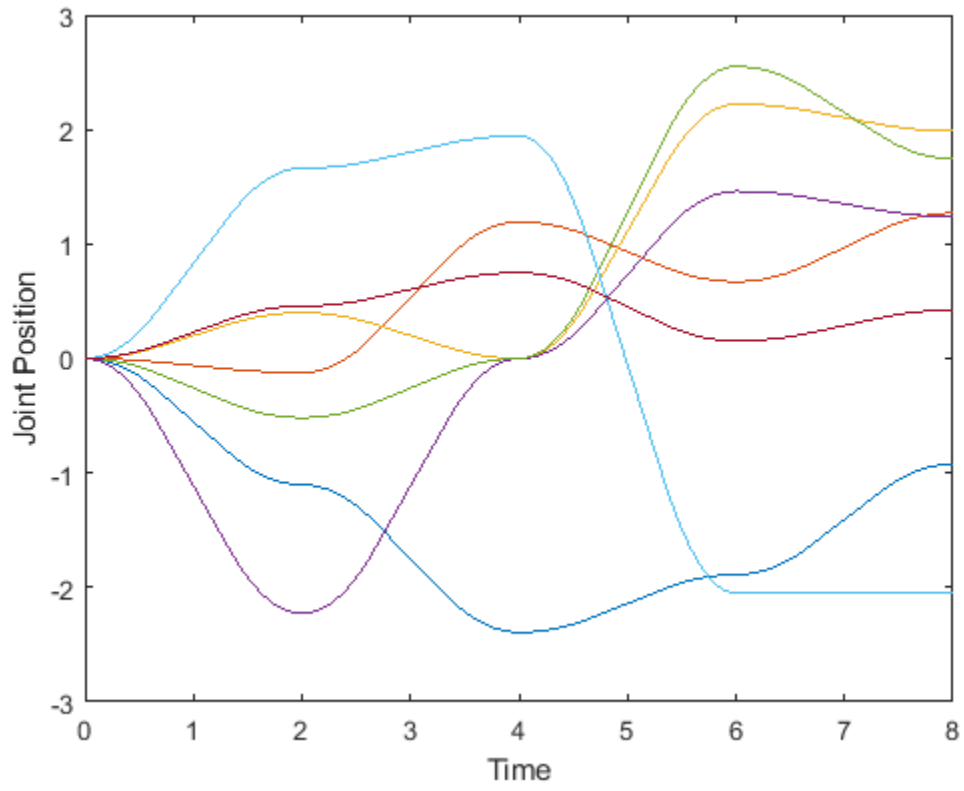


Plot the joint positions over time.

```

figure
plot(t,q)
xlabel("Time")
ylabel("Joint Position")

```

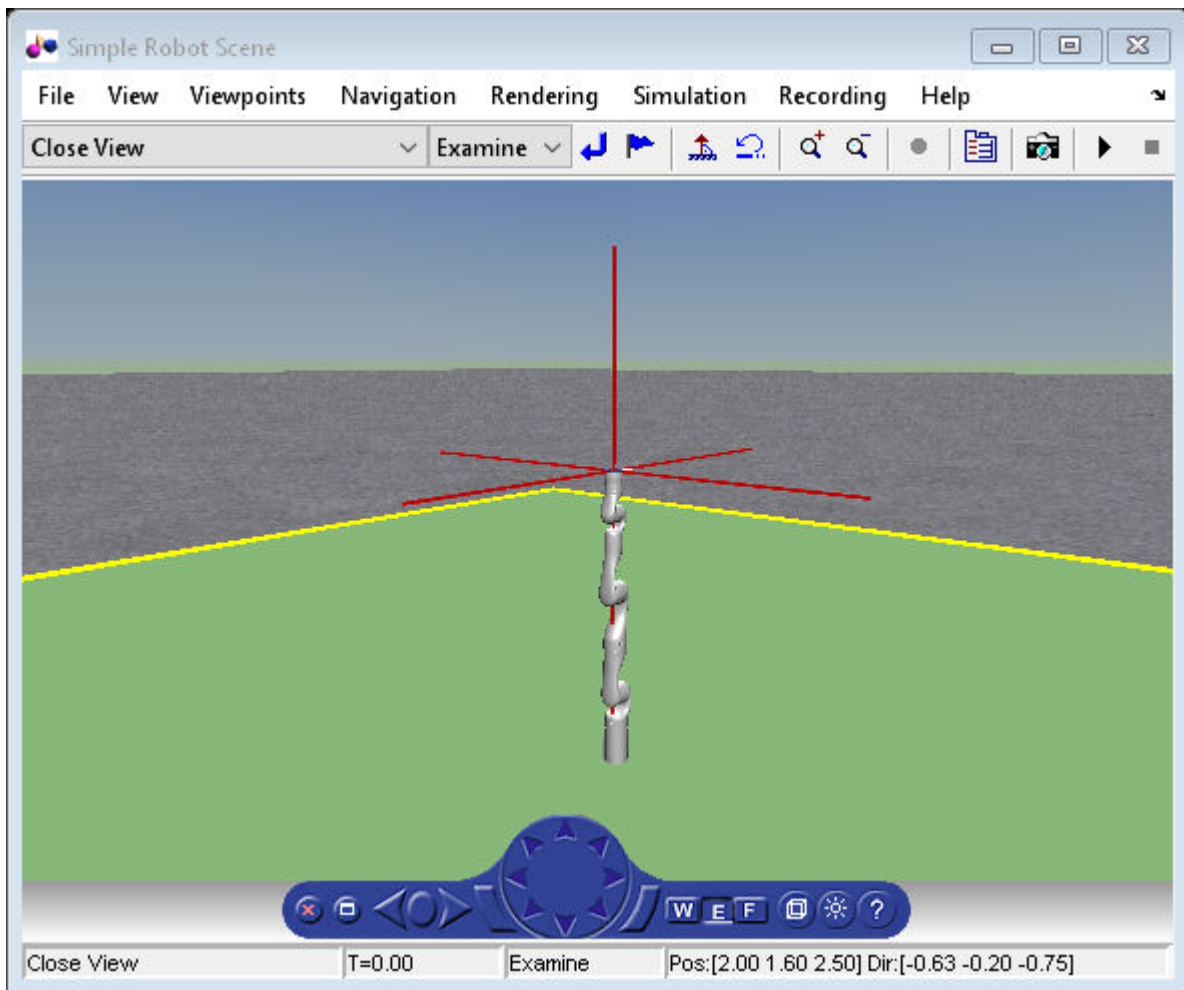
Visualize Manipulator Trajectory Tracking with Simulink 3D Animation

Simulate joint-space trajectories for a rigid body tree robot model and visualize the results with Simulink 3D Animation™.

Model Overview

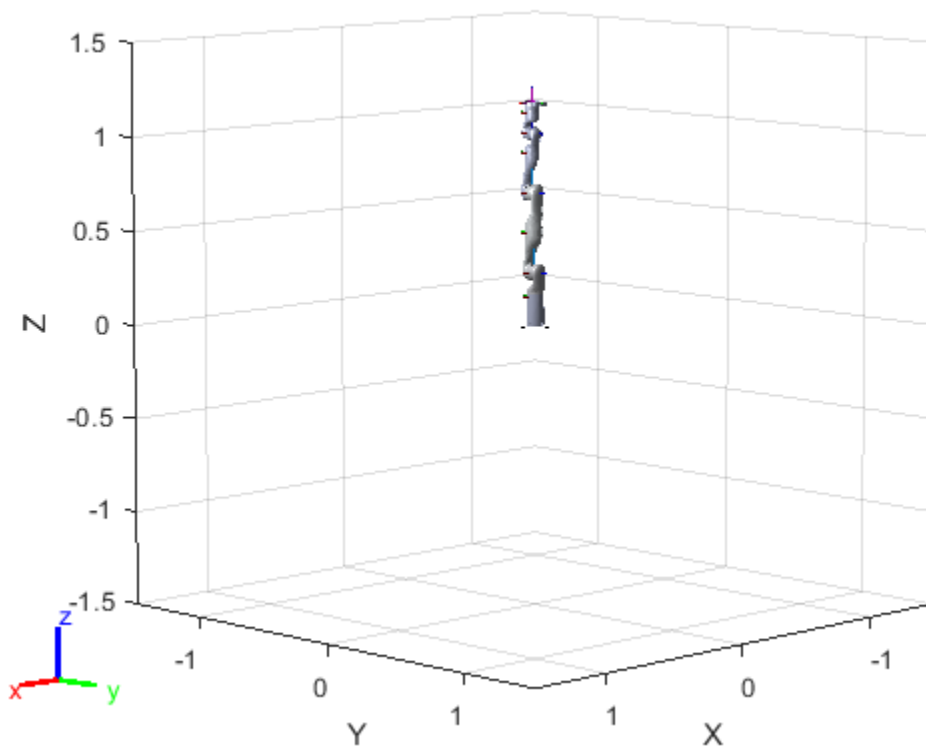
Load the model with the following command:

```
open_system("SL3DJointSpaceManipulatorTrajectory")
```



This example uses a Kinova Gen3 manipulator, which is stored in the model workspace. However, load and visualize the robot with the following commands:

```
gen3 = loadrobot("kinovaGen3", "DataFormat", "column");
show(gen3);
```

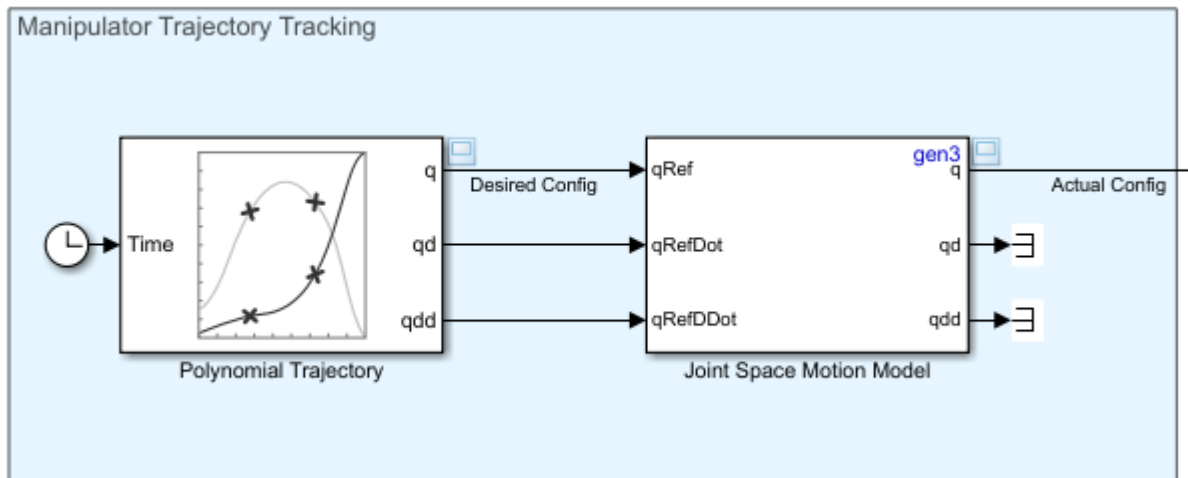


The model is split into two sections:

- Manipulator Trajectory Tracking
- Visualization in Simulink 3D Animation™

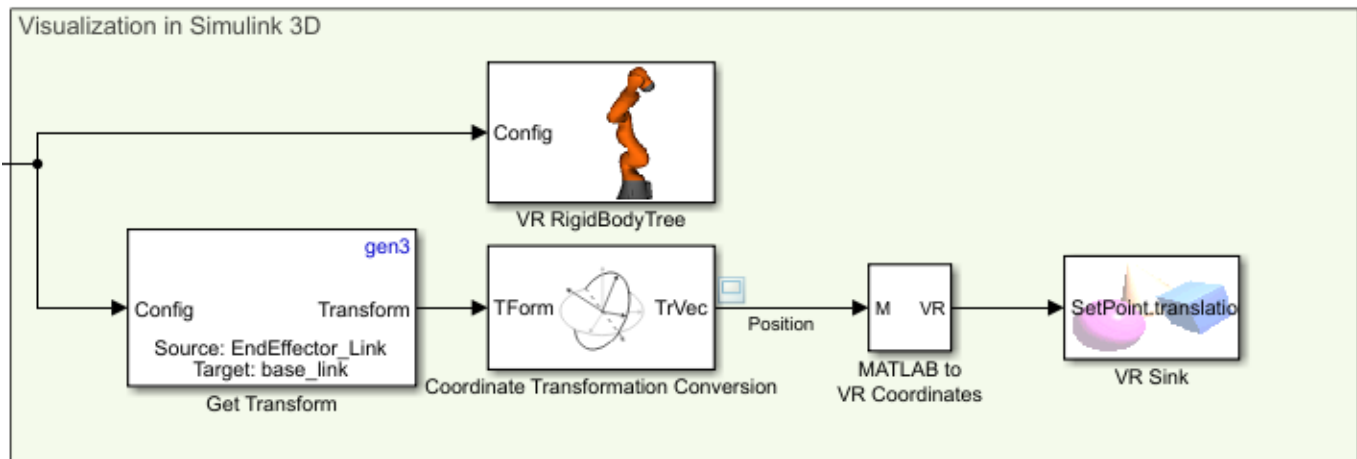
Manipulator Trajectory Tracking

The **Polynomial Trajectory** block generates continuous joint-space trajectories from random sets of waypoints in the range $[-0.375\pi \ 0.375\pi]$, stopping at each of the waypoints. The **Joint-Space Motion Model** block simulates the closed-loop tracking of these trajectories for a Kinova Gen3 manipulator with computed-torque control.



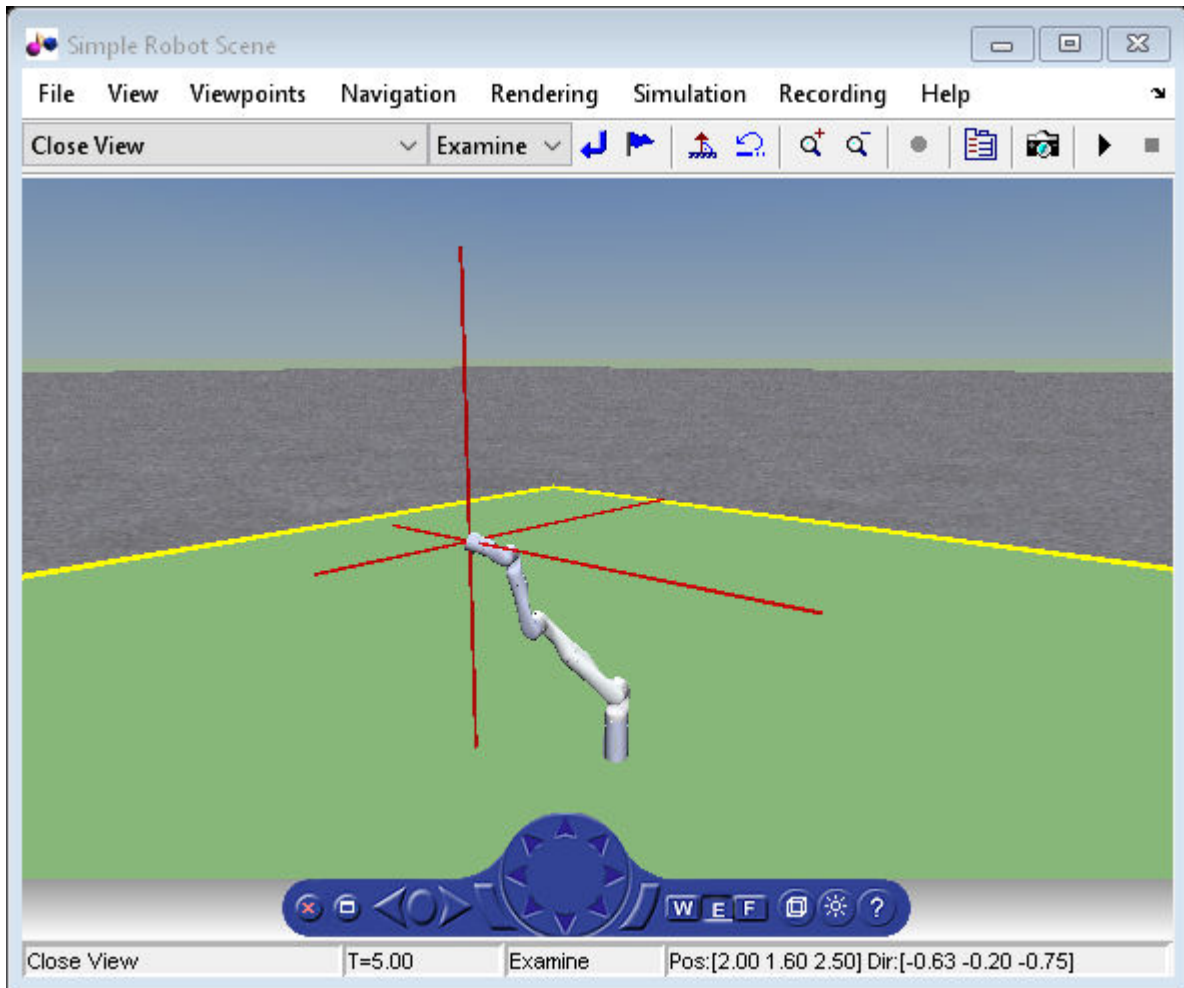
Visualization in Simulink 3D Animation™

The **VR RigidBodyTree** block inserts the manipulator into the scene defined by the associated world file, `robot_scene.world`. The **VR Sink** block provides a visualization for the world. In the block parameters, the **VR Sink** block has been modified to treat the setpoint, indicated by the red axes in the output, as an input. The **Get Transform** block is used to get the position of the end effector, which is then converted from a homogeneous transform matrix to a translation vector, and then from MATLAB to VR coordinates.

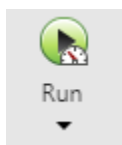


Simulate the Model

```
sim("SL3DJointSpaceManipulatorTrajectory.slx");
```



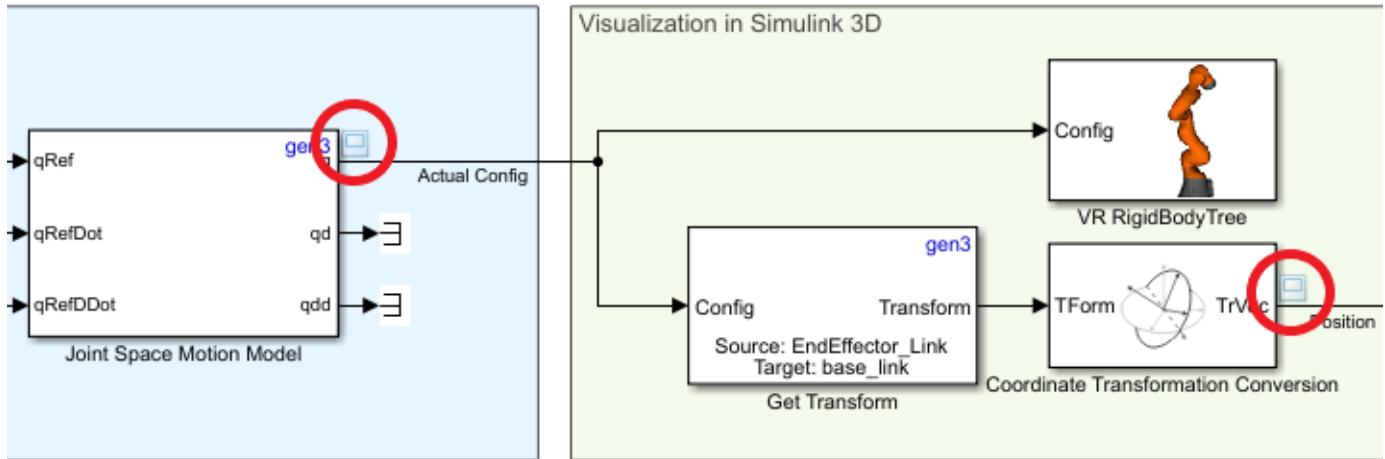
In the model, pacing is active, as indicated by the clock symbol below the run button:



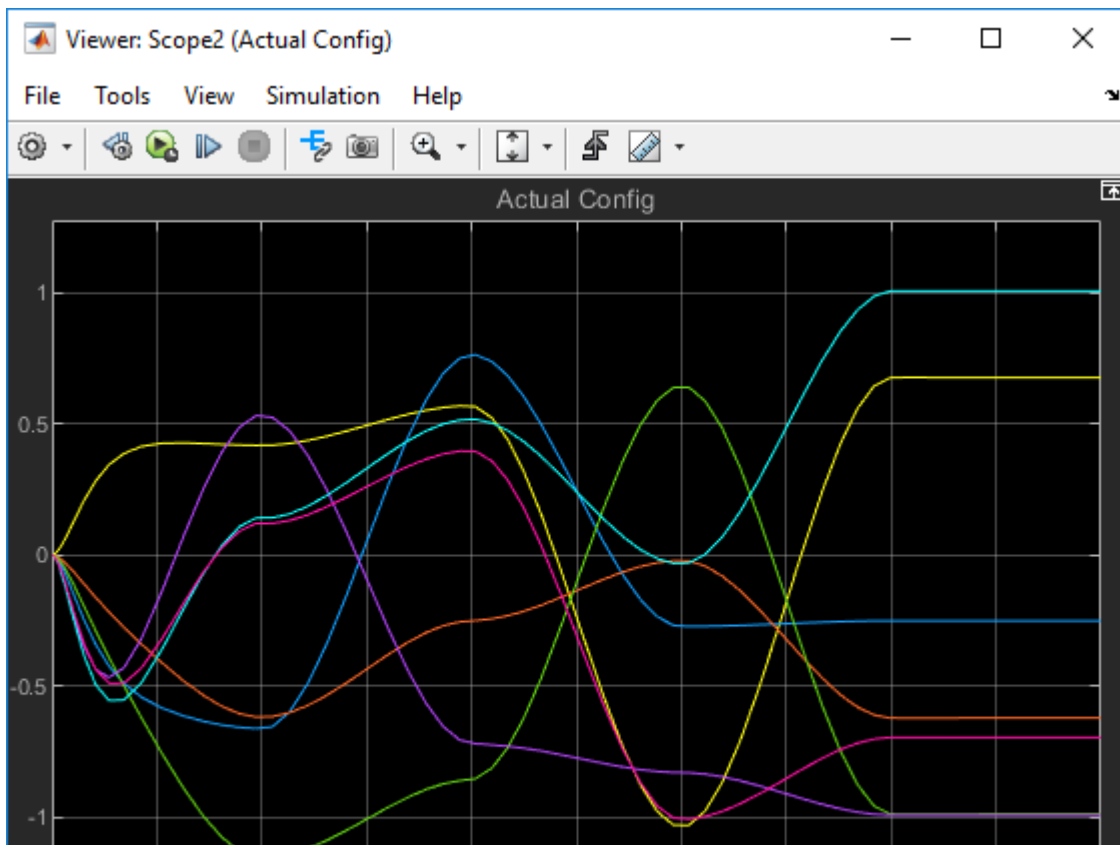
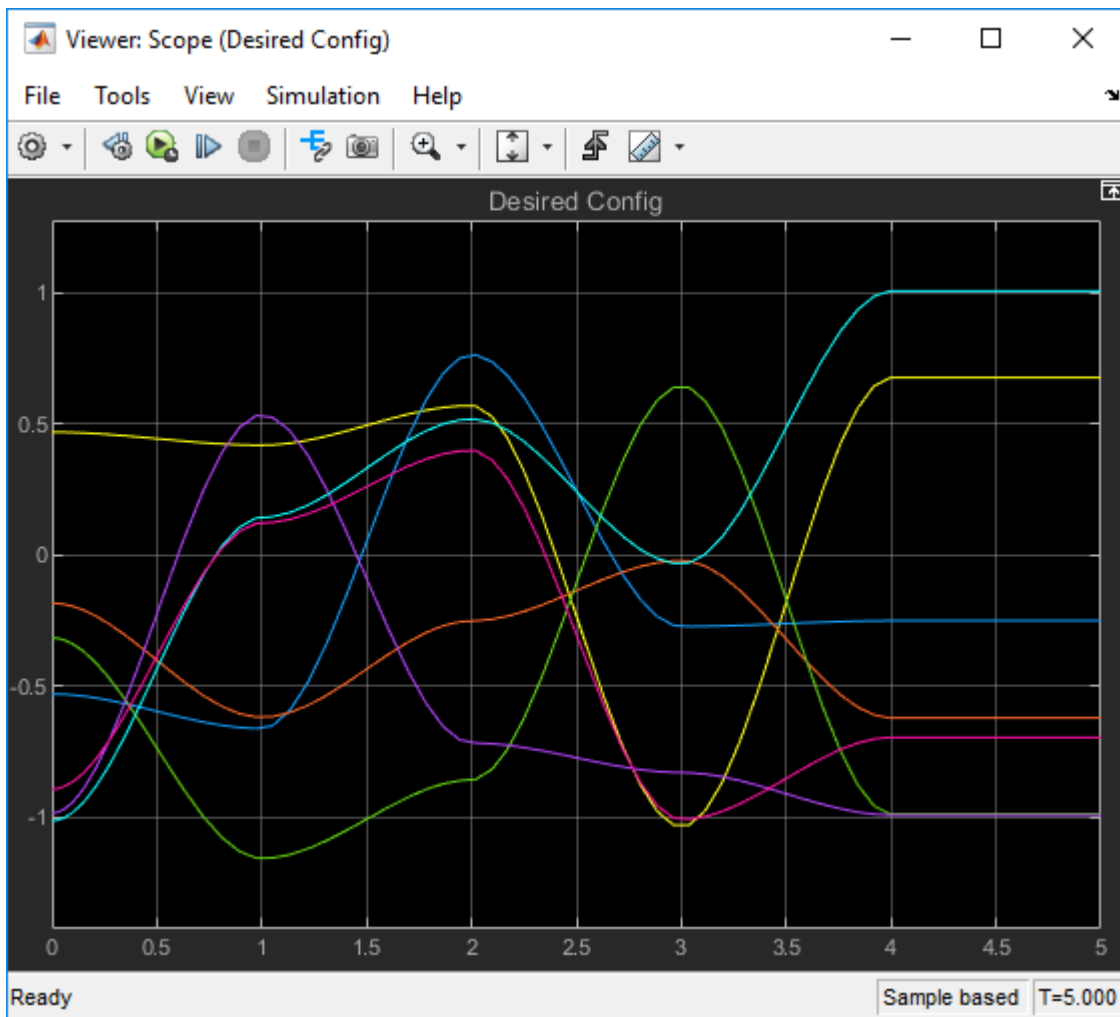
This ensures that the model is slowed down to near real-time speed, so that the visualization can be updated at a realistic pace.

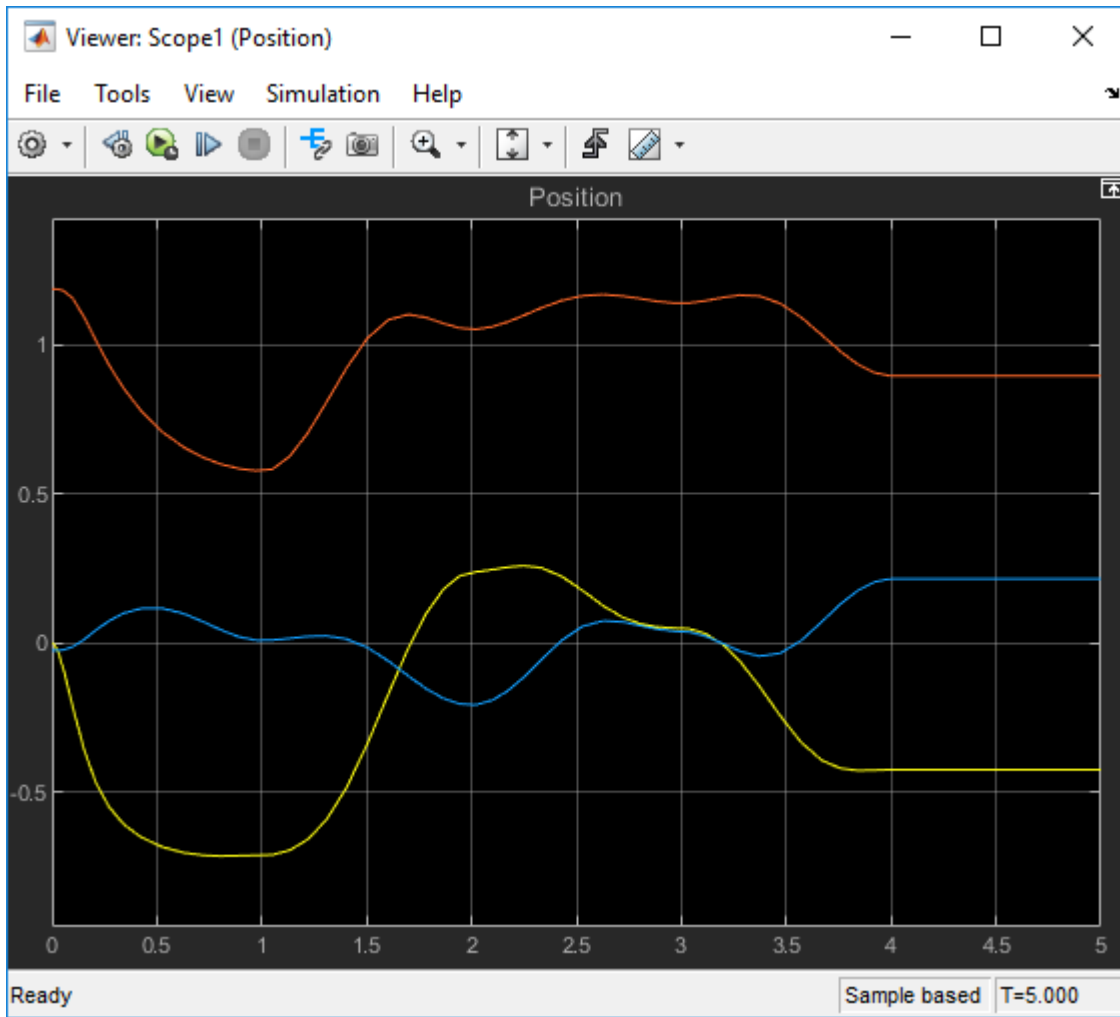
Trajectory Visualization

By default, the model opens both the VR visualization and the scopes that display velocity and position information. However, if they are closed, the VR view can be reopened by clicking on the **VR Sink** block, and the scopes can be opened by double-clicking the associated viewer icons:



The scopes show the tracking results of the **Joint Space Motion Model** block. As can be seen on the left in the figures below, the initial configuration of the robot differs from the reference trajectories, but the controlled motion ensures that the trajectory is reached and tracked for the duration of the simulation. The final scope displays the X, Y, and Z position of the end effector in the world frame.





Simulate Joint-Space Trajectory Tracking in MATLAB

This example shows how to simulate the joint-space motion of a robotic manipulator under closed-loop control.

Define Robot and Initial State

Load an ABB IRB-120T from the robot library using the `loadrobot` function.

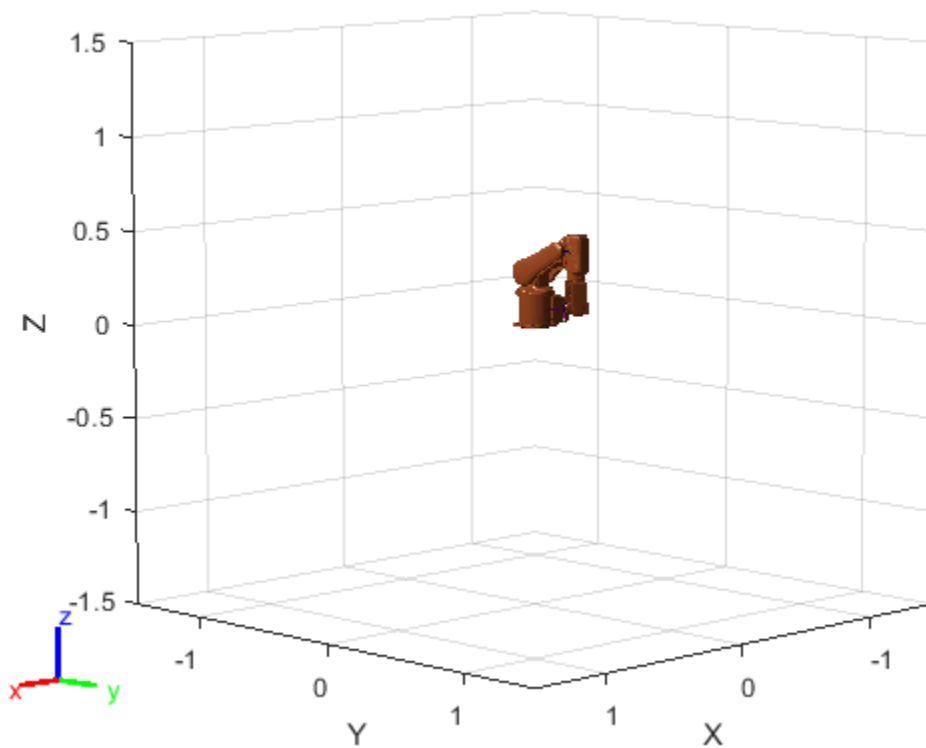
```
robot = loadrobot("abbIrb120T","DataFormat","column","Gravity",[0 0 -9.81]);  
numJoints = numel(homeConfiguration(robot));
```

Define simulation parameters, including the time range over which the trajectory is simulated, the initial state as [joint configuration; jointVelocity], and the joint-space set point.

```
% Set up simulation parameters  
tSpan = 0:0.01:0.5;  
q0 = zeros(numJoints,1);  
q0(2) = pi/4; % Something off center  
qd0 = zeros(numJoints,1);  
initialState = [q0; qd0];  
  
% Set up joint control targets  
targetJointPosition = [pi/2 pi/3 pi/6 2*pi/3 -pi/2 -pi/3]';  
targetJointVelocity = zeros(numJoints,1);  
targetJointAcceleration = zeros(numJoints,1);
```

Visualize the goal position.

```
show(robot,targetJointPosition)
```



```
ans =
  Axes (Primary) with properties:
      XLim: [-1.5000 1.5000]
      YLim: [-1.5000 1.5000]
      XScale: 'linear'
      YScale: 'linear'
      GridLineStyle: '-'
      Position: [0.1300 0.1100 0.7750 0.8150]
      Units: 'normalized'
```

Show all properties

Model Behavior with Joint-Space Control

Using a `jointSpaceMotionModel` object, simulate the closed-loop motion of the model under a variety of controllers. This example compares a few of them. Each instance uses the `derivative` function to compute the state derivative. Here, the state is $2n$ -element vector `[joint configuration; joint velocity]`, where n is the number of joints in the associated `rigidBodyTree` object.

Computed-Torque Control

Computed-torque control uses an inverse-dynamics computation to compensate for the robot dynamics. The controller drives the closed-loop error dynamics of each joint based on a second-order response.

Create a `jointSpaceMotionModel` and specify the robot model. Set the "MotionType" to "ComputedTorqueControl". Update the error dynamics using `updateErrorDynamicsFromStep` and specify the desired settling time and overshoot respectively. Alternatively, you can set the damping ratio and natural frequency directly in the object.

```
computedTorqueMotion = jointSpaceMotionModel("RigidBodyTree", robot, "MotionType", "ComputedTorqueControl");
updateErrorDynamicsFromStep(computedTorqueMotion, 0.2, 0.1);
```

This motion model requires position, velocity, and acceleration to be provided.

```
qDesComputedTorque = [targetJointPosition; targetJointVelocity; targetJointAcceleration];
```

To view an example of this controller in practice in Simulink, see the “Perform Safe Trajectory Tracking Control Using Robotics Manipulator Blocks” on page 1-194 example.

Independent Joint Control

With independent joint control, model each joint as a separate system that has a second-order tracking response. This type of model is an idealized behavior, and is best used when the response is slow, or when the dynamics will not have a significant impact on the resultant trajectory. In those cases, it will behave the same as computed-torque control, but with less computational overhead.

Create another `jointSpaceMotionModel` using the "IndependentJointMotion" motion type.

```
IndepJointMotion = jointSpaceMotionModel("RigidBodyTree", robot, "MotionType", "IndependentJointMotion");
updateErrorDynamicsFromStep(IndepJointMotion, 0.2, 0.1);
```

This motion model requires position, velocity, and acceleration to be provided.

```
qDesIndepJoint = [targetJointPosition; targetJointVelocity; targetJointAcceleration];
```

Proportional-Derivative Control

Proportional-Derivative Control, or PD Control, combines gravity compensation with proportional and derivative gains. Despite the simpler nature relative to other closed-form models, the PD Controller can be stable for all positive gain values, which makes it a desirable option. Here, the PD Gains are set as n -by- n matrices, where n is the number of joints in the associated `rigidBodyTree` object. For this robot, $n = 6$. Additionally, PD Control does not require an acceleration profile, so its state vector is just a $2n$ -element vector of joint configurations and joint velocities.

```
pdMotion = jointSpaceMotionModel("RigidBodyTree", robot, "MotionType", "PDControl");
pdMotion.Kp = diag(300*ones(1,6));
pdMotion.Kd = diag(10*ones(1,6));
```

This motion model requires position and velocity to be provided.

```
qDesPD = [targetJointPosition; targetJointVelocity];
```

Simulate using an ODE Solver

The derivative function outputs the state derivative, which can be integrated using an ordinary differential equation (ODE) solver such as `ode45`. For each motion model, the ODE solver outputs a m -element column vector that covers `tspan` and a 2-by- m matrix of the $2n$ -element state vector at each instant in time.

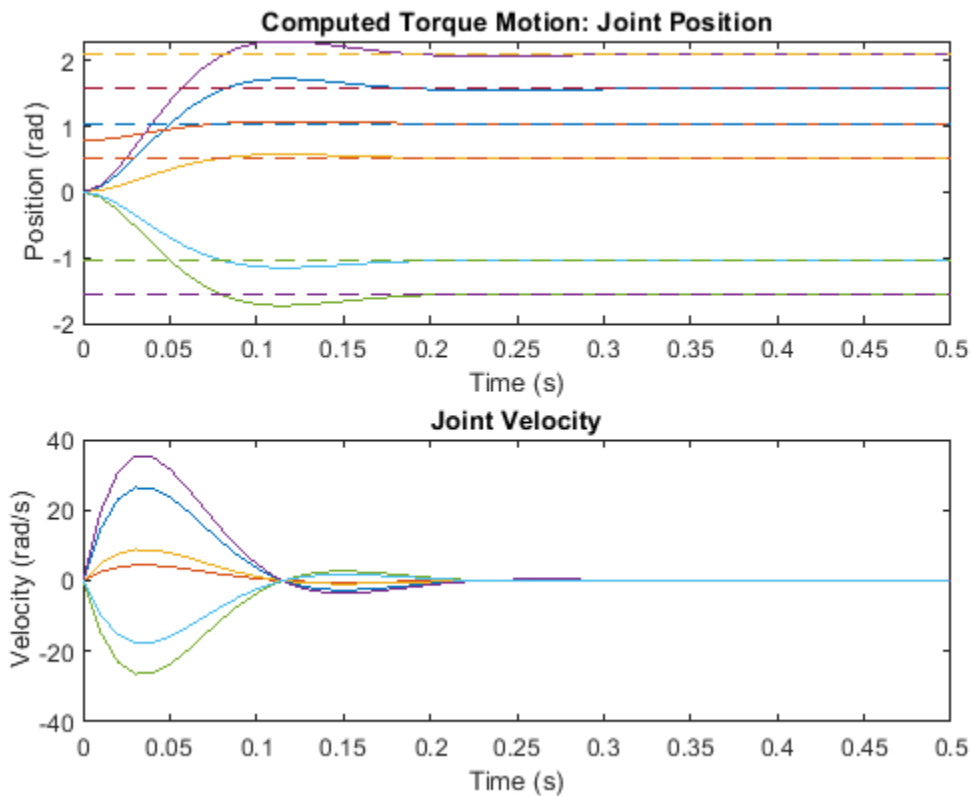
Calculate the trajectory for each motion model, using the most appropriate ODE solver for each system.

```
[tComputedTorque,yComputedTorque] = ode45(@(t,y)derivative(computedTorqueMotion,y,qDesComputedTo
[tIndepJoint,yIndepJoint] = ode45(@(t,y)derivative(IndepJointMotion,y,qDesIndepJoint),tSpan,init
[tPD,yPD] = ode15s(@(t,y)derivative(pdMotion,y,qDesPD),tSpan,initialState);
```

Plot Results

Once the simulation is complete, compare the results side-by-side. Each plot shows the joint position on the top, and velocity on the bottom. The dashed lines indicate the reference trajectories, while the solid lines display the simulated response.

```
% Computed Torque Control
figure
subplot(2,1,1)
plot(tComputedTorque,yComputedTorque(:,1:numJoints)) % Joint position
hold all
plot(tComputedTorque,targetJointPosition*ones(1,length(tComputedTorque)),'--') % Joint setpoint
title('Computed Torque Motion: Joint Position')
xlabel('Time (s)')
ylabel('Position (rad)')
subplot(2,1,2)
plot(tComputedTorque,yComputedTorque(:,numJoints+1:end)) % Joint velocity
title('Joint Velocity')
xlabel('Time (s)')
ylabel('Velocity (rad/s)')
```

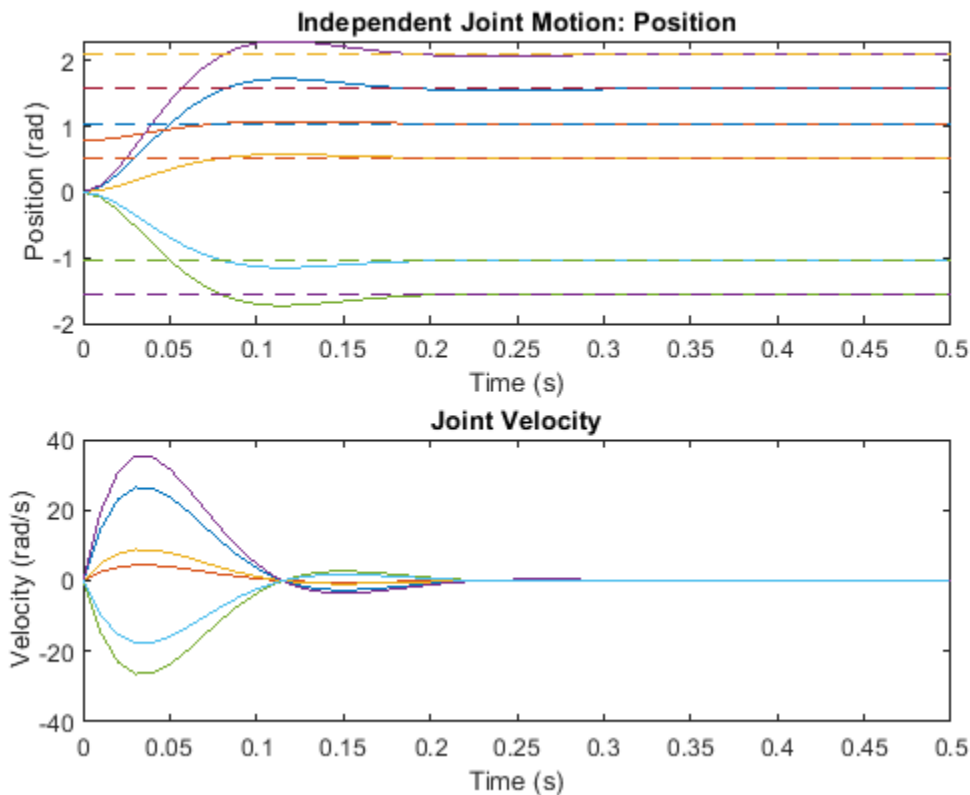


In the following plot, use independent joint control to confirm that the computed torque motion behaves equivalently under some simplifying assumptions.

```

% Independent Joint Motion
figure
subplot(2,1,1)
plot(tIndepJoint,yIndepJoint(:,1:numJoints))
hold all
plot(tIndepJoint,targetJointPosition*ones(1,length(tIndepJoint)),'--')
title('Independent Joint Motion: Position')
xlabel('Time (s)')
ylabel('Position (rad)')
subplot(2,1,2);
plot(tIndepJoint,yIndepJoint(:,numJoints+1:end))
title('Joint Velocity')
xlabel('Time (s)')
ylabel('Velocity (rad/s)')

```



Finally, the PD Controller uses fairly aggressive gains to achieve similar rise times, but unlike the other approaches, the individual joints behave differently, since each joint and the associated bodies have slightly different dynamic properties that are not compensated by the controller.

```

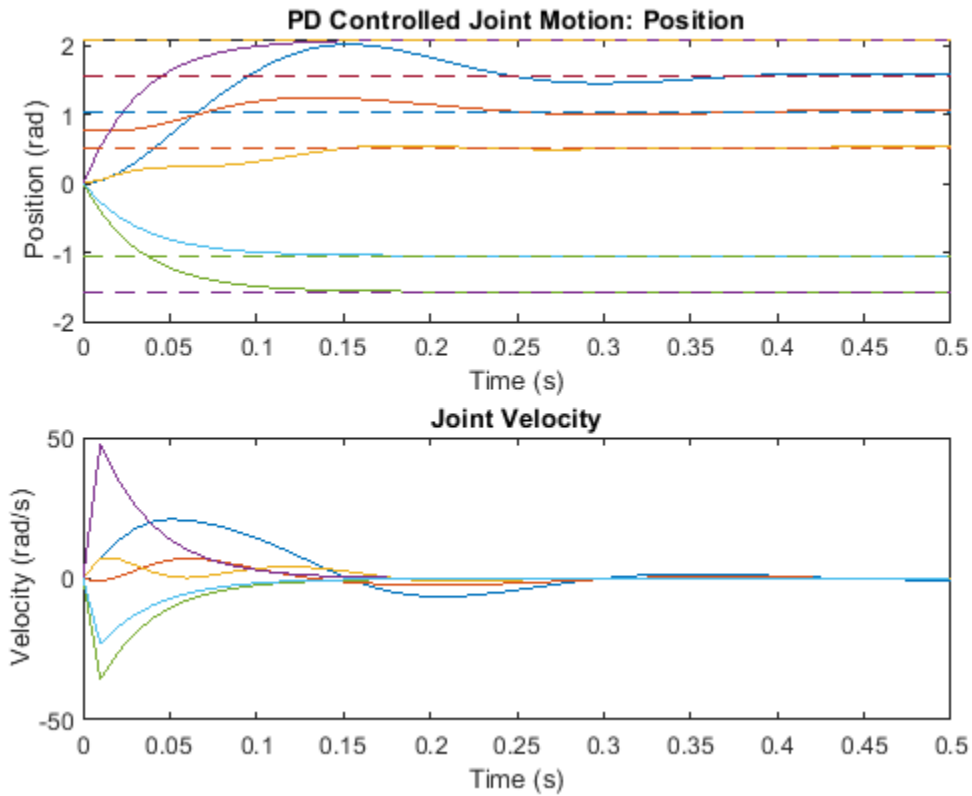
% PD with Gravity Compensation
figure
subplot(2,1,1)
plot(tPD,yPD(:,1:numJoints))
hold all
plot(tPD,targetJointPosition*ones(1,length(tPD)),'--')
title('PD Controlled Joint Motion: Position')
xlabel('Time (s)')

```

```

ylabel('Position (rad)')
subplot(2,1,2)
plot(tPD,yPD(:,numJoints+1:end))
title('Joint Velocity')
xlabel('Time (s)')
ylabel('Velocity (rad/s)')

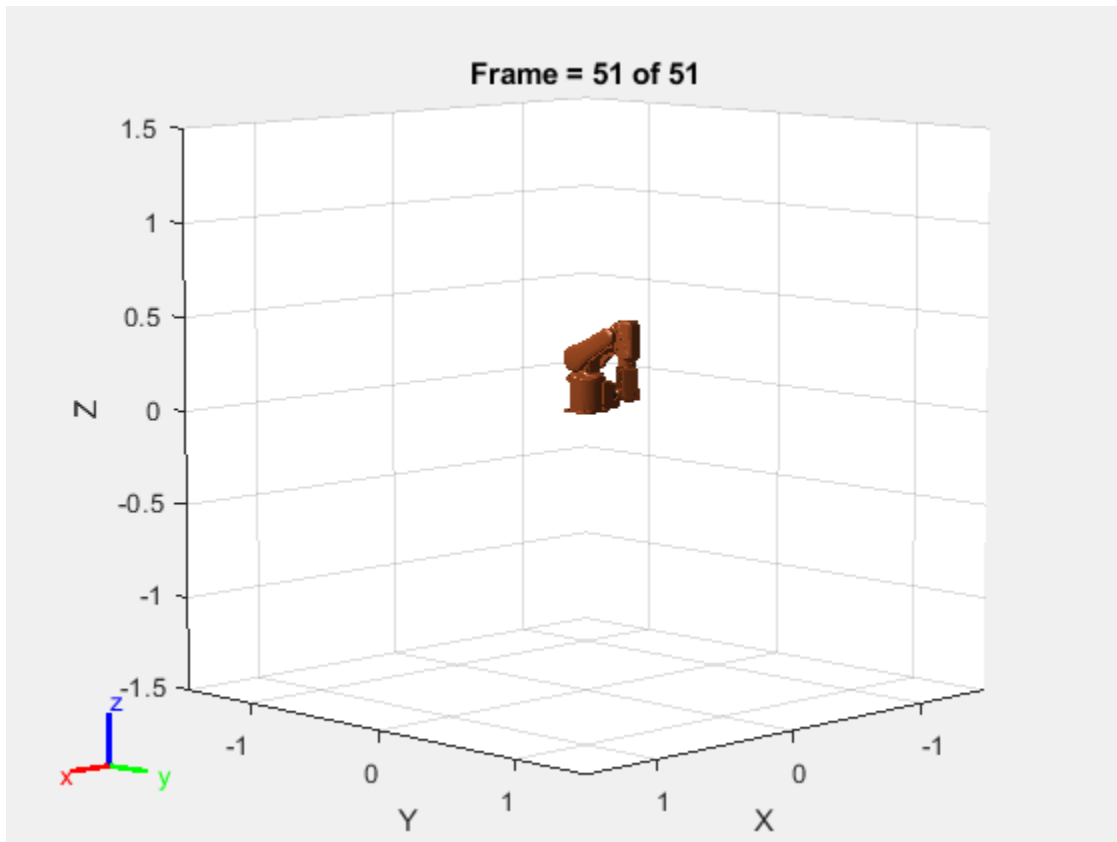
```



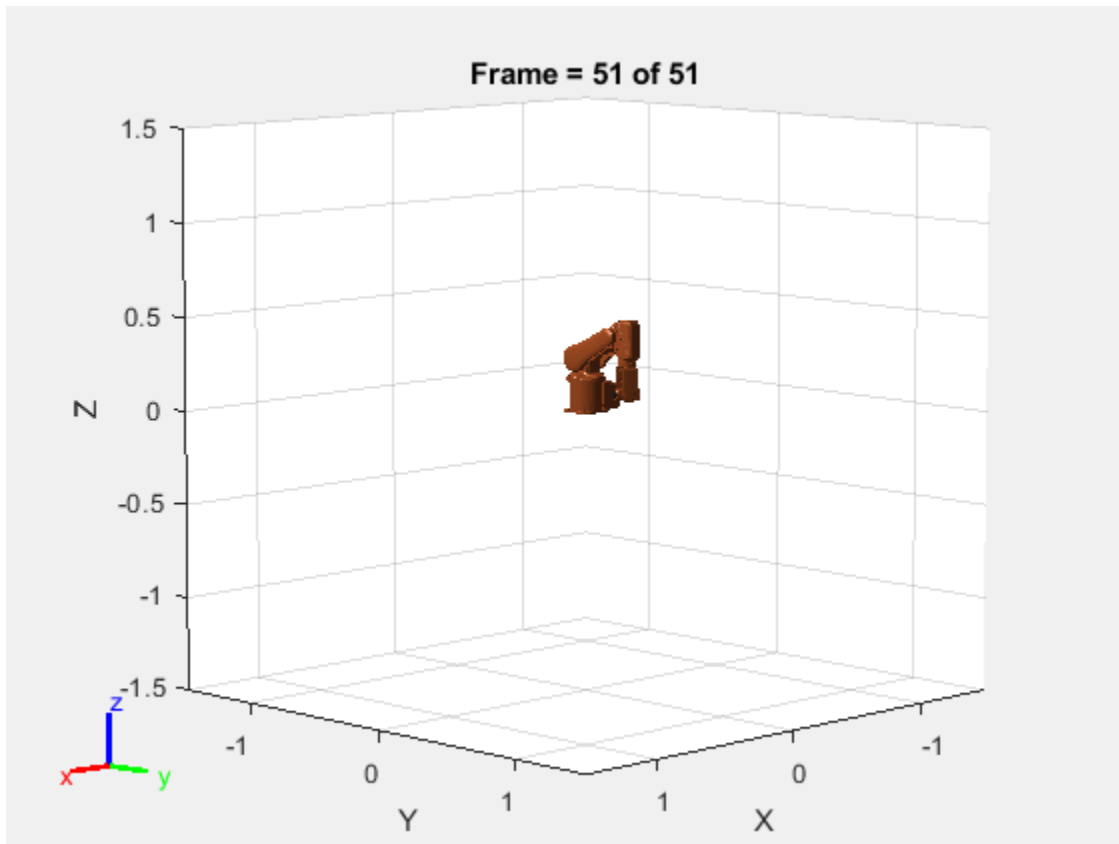
Visualize the Trajectories as an Animation

To see what this behavior looks like in 3-D, the following example helper plots the robot motion in time. The third input is the number of frames between each sample.

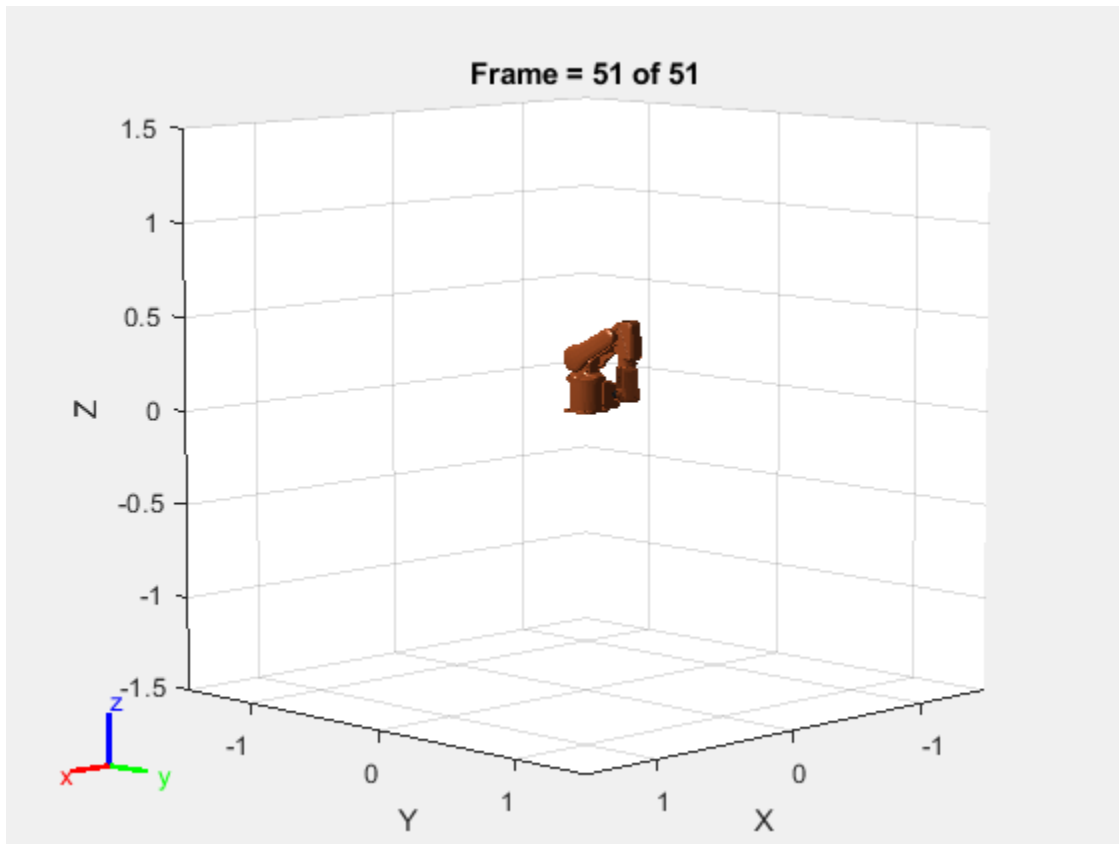
```
exampleHelperRigidBodyTreeAnimation(robot,yComputedTorque,1);
```



```
exampleHelperRigidBodyTreeAnimation(robot,yIndepJoint,1);
```



```
exampleHelperRigidBodyTreeAnimation(robot,yPD,1);
```

Model And Control A Manipulator Arm With Robotics And Simscape

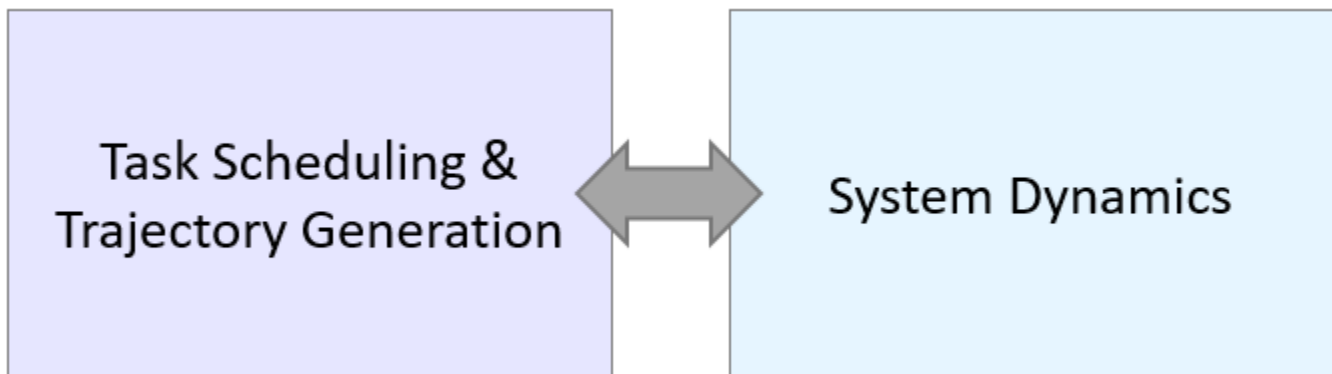
Execute a pick-and-place workflow using an ABB YuMi robot, which demonstrates how to design robot algorithms in Simulink®, and then simulate the action in a test environment using Simscape™. The example also shows how to model a system with different levels of fidelity to focus on better focus on the associated algorithm design.

The design elements of this example are split into three sections to more easily focus on different aspects of the model design:

- 1 **Create a Task & Trajectory Scheduler for Pick-And-Place using Simplified Manipulator System Dynamics:**
- 2 **Add Core Manipulator Dynamics and Design a Controller**
- 3 **Verify Complete Workflow on Simscape Model of the Robot and Environment**

High Level Goals

In the “Interactively Build a Trajectory For an ABB YuMi Robot” on page 1-97 example, a robot waypoint sequence was designed and replayed using a continuous trajectory. In this example, Simulink models convert these waypoints to a complete and repeatable pick-and-place workflow. The model has the two key elements:



The task scheduling and trajectory generation portion defines how the robot traverses through the states. This includes the robot configuration state at any instant, what the goal position is, whether the gripper should be open or closed, and the current trajectory being sent to the robot.

The system dynamics portion models the robot behavior. This defines how the robot moves given a set of reference trajectories and a boolean gripper command (open or closed). The system dynamics can be modeled with different levels of fidelity, depending on the aim of the overall model.

For this example, during the task scheduler design, the aim is to ensure the scheduler behaves correctly under the assumption that the robot is under stable motion control. For this portion, a straightforward model that simulates quickly desirable, so the system dynamics are modeled using the **Joint Space Motion Model** block. This block simulates the manipulator motion given joint-space reference trajectories under a stable controller with predefined response parameters. Once the task scheduling is complete, the focus of the model is shifted to controller design and system verification, which requires more complex system dynamics models.

Define a Robot and Environment

Load an ABB YuMi robot model. The robot is an industrial manipulator with two arms. This example only uses a single arm.

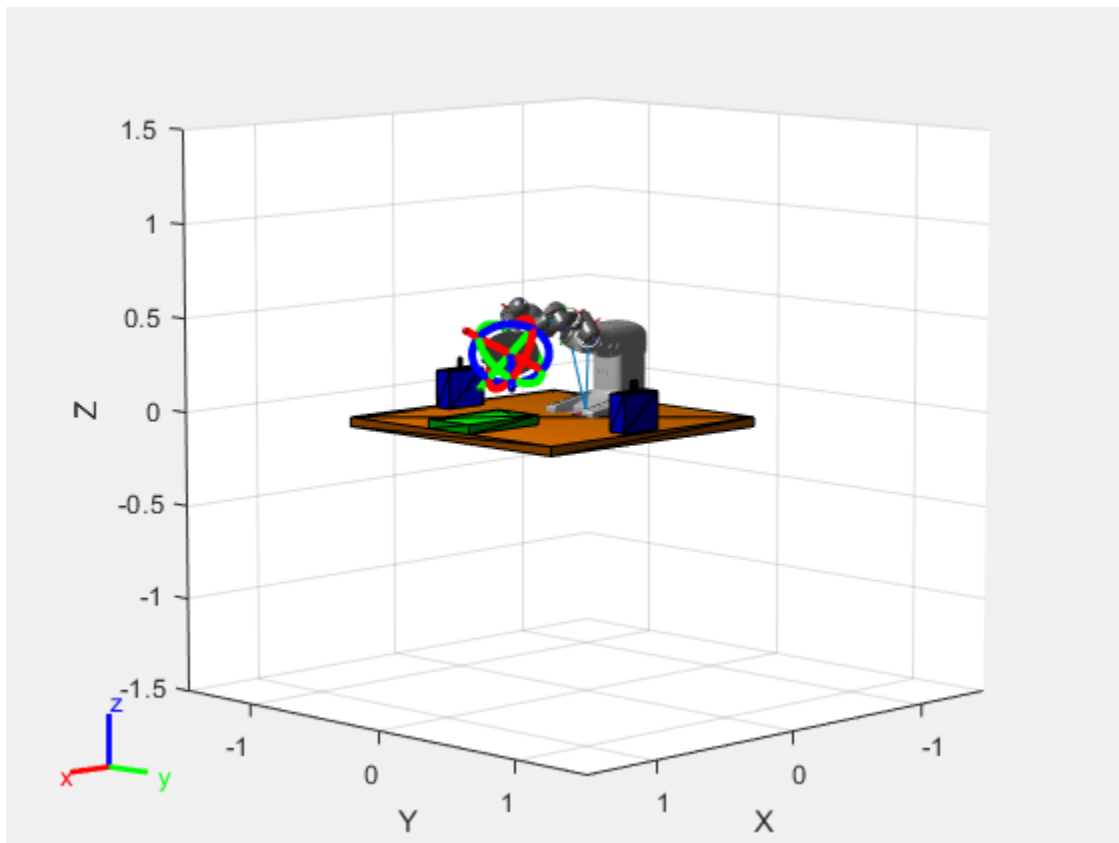
```
robot = loadrobot('abbYumi','Gravity',[0 0 -9.81]);
```

Create a visualization to replay simulated trajectories.

```
iviz = interactiveRigidBodyTree(robot);  
ax = gca;
```

Add an environment by creating a set of collision objects using an example helper function.

```
exampleHelperSetupWorkspace(ax);
```



Initialize Shared Simulation Parameters

This example uses a set of predefined configurations, `configSequence`, as robot states. These are stored in an associated MAT file and were initially defined in “Interactively Build a Trajectory For an ABB YuMi Robot” on page 1-97.

```
load abbSavedConfigs.mat configSequence
```

For the simulation, the initial state of the robot must be defined including position, velocity, and acceleration of each joint.

```
% Define initial state  
q0 = configSequence(:,1); % Position
```

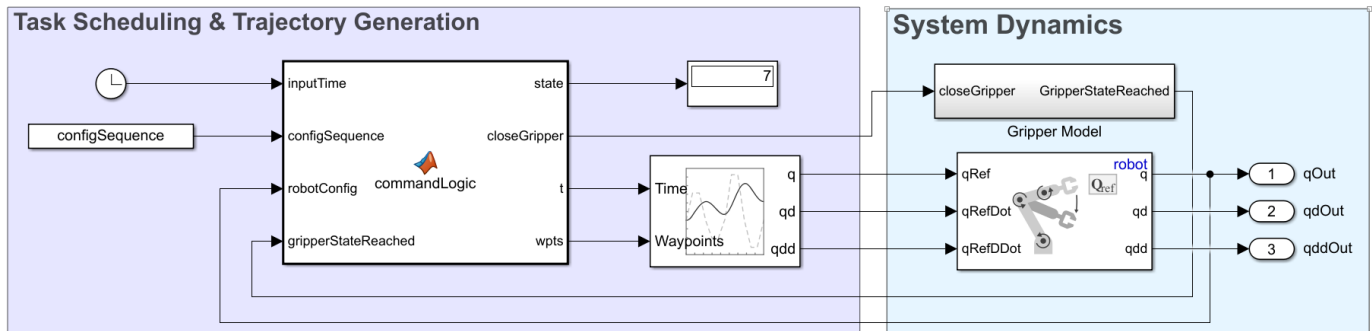
```

dq0 = zeros(size(q0)); % Velocity
ddq0 = zeros(size(q0)); % Acceleration
    
```

Create a Task & Trajectory Scheduler

Load the first model, which focuses on the task scheduling and trajectory generation section of the model.

```
open_system('modelWithSimplifiedSystemDynamics.slx');
```



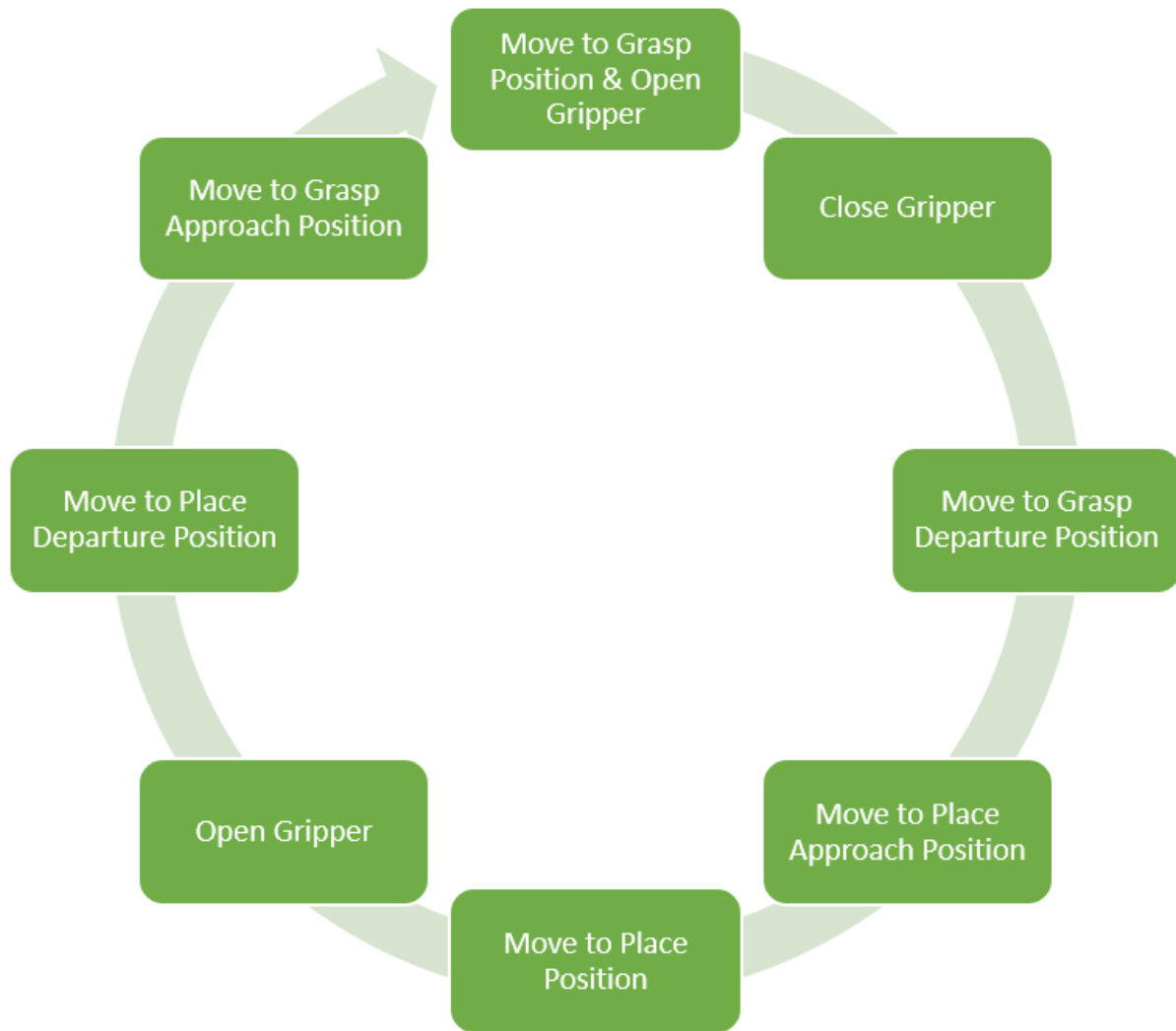
Simplified System Dynamics

To focus on the scheduling portion of the model, the system dynamics are modeled using the **Joint Space Motion Model** block. This motion model assumes the robot can reach specified configurations under stable, accurate control. Later, the example details more accurate modelling of the system dynamics.

The gripper is modeled as a simple Boolean command input as 0 or 1 (open or closed), and an output that indicates whether the gripper achieved the commanded position. Typically, robots treat the gripper command separately from the other configuration inputs.

Task Scheduling

The series of tasks the robot through are eight states:



The scheduler is implemented using a MATLAB Function block, `commandLogic`. The scheduler advances states when the gripper state is reached and all the manipulator joints have reached their target positions within a predefined threshold. Each task is input to the **Trapezoidal Velocity Profile Trajectory** block which generates a smooth trajectory between each waypoint.

Simulate the Model

The provided Simulink model stores variables relevant to the example in the Model Workspace. Click **Load Default Parameters** to reinitialize the variables if needed. For more information, see “Model Workspaces” (Simulink).

Run the model by calling `sim`.

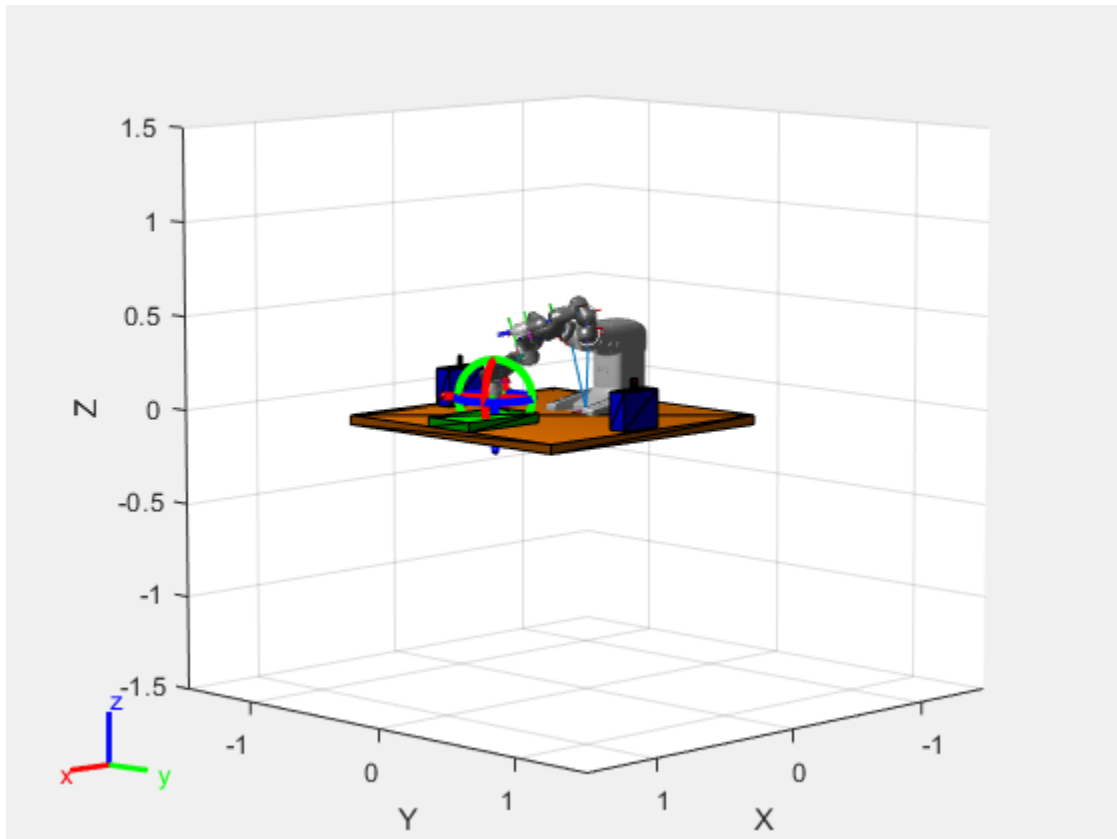
Use the interactive visualization to play back the motion. The model is simulated for a few extra seconds to ensure that the cycle loops as expected after the first motion. This model does not simulate any environment interaction, so the robot does not actually grab objects in this simulation.

```

simout = sim('modelWithSimplifiedSystemDynamics.slx');

% Visualize the motion using the interactiveRigidBodyTree object.
iviz.ShowMarker = false;
iviz.showFigure;
rateCtrlObj = rateControl(length(simout.tout)/(max(simout.tout)));
for i = 1:length(simout.tout)
    iviz.Configuration = simout.yout{1}.Values.Data(i,:);
    waitfor(rateCtrlObj);
end

```



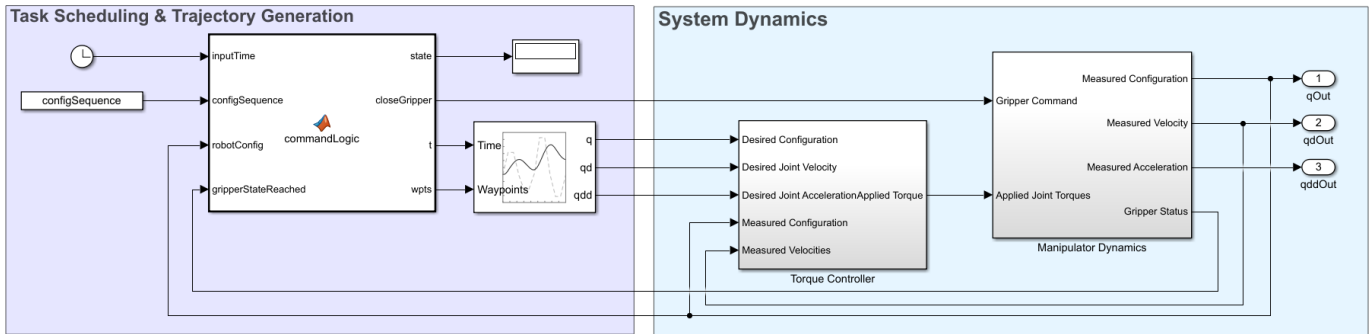
Add Core Manipulator Dynamics and Design a Controller

Now that the scheduler has been designed and verified, add a controller for the robot with two elements

- A more complex manipulator dynamics model that accepts joint torques and gripper commands
- A joint-space controller that returns joint torques given desired and current manipulator states

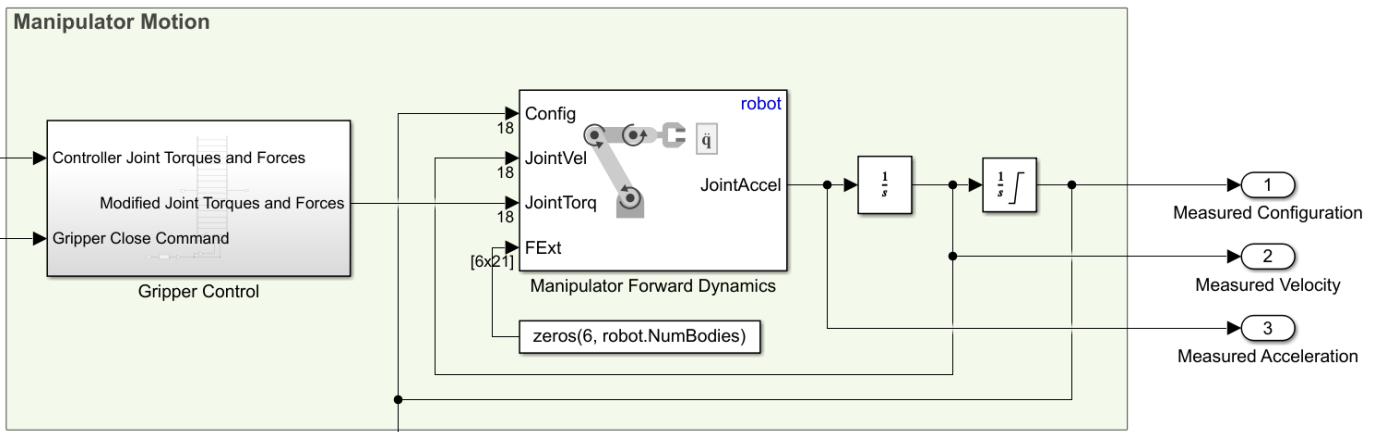
Open the next provided model with the added controller.

```
open_system('modelWithControllerAndBasicRobotDynamics.slx');
```



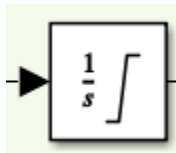
Manipulator Dynamics

For the purpose of designing a controller, the manipulator dynamics have to represent the manipulator joint positions given torque inputs. This is achieved inside the **Manipulator Dynamics** subsystem using a **Forward Dynamics** block to convert joint torques to joint acceleration given the current state, and then integrating twice to get the complete joint configuration. The integrators are initialized to q_0 and dq_0 , the initial joint position and velocity.



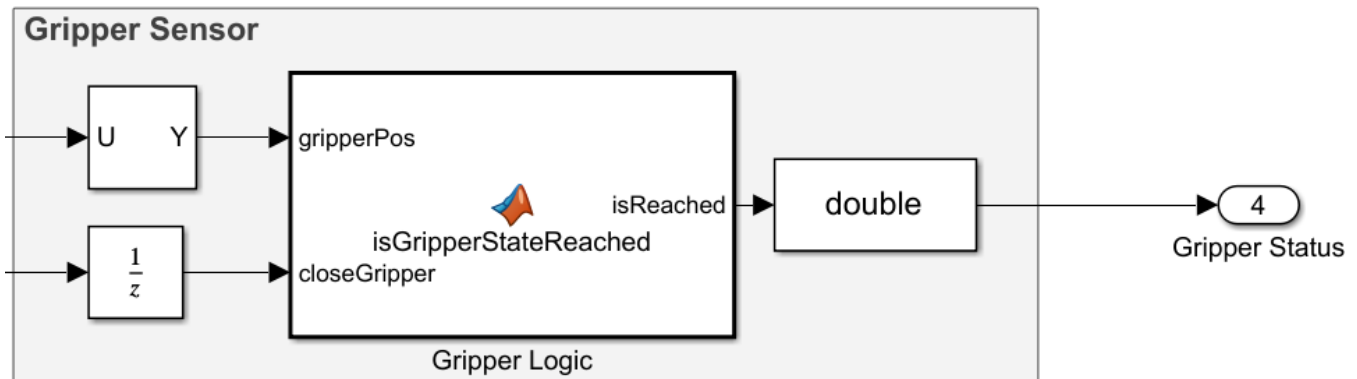
Additionally, the gripper control subsystem overrides the joint control torques to the gripper actuators with 10 N of force that is applied to close or open the gripper.

Note that the second integrator is saturated.



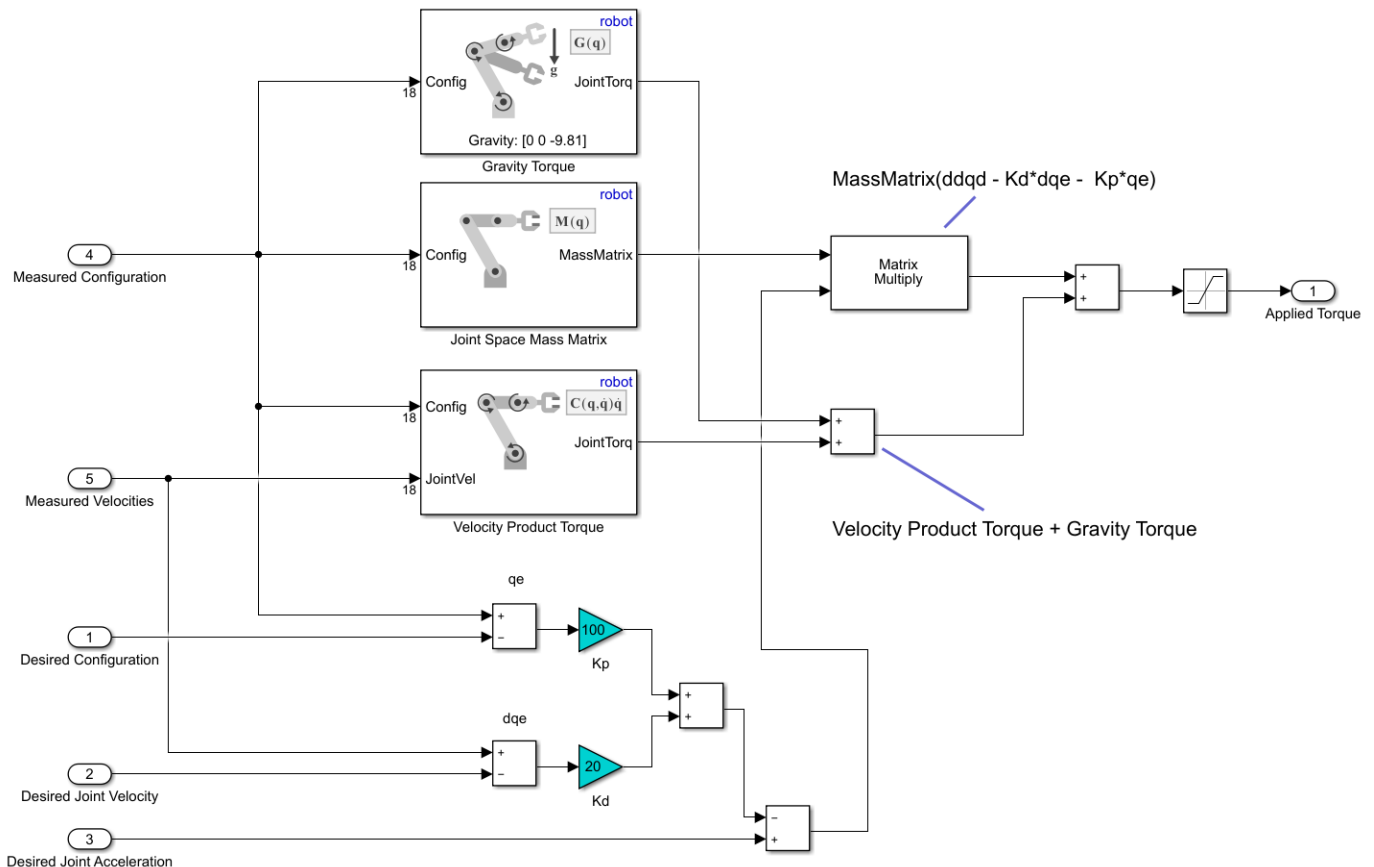
While manipulators under well-designed position controllers typically will not reach joint limits, the addition of open-loop forces from the gripper action mean that joint limits are required to ensure a realistic response. For a more accurate model, the joint saturation could be connected to the velocity to reset integration, but for this model, this level of accuracy is sufficient.

Gripper Sensor



This model also adds a more detailed gripper sensor to check when the gripper has actually been opened or closed. The gripper sensor extracts the last two values of the joint configuration (the values that correspond to the gripper position), and compares them to the intended gripper position, given by the `closeGripper` command, in a MATLAB Function block, **Gripper Logic**. The **Gripper Status** returns 1 when the positions of the gripper joints match the desired state given by the `closeGripper` command. When the gripper has not yet reached those states, **Gripper Status** returns zero. This matches the behavior of the **Gripper Model** in the earlier, simplified model.

Joint-Space Controller



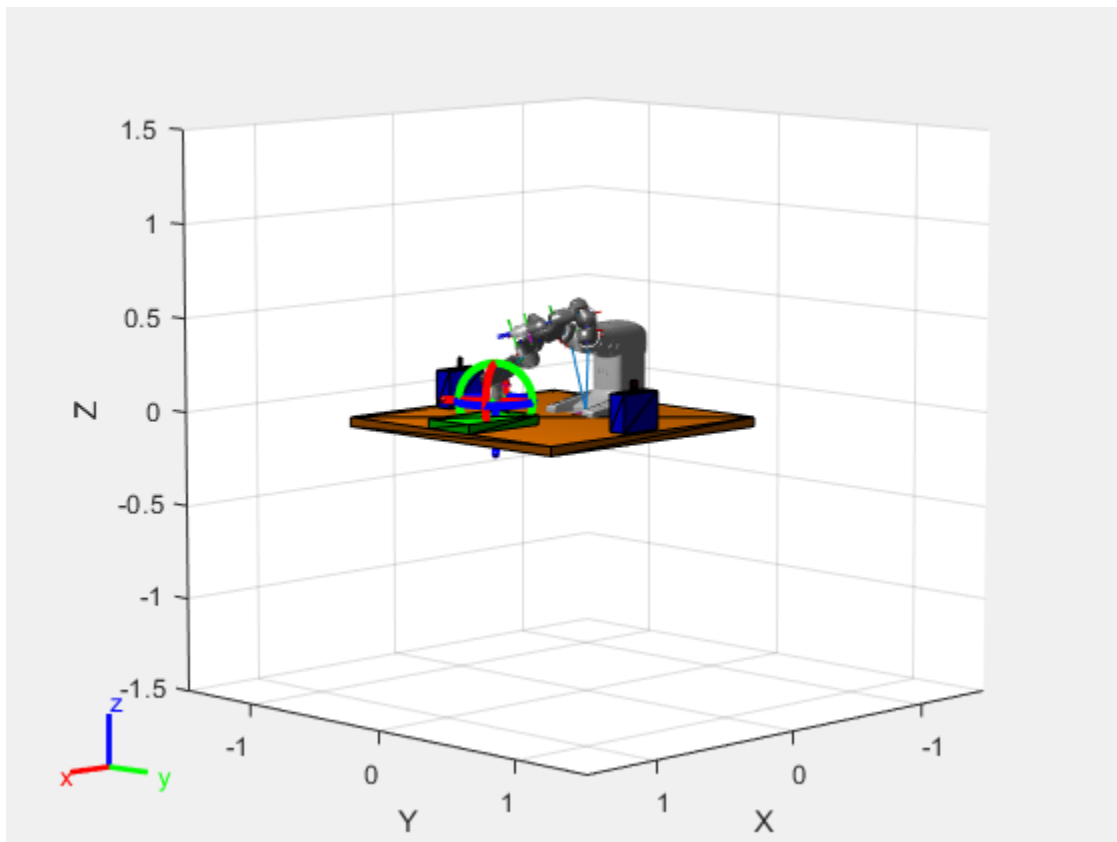
This model also adds a computed torque controller which implements a model-based approach to joint control. For more details, see Build Computed Torque Controller Using Robotics Manipulator Blocks in the “Perform Safe Trajectory Tracking Control Using Robotics Manipulator Blocks” on page 1-194 example. This model uses the same controller, but with the ABB YuMi as the `rigidBodyTree` input rather than the Rethink Sawyer.

Simulate the Model

Simulate and visualize the results using the new model.

```
simout = sim('modelWithControllerAndBasicRobotDynamics.slx');

% Visualize the motion using the interactiveRigidBodyTree
iviz.ShowMarker = false;
iviz.showFigure;
rateCtrlObj = rateControl(length(simout.tout)/(max(simout.tout)));
for i = 1:length(simout.tout)
    iviz.Configuration = simout.yout{1}.Values.Data(i,:);
    waitfor(rateCtrlObj);
end
```



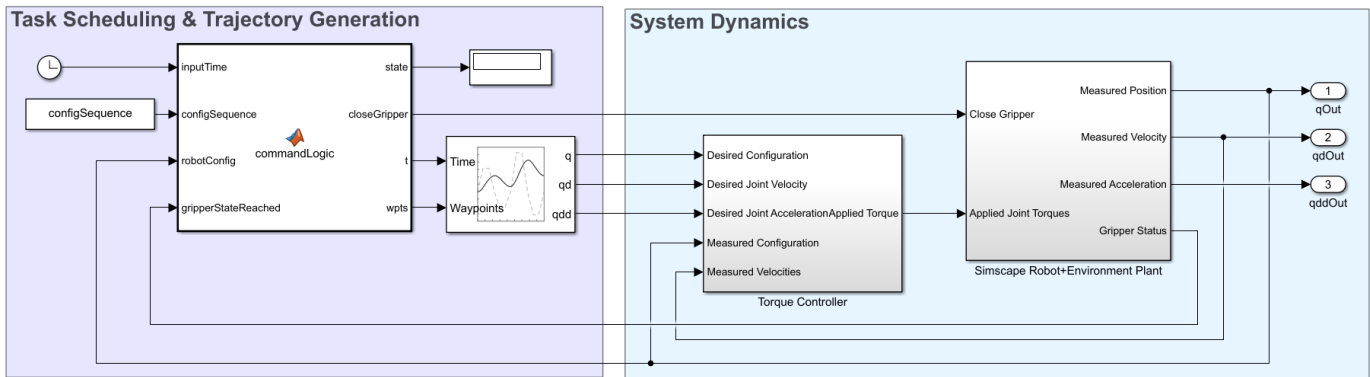
Verify Complete Workflow on Simscape Model of the Robot and Environment

Now that the task scheduler and controller have been designed, add more complex robot and environment models. Use Simscape Multibody™ which can create high-fidelity models of physical systems. In this application, Simscape adds dynamics with built-in joint limits and contact modeling. This last step adds simulation accuracy at the cost of modeling complexity and simulation speed.

Simcape also provides a built-in visualization, **Mechanics Explorer**, that can be viewed during and after simulation.

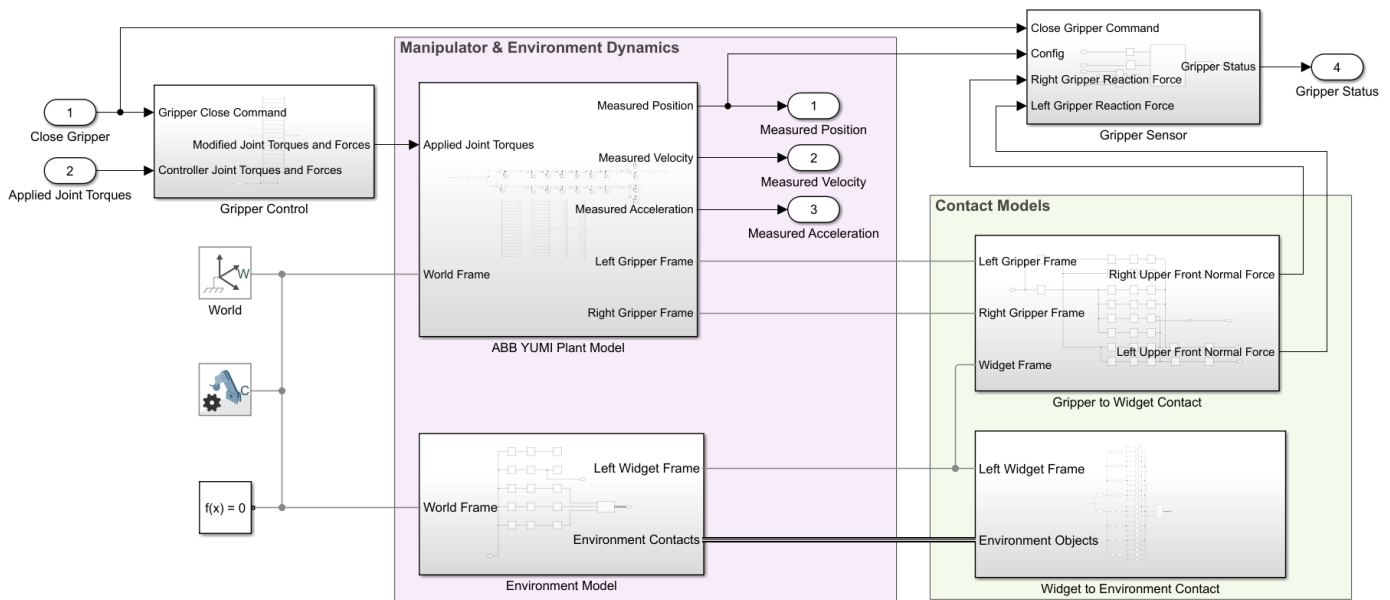
Load the final provided model, which has the same top view.

```
open_system('modelWithSimscapeRobotAndEnvironmentDynamics.slx');
```



Simscape Robot & Environment Plant

This main different from the previous model is the plant model. The core manipulator dynamics from the previous model have been replaced with a Simscape model for the robot and the environment:



Manipulator & Environment Dynamics

The manipulator and environment are constructed using Simscape Multibody. The robot model was created by calling `smimport` on the robot URDF file with the provided meshes. Then, the joints were actuated with joint torques by linking via **muxes** and **GoTo** tags and outfitted with sensors that return joint position, velocity, and acceleration.

The objects, or widgets, are actually picked up in this simulation, so define the widget size.

```
widgetDimensions = [0.02 0.02 0.07];
```

Contact Models

The contact in this model is split into two categories:

- Contact between the gripper and the widget
- Contact between the widget and the environment

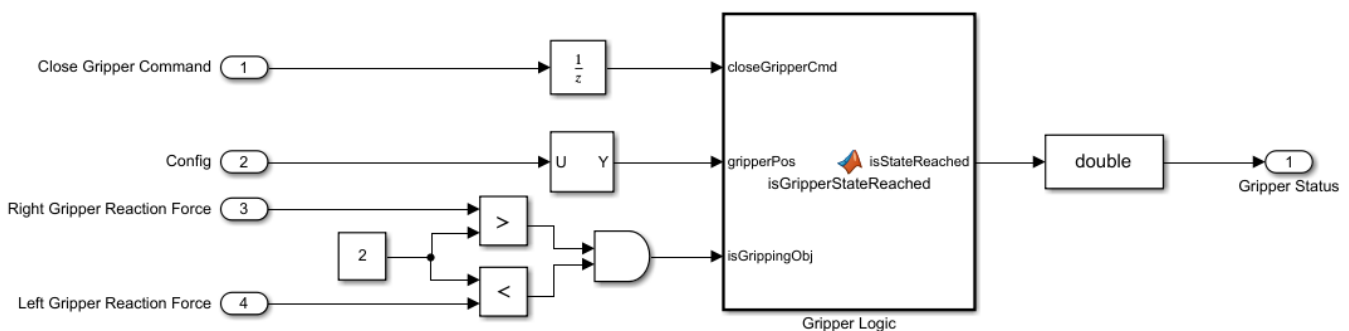
In both cases, *contact proxies* are used in lieu of direct surface-to-surface contact. The use of contact proxies speed up modeling to improve performance. For the gripper-widget contact, the gripper contacts are modeled using two brick solids, while eight spherical contacts are used to model the widget interface. Similarly, the widget-to-environment contact uses spheres at each of the four corners of the widget that contact the brick solids representing the environment.

Define the parameters for the contact models to be close to their default states.

```
% Contact parameters
stiffness = 1e4;
damping = 30;
transition_region_width = 1e-4;
static_friction_coef = 1;
kinetic_friction_coef = 1;
critical_velocity = 1;
```

Gripper Control & Sensing

The **Gripper Control** is the same, but the **Gripper Sensor** is modified. Since this gripper can actually pick up objects, the closed gripper state is reached when the grasp is firm. The actual closed position may never be reached. Therefore, extra logic has been added that returns a value, `isGrippingObj`, that is true when both the left and right gripper reaction forces exceed a threshold value. The **Gripper Logic** MATLAB Function block accepts this variable as an input.

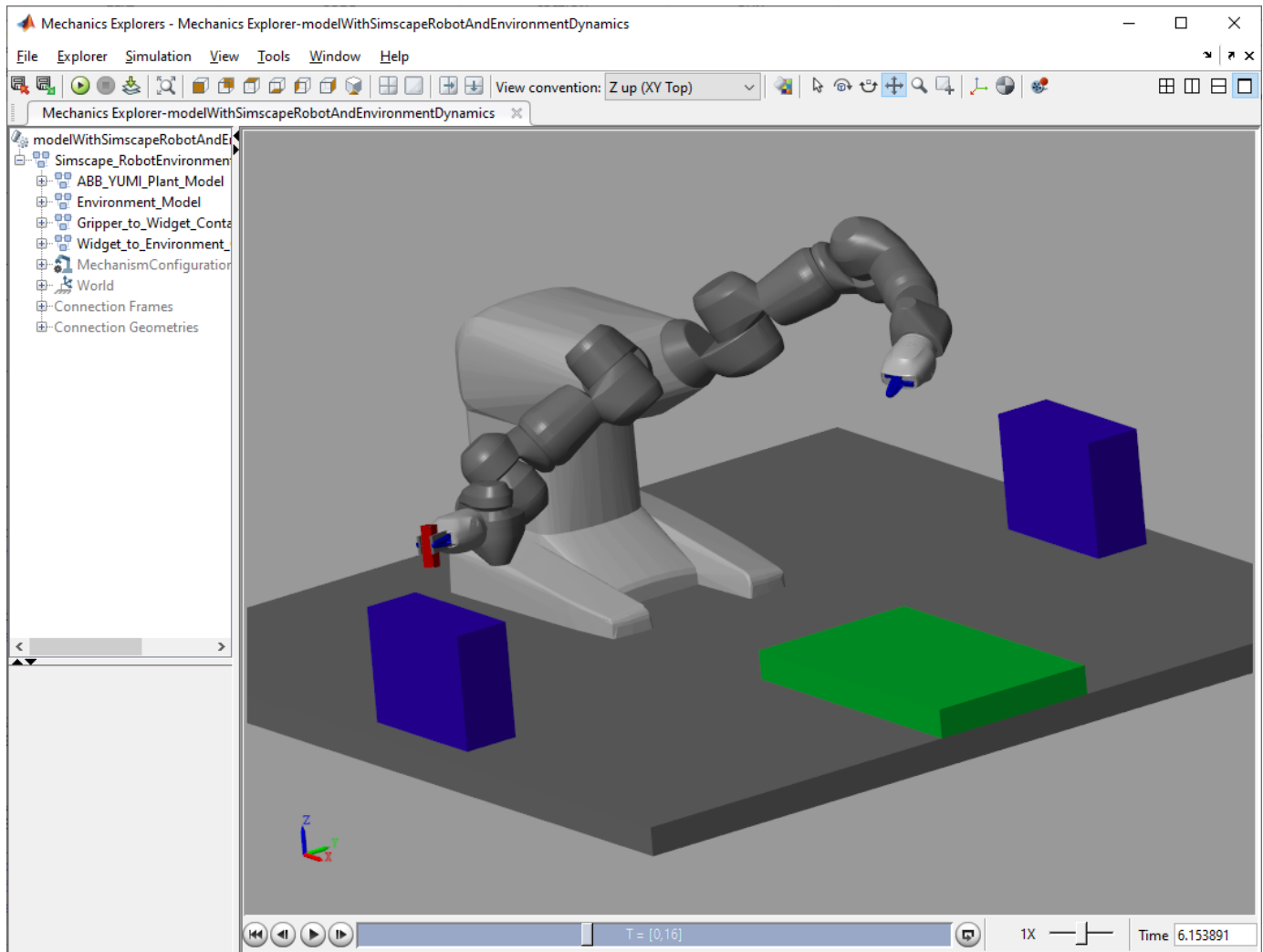


Simulate the Model

Simulate the robot. Due to the high complexity, this may take several minutes.

```
simout = sim('modelWithSimscapeRobotAndEnvironmentDynamics.slx');
```

Use the **Mechanics Explorer** to visualize the performance during and after simulation.



Extensibility

This example has focused on the design of a scheduling and control system for a pick-and-place application. Further investigations might include the effect of sampling on the controller, the impact of unexpected contact using Simscape Multibody, or the extension to a multi-domain model like detailing the behavior of the electrical motors that the robot uses.

Plan and Execute Task- and Joint-space Trajectories using KINOVA Gen3 Manipulator

This example shows how to generate and simulate interpolated joint trajectories to move from an initial to a desired end-effector pose. The timing of the trajectories is based on an approximate desired end of arm tool (EOAT) speed.

Load the KINOVA Gen3 rigid body tree (RBT) robot model.

```
robot = loadrobot('kinovaGen3','DataFormat','row','Gravity',[0 0 -9.81]);
```

Set current robot joint configuration.

```
currentRobotJConfig = homeConfiguration(robot);
```

Get number of joints and the end-effector RBT frame.

```
numJoints = numel(currentRobotJConfig);
endEffector = "EndEffector_Link";
```

Specify the trajectory time step and approximate desired tool speed.

```
timeStep = 0.1; % seconds
toolSpeed = 0.1; % m/s
```

Set the initial and final end-effector pose.

```
jointInit = currentRobotJConfig;
taskInit = getTransform(robot,jointInit,endEffector);

taskFinal = trvec2tform([0.4,0,0.6])*axang2tform([0 1 0 pi]);
```

Generate Task-Space Trajectory

Compute task-space trajectory waypoints via interpolation.

First, compute tool traveling distance.

```
distance = norm(tform2trvec(taskInit)-tform2trvec(taskFinal));
```

Next, define trajectory times based on traveling distance and desired tool speed.

```
initTime = 0;
finalTime = (distance/toolSpeed) - initTime;
trajTimes = initTime:timeStep:finalTime;
timeInterval = [trajTimes(1); trajTimes(end)];
```

Interpolate between taskInit and taskFinal to compute intermediate task-space waypoints.

```
[taskWaypoints,taskVelocities] = transformtraj(taskInit,taskFinal,timeInterval,trajTimes);
```

Control Task-Space Motion

Create a joint space motion model for PD control on the joints. The `taskSpaceMotionModel` object models the motion of a rigid body tree model under task-space proportional-derivative control.

```
tsMotionModel = taskSpaceMotionModel('RigidBodyTree',robot,'EndEffectorName','EndEffector_Link')
```

Set the proportional and derivative gains on orientation to zero, so that controlled behavior just follows the reference positions:

```
tsMotionModel.Kp(1:3,1:3) = 0;  
tsMotionModel.Kd(1:3,1:3) = 0;
```

Define the initial states (joint positions and velocities).

```
q0 = currentRobotJConfig;  
qd0 = zeros(size(q0));
```

Use `ode15s` to simulate the robot motion. Since reference state changes at each instant, a wrapper function is required to update the interpolated trajectory input to the state derivative at each instant. Therefore, an example helper function is passed as the function handle to the ODE solver. The resultant manipulator states are output in `stateTask`.

```
[tTask,stateTask] = ode15s(@(t,state) exampleHelperTimeBasedTaskInputs(tsMotionModel,timeInterval),t0,tFinal,q0,qd0);
```

Generate Joint-Space Trajectory

Create an inverse kinematics object for the robot.

```
ik = inverseKinematics('RigidBodyTree',robot);  
ik.SolverParameters.AllowRandomRestart = false;  
weights = [1 1 1 1 1 1];
```

Calculate the initial and desired joint configurations using inverse kinematics.

```
initialGuess = wrapToPi(jointInit);  
jointFinal = ik(endEffector,taskFinal,weights,initialGuess);  
jointFinal = wrapToPi(jointFinal);
```

Interpolate between them using a cubic polynomial function to generate an array of evenly-spaced joint configurations. Use a B-spline to generate a smooth trajectory.

```
ctrlpoints = [jointInit',jointFinal'];  
jointConfigArray = cubicpolytraj(ctrlpoints,timeInterval,trajectories);  
jointWaypoints = bsplinepolytraj(jointConfigArray,timeInterval,1);
```

Control Joint-Space Trajectory

Create a joint space motion model for PD control on the joints. The `jointSpaceMotionModel` object models the motion of a rigid body tree model and uses proportional-derivative control on the specified joint positions.

```
jsMotionModel = jointSpaceMotionModel('RigidBodyTree',robot,'MotionType','PDControl');
```

Set initial states (joint positions and velocities).

```
q0 = currentRobotJConfig;  
qd0 = zeros(size(q0));
```

Use `ode15s` to simulate the robot motion. Again, an example helper function is used as the function handle input to the ODE solver in order to update the reference inputs at each instant in time. The joint-space states are output in `stateJoint`.

```
[tJoint,stateJoint] = ode15s(@(t,state) exampleHelperTimeBasedJointInputs(jsMotionModel,timeInterval),t0,tFinal,q0,qd0);
```

Visualize and Compare Robot Trajectories

Show the initial configuration of the robot.

```
show(robot,currentRobotJConfig,'PreservePlot',false,'Frames','off');
hold on
axis([-1 1 -1 1 -0.1 1.5]);
```

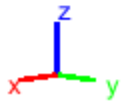
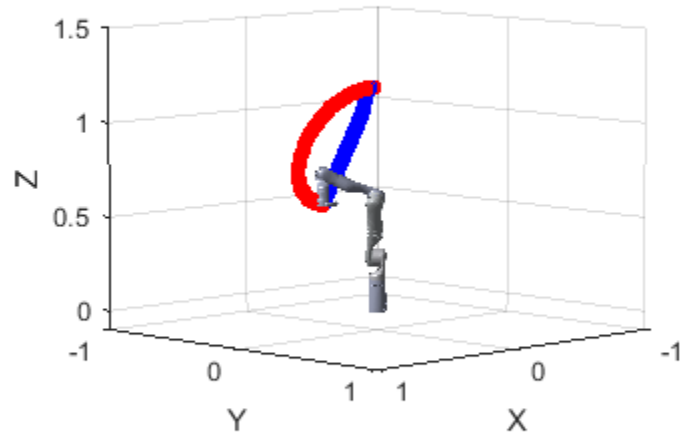
Visualize the task-space trajectory. Iterate through the stateTask states and interpolate based on the current time.

```
for i=1:length(trajTimes)
    % Current time
    tNow= trajTimes(i);
    % Interpolate simulated joint positions to get configuration at current time
    configNow = interp1(tTask,stateTask(:,1:numJoints),tNow);
    poseNow = getTransform(robot,configNow,endEffector);
    show(robot,configNow,'PreservePlot',false,'Frames','off');
    plot3(poseNow(1,4),poseNow(2,4),poseNow(3,4),'b.','MarkerSize',20)
    drawnow;
end
```

Visualize the joint-space trajectory. Iterate through the jointTask states and interpolate based on the current time.

```
% Return to initial configuration
show(robot,currentRobotJConfig,'PreservePlot',false,'Frames','off');

for i=1:length(trajTimes)
    % Current time
    tNow= trajTimes(i);
    % Interpolate simulated joint positions to get configuration at current time
    configNow = interp1(tJoint,stateJoint(:,1:numJoints),tNow);
    poseNow = getTransform(robot,configNow,endEffector);
    show(robot,configNow,'PreservePlot',false,'Frames','off');
    plot3(poseNow(1,4),poseNow(2,4),poseNow(3,4),'r.','MarkerSize',20)
    drawnow;
end
```



Plan and Execute Collision-Free Trajectories using KINOVA Gen3 Manipulator

This example shows how to plan closed-loop collision-free robot trajectories from an initial to a desired end-effector pose using nonlinear model predictive control. The resulting trajectories are executed using a joint-space motion model with computed torque control. Obstacles can be static or dynamic, and can be either set as primitives (spheres, cylinders, boxes) or as custom meshes.

Robot Description and Poses

Load the KINOVA Gen3 rigid body tree (RBT) model.

```
robot = loadrobot('kinovaGen3', 'DataFormat', 'column');
```

Get the number of joints.

```
numJoints = numel(homeConfiguration(robot));
```

Specify the robot frame where the end-effector is attached.

```
endEffector = "EndEffector_Link";
```

Specify initial and desired end-effector poses. Use inverse kinematics to solve for the initial robot configuration given a desired pose.

```
% Initial end-effector pose
```

```
taskInit = trvec2tform([0.4 0 0.2])*axang2tform([0 1 0 pi]);
```

```
% Compute current robot joint configuration using inverse kinematics
```

```
ik = inverseKinematics('RigidBodyTree', robot);
```

```
ik.SolverParameters.AllowRandomRestart = false;
```

```
weights = [1 1 1 1 1 1];
```

```
currentRobotJConfig = ik(endEffector, taskInit, weights, robot.homeConfiguration);
```

```
currentRobotJConfig = wrapToPi(currentRobotJConfig);
```

```
% Final (desired) end-effector pose
```

```
taskFinal = trvec2tform([0.35 0.55 0.35])*axang2tform([0 1 0 pi]);
```

```
anglesFinal = rotm2eul(taskFinal(1:3,1:3), 'XYZ');
```

```
poseFinal = [taskFinal(1:3,4);anglesFinal']; % 6x1 vector for final pose: [x, y, z, phi, theta, psi]
```

Collision Meshes and Obstacles

To check for and avoid collisions during control, you must setup a collision world as a set of collision objects. This example uses `collisionSphere` objects as obstacles to avoid. Change the following boolean to plan using static instead of moving obstacles.

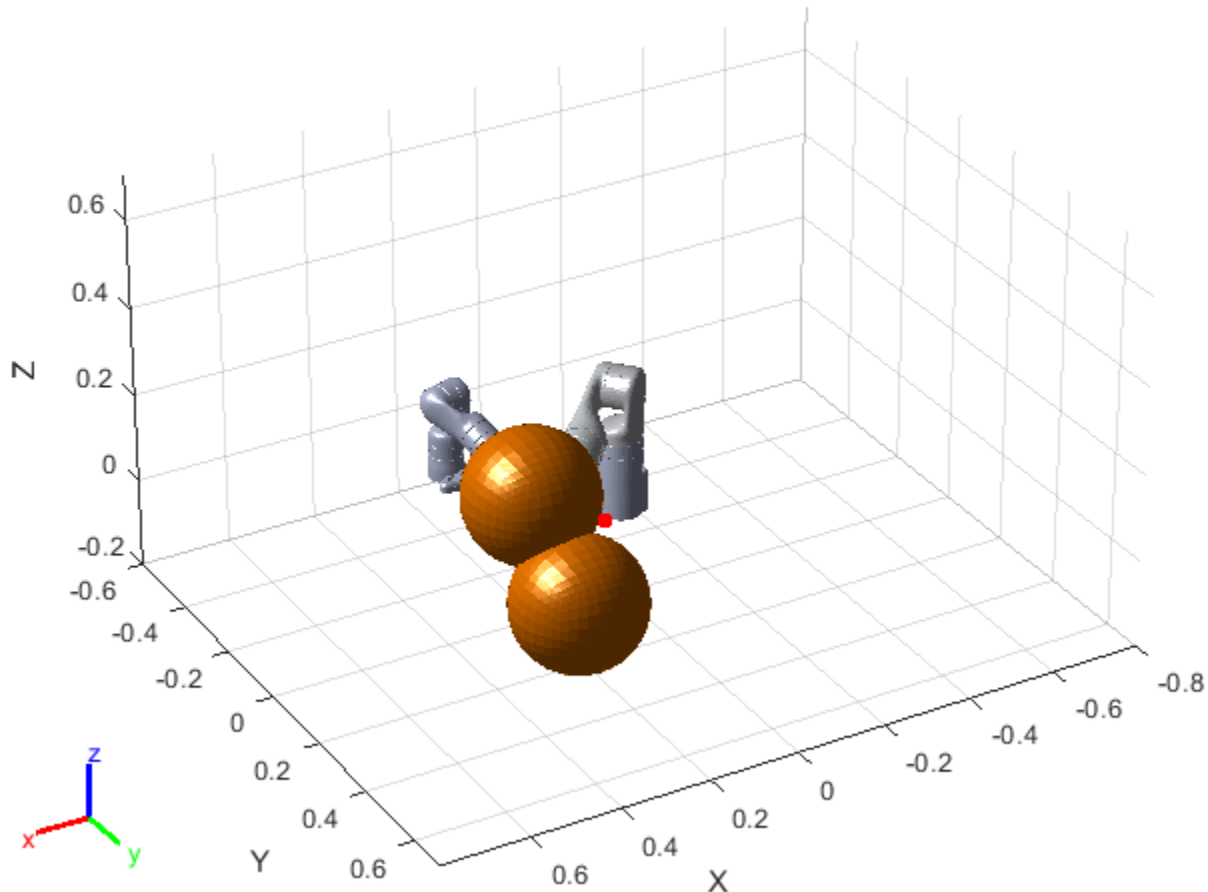
```
isMovingObst = true;
```

The obstacle sizes and locations are initialized in the following helper function. To add more static obstacles, add collision objects in the world array.

```
helperCreateObstaclesKINOVA;
```

Visualize the robot at the initial configuration. You should see the obstacles in the environment as well.

```
x0 = [currentRobotJConfig', zeros(1,numJoints)];
helperInitialVisualizerKINOVA;
```



Specify a safety distance away from the obstacles. This value is used in the inequality constraint function of the nonlinear MPC controller.

```
safetyDistance = 0.01;
```

Design Nonlinear Model Predictive Controller

You can design the nonlinear model predictive controller using the following helper file, which creates an `nlpmpc` (Model Predictive Control Toolbox) controller object. To view the file, type `edit helperDesignNLMPCCobjKINOVA`.

```
helperDesignNLMPCCobjKINOVA;
```

The controller is designed based on the following analysis. The maximum number of iterations for the optimization solver is set to 5. The lower and upper bounds for the joint position and velocities (states), and accelerations (control inputs) are set explicitly.

- The robot joints model is described by double integrators. The states of the model are $x = [q, \dot{q}]$, where the 7 joint positions are denoted by q and their velocities are denoted by \dot{q} . The inputs of the model are the joint accelerations $u = \ddot{q}$. The dynamics of the model are given by

$$\dot{x} = \begin{bmatrix} 0 & I_7 \\ 0 & 0 \end{bmatrix} x + \begin{bmatrix} 0 \\ I_7 \end{bmatrix} u$$

where I_7 denotes the 7×7 identity matrix. The output of the model is defined as

$$y = [I_7 \ 0]x.$$

Therefore, the nonlinear model predictive controller (`nlobj`) has 14 states, 7 outputs, and 7 inputs.

- The cost function for `nlobj` is a custom nonlinear cost function, which is defined in a manner similar to a quadratic tracking cost plus a terminal cost.

$$J = \int_0^T (p_{\text{ref}} - p(q(t)))' Q_r (p_{\text{ref}} - p(q(t))) + u'(t) Q_u u(t) dt + (p_{\text{ref}} - p(q(T)))' Q_t (p_{\text{ref}} - p(q(T))) + \dot{q}'(T) Q_v \dot{q}(T)$$

Here, $p(q(t))$ transforms the joint positions $q(t)$ to the frame of end effector using forward kinematics and `getTransform`, and p_{ref} denotes the desired end-effector pose.

The matrices Q_r , Q_u , Q_t , and Q_v are constant weight matrices.

- To avoid collisions, the controller has to satisfy the following inequality constraints.

$$d_{i,j} \geq d_{\text{safe}}$$

Here, $d_{i,j}$ denotes the distance from the i -th robot body to the j -th obstacle, computed using `checkCollision`.

In this example, i belongs to $\{1, 2, 3, 4, 5, 6\}$ (the base and end-effector robot bodies are excluded), and j belongs to $\{1, 2\}$ (2 obstacles are used).

The Jacobians of the state function, output function, cost function, and inequality constraints are all provided for the prediction model to improve the simulation efficiency. To calculate the inequality constraint Jacobian, use the `geometricJacobian` function and the Jacobian approximation in [1].

Closed-Loop Trajectory Planning

Simulate the robot for a maximum of 50 steps with correct initial conditions.

```
maxIters = 50;
u0 = zeros(1,numJoints);
mv = u0;
time = 0;
goalReached = false;
```

Initialize the data array for control.

```
positions = zeros(numJoints,maxIters);
positions(:,1) = x0(1:numJoints)';

velocities = zeros(numJoints,maxIters);
velocities(:,1) = x0(numJoints+1:end)';

accelerations = zeros(numJoints,maxIters);
accelerations(:,1) = u0';
```

```
timestamp = zeros(1,maxIters);
timestamp(:,1) = time;
```

Use the `nlpmove` (Model Predictive Control Toolbox) function for closed-loop trajectory generation. Specify the trajectory generation options using an `nlpmoveopt` (Model Predictive Control Toolbox) object. Each iteration calculates the position, velocity, and acceleration of the joints to avoid obstacles as they move towards the goal. The `helperCheckGoalReachedKINOVA` script checks if the robot has reached the goal. The `helperUpdateMovingObstacles` script moves the obstacle locations based on the time step.

```
options = nlpmoveopt;
for timestep=1:maxIters
    disp(['Calculating control at timestep ', num2str(timestep)]);
    % Optimize next trajectory point
    [mv,options,info] = nlpmove(nlobj,x0,mv,[],[], options);
    if info.ExitFlag < 0
        disp('Failed to compute a feasible trajectory. Aborting...')
        break;
    end
    % Update states and time for next iteration
    x0 = info.Xopt(2,:);
    time = time + nlobj.Ts;
    % Store trajectory points
    positions(:,timestep+1) = x0(1:numJoints)';
    velocities(:,timestep+1) = x0(numJoints+1:end)';
    accelerations(:,timestep+1) = info.MVopt(2,:)';
    timestamp(timestep+1) = time;
    % Check if goal is achieved
    helperCheckGoalReachedKINOVA;
    if goalReached
        break;
    end
    % Update obstacle pose if it is moving
    if isMovingObst
        helperUpdateMovingObstaclesKINOVA;
    end
end
```

```
Calculating control at timestep 1
```

```
Slack variable unused or zero-weighted in your custom cost function. All constraints will be hard
```

```
Calculating control at timestep 2
```

```
Slack variable unused or zero-weighted in your custom cost function. All constraints will be hard
```

```
Calculating control at timestep 3
```

```
Slack variable unused or zero-weighted in your custom cost function. All constraints will be hard
```

```
Calculating control at timestep 4
```

```
Slack variable unused or zero-weighted in your custom cost function. All constraints will be hard
```

```
Calculating control at timestep 5
```

```
Slack variable unused or zero-weighted in your custom cost function. All constraints will be hard
```

```
Calculating control at timestep 6
```

Slack variable unused or zero-weighted in your custom cost function. All constraints will be hard.

Calculating control at timestep 7

Slack variable unused or zero-weighted in your custom cost function. All constraints will be hard.

Target configuration reached.

Execute Planned Trajectory using Joint-Space Robot Simulation and Control

Trim the trajectory vectors based on the time steps calculated from the plan.

```
tFinal = timestep+1;
positions = positions(:,1:tFinal);
velocities = velocities(:,1:tFinal);
accelerations = accelerations(:,1:tFinal);
timestamp = timestamp(:,1:tFinal);
```

```
visTimeStep = 0.2;
```

Use a `jointSpaceMotionModel` to track the trajectory with computed-torque control. The `helperTimeBasedStateInputsKINOVA` function generates the derivative inputs for the `ode15s` function for modelling the computed robot trajectory.

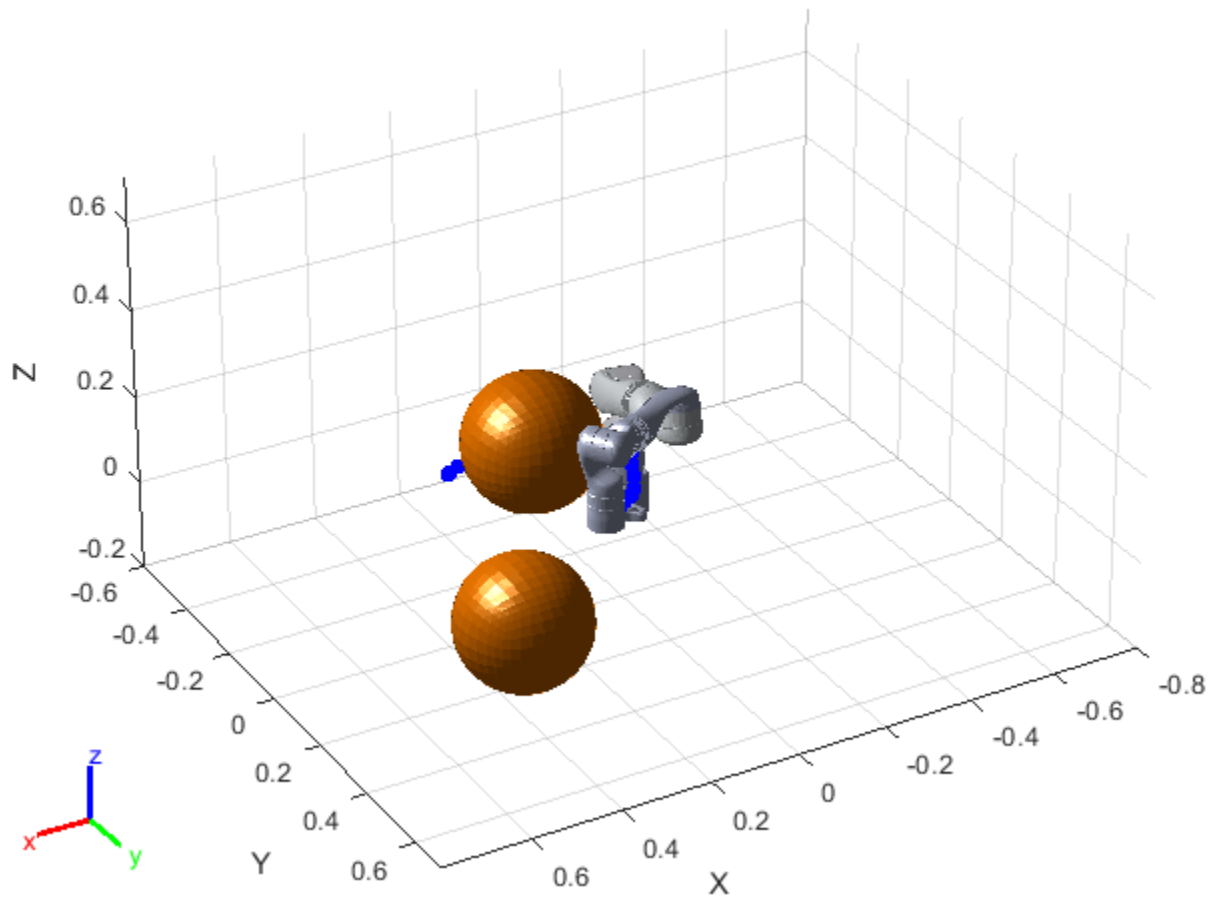
```
motionModel = jointSpaceMotionModel('RigidBodyTree', robot);
```

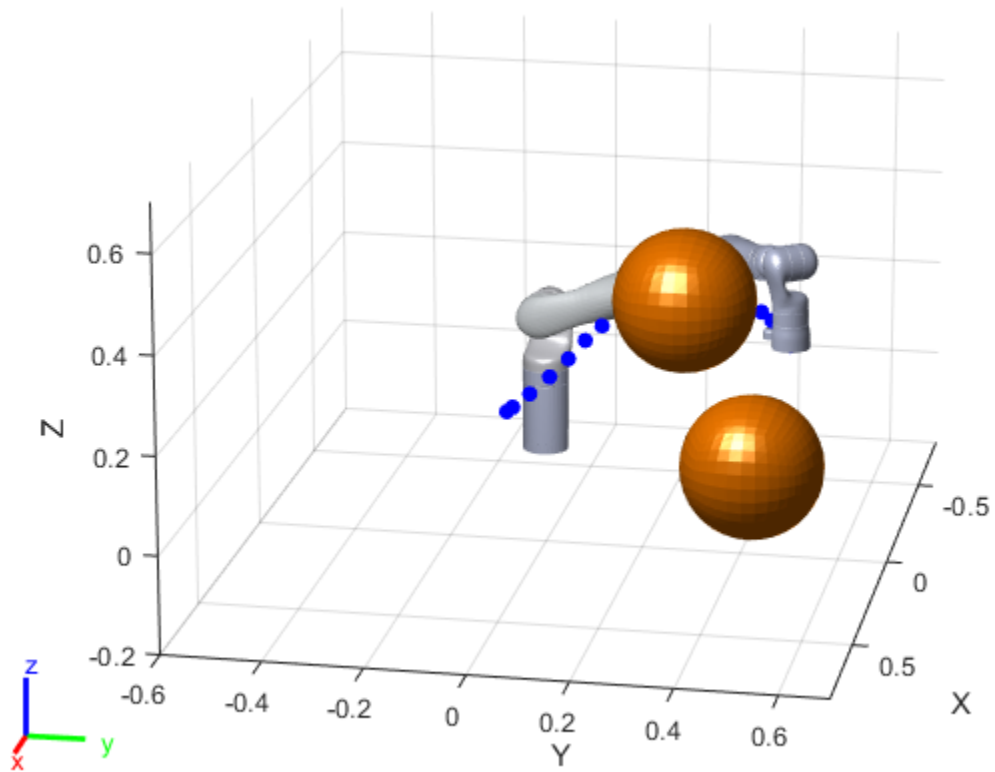
```
% Control robot to target trajectory points in simulation using low-fidelity model
```

```
initState = [positions(:,1);velocities(:,1)];
targetStates = [positions;velocities;accelerations]';
[t,robotStates] = ode15s(@(t,state) helperTimeBasedStateInputsKINOVA(motionModel, timestamp, tar
```

Visualize the robot motion.

```
helperFinalVisualizerKINOVA;
```





[1] Schulman, J., et al. "Motion planning with sequential convex optimization and convex collision checking." *The International Journal of Robotics Research* 33.9 (2014): 1251-1270.

Perform Safe Trajectory Tracking Control Using Robotics Manipulator Blocks

This example shows you how to use Simulink® with Robotics System Toolbox™ manipulator algorithm blocks to achieve safe trajectory tracking control for a simulated robot running in Simscape™ Multibody™.

Both Robotics System Toolbox and Simscape Multibody are required to run this example.

Introduction

In this example, you will run a model that implements a computed-torque controller with joint position and velocity feedback using manipulator algorithm blocks. The controller receives joint position and velocity information from a simulated robot (implemented using Simscape Multibody) and sends torque commands to drive the robot along a given joint trajectory. A planar object is placed in front of the robot so that the end effector of the robot arm will collide with it when the trajectory tracking control is executed. Without any additional setup, the increasing torque due to colliding with the object can cause damage on the robot or the object. To achieve safe trajectory tracking, a trajectory scaling block is built to adjust the time stamp when assigning the desired motion to the controller. You may adjust some parameters and interact with the robot while the model is running and observe the effect on the simulated robot.



Set Up the Robot Model in Workspace

This example uses a model of the Rethink Sawyer, a 7 degree-of-freedom robot manipulator. Call `importrobot` to generate a `rigidBodyTree` model from a description stored in a Unified Robot Description Format (URDF) file. Set the `DataFormat` and `Gravity` properties to be consistent with Simscape.

```
sawyer = importrobot('sawyer.urdf');  
sawyer.removeBody('head');  
sawyer.DataFormat = 'column';  
sawyer.Gravity = [0, 0, -9.80665];
```

Trajectory Generation and Related Setup

First, assign the start time and duration for the trajectory.


```
tStart = 0.5;
tDuration = 3;
```

Next, assign the initial and target configuration. q_0 is the initial configuration and q_1 is the target configuration.

```
q0 = [0; -1.18; 0; 2.18; 0; -1.0008; 3.3161];
q1 = zeros(7,1);
```

The following figures show the robot visualization of the initial configuration and the target configuration related to the location of the planar object. The planar object is placed so that the robot will collide to it during trajectory tracking.



Use `exampleHelperPolynomialTrajectory` to generate the desired motion trajectory for each joint. `exampleHelperPolynomialTrajectory` generates the polynomial coefficients of a trajectory that satisfies the desired joint position, zero velocity and zero acceleration based on the initial and target configurations and the trajectory duration.

```
p = exampleHelperPolynomialTrajectory(q0,q1,tDuration);
```

Simulink Model Overview

Next, open the Simulink model. The variables generated above are already stored in Simulink model workspace:

```
open_system('robotSafeTrajectoryTracking.slx');
```

The `robotSafeTrajectoryTracking` model implements a computed torque controller with trajectory scaling for safe trajectory tracking. There are three main subsystems in this model:

- Computed Torque Controller
- Trajectory Scaling and Desired Motion
- Simscape Multibody Model with Simple Contact Mechanics

On each time step, if the trajectory scaling switch is on, the modified time stamp is used for evaluating the desired joint position, velocity and acceleration. Then, the computed torque controller uses the manipulator blocks associated with the `RigidBodyTree` model to track the desired motion. The derived control input is fed into the Sawyer model in Simscape Multibody (where the planar object for interacting with the robot is included).

Build Computed Torque Controller Using Robotics Manipulator Blocks

For a manipulator with n non-fixed joints, the system dynamics can be expressed as:

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) = u$$

where $q, \dot{q}, \ddot{q} \in R^n$ are the position, velocity and acceleration of the generalized coordinate, $u \in R^n$ is the control input (torque), $M(q)$ is the joint space mass matrix, $C(q, \dot{q})\dot{q}$ is the velocity product torque, $G(q)$ is the gravity torque. To track along a desired joint trajectory with desired position q_d , velocity \dot{q}_d and acceleration \ddot{q}_d , the computed torque controller calculates the torque needed to obtain a given configuration and velocity, provided the robot dynamics variables $M(q)$, $C(q, \dot{q})\dot{q}$, and $G(q)$. In Simulink, these variables can be easily derived using robotics manipulator blocks from Robotics System Toolbox to design the following computed torque controller:

$$u = M(q)(\ddot{q}_d - K_d\dot{q}_e - K_p q_e) + C(q, \dot{q})\dot{q} + G(q)$$

where $q_e = q - q_d$ is the position error and $\dot{q}_e = \dot{q} - \dot{q}_d$ is the velocity error. With this controller input, the system dynamics becomes a second-order ODE:

$$\ddot{q}_e + K_d\dot{q}_e + K_p q_e = 0$$

By choosing K_d and K_p properly, the tracking error q_e will converge to zero when time approaches infinity.

The **Computed Torque Controller** subsystem is built using three robotics manipulator blocks: Joint Space Mass Matrix, Velocity Product Torque, and Gravity Torque. Note that the associated `rigidBodyTree` model, `sawyer`, is assigned in all those blocks, and the configuration and velocity need to be inserted as column vectors.

```
open_system('robotSafeTrajectoryTracking/Computed Torque Controller');
```

Inside the Computed Torque Controller, there are two tunable parameters (indicated by colored blocks):

- Gain K_p : The proportional gain when correcting the robot configuration
- Gain K_d : The derivative gain when correcting the robot configuration

A standard way to determine the K_p and K_d is to calculate them as:

$$K_p = \omega_n^2$$

$$K_d = 2\omega_n\xi$$

where ω_n and ξ are the natural frequency and damping ratio of the second-order ODE. In this example, the default value of K_p and K_d are derived by setting the natural frequency and damping ratio as $\omega_n = 10$ and $\xi = 1$ to make the second-order ODE a critical damped system.

Trajectory Scaling

There are two main blocks in this subsystem:

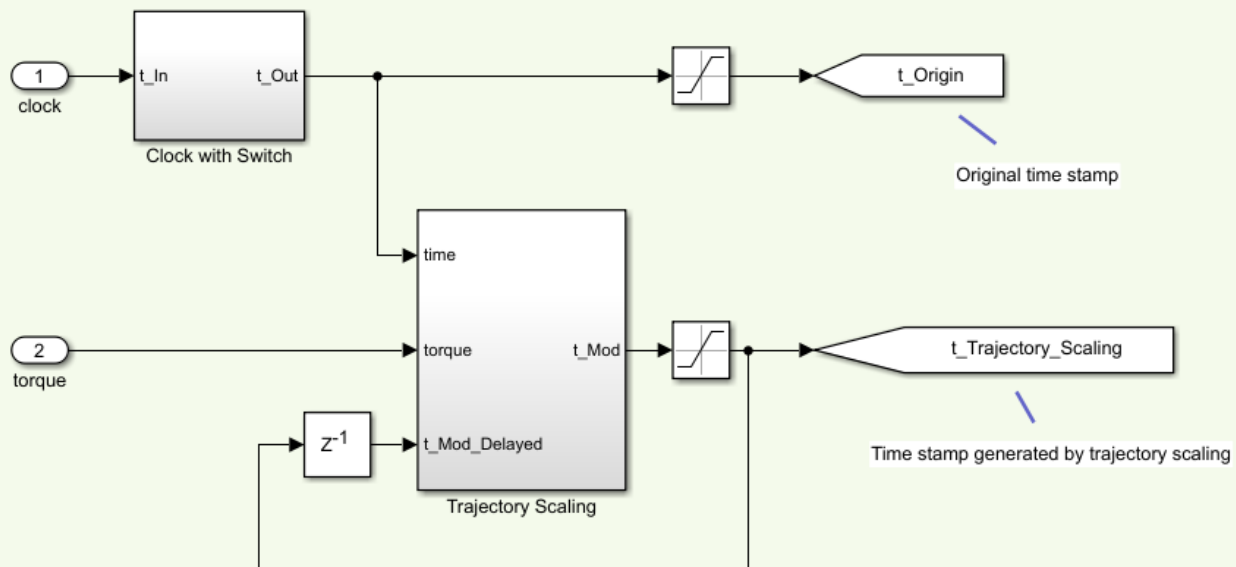
- Trajectory Scaling

- Desired Motion

Trajectory Scaling is the main block deployed for safe trajectory tracking in this example. At each time step t_i , the original time stamp is calculated as $t_i = t_{i-1} + \Delta t$. However, when the robot collides with an unexpected object, the increasing torque and deviance from the planned trajectory can be destructive for both the robot and the object. The main idea of trajectory scaling is to calculate the time stamp as $t_i = t_{i-1} + f_s(q_d, \dot{q}_d, \ddot{q}_d, \tau_{mea})\Delta t$ by introducing $f_s(q_d, \dot{q}_d, \ddot{q}_d, \tau_{mea}) \in [-1, 1]$, which is a function of the desired motion and measured torque τ_{mea} . The function $f_s()$ controls the speed of the robot motion and is determined based on the interference felt by the robot. If the measured torques are greater than expected, $f_s()$ is decreased to make the robot slow down or even move backward until the desired torques are achieved. These values of $f_s()$ have the following effects on the robot's motion:

- $f_s() > 0$, the robot moves forward ($f_s() = 1$ is the normal speed).
- $f_s() = 0$, the robot stops.
- $f_s() < 0$, the robot moves backward.

Trajectory Scaling



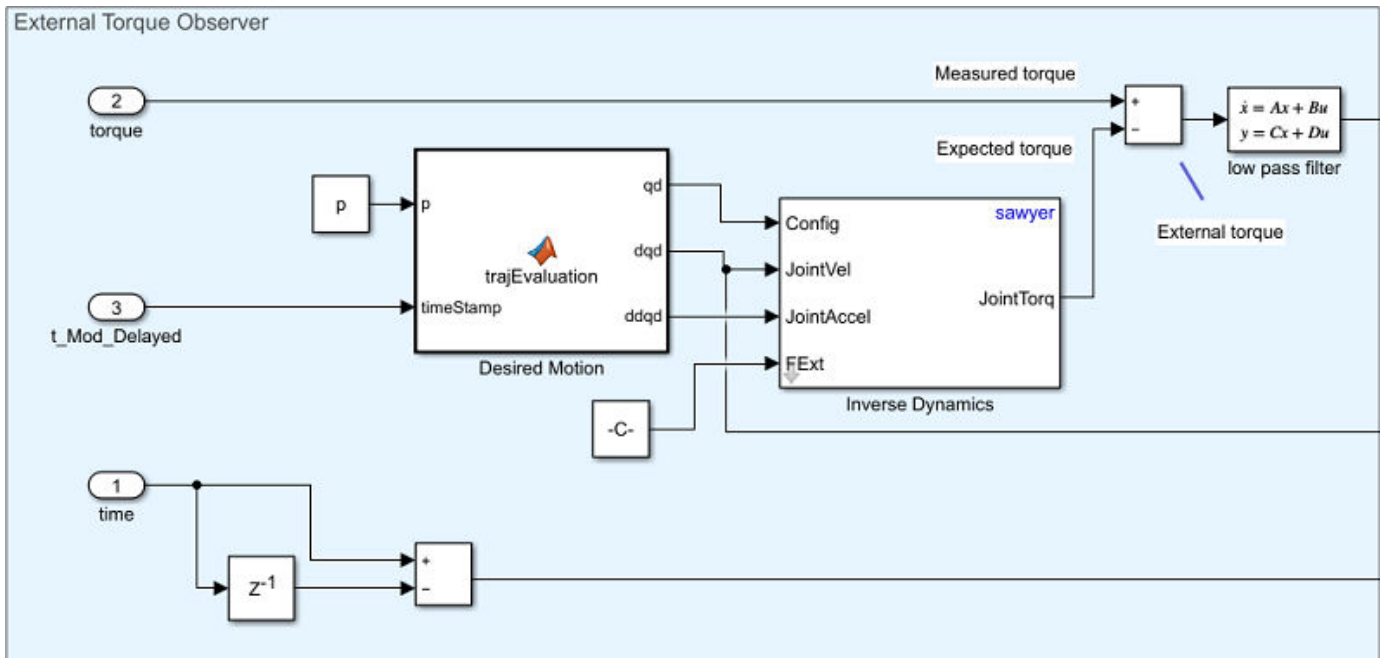
Basic algorithm:

- Calculate the time stamp $t_{(i)}$ as $t_{(i-1)} + f_s \cdot dt$ instead of $t_{(i-1)} + dt$.
- Map the measured torque and the desired motion to a scalar function f_s in the range of $[-1, 1]$.
- Add dead zones for smooth change of f_s during the transitions between different levels of interference.

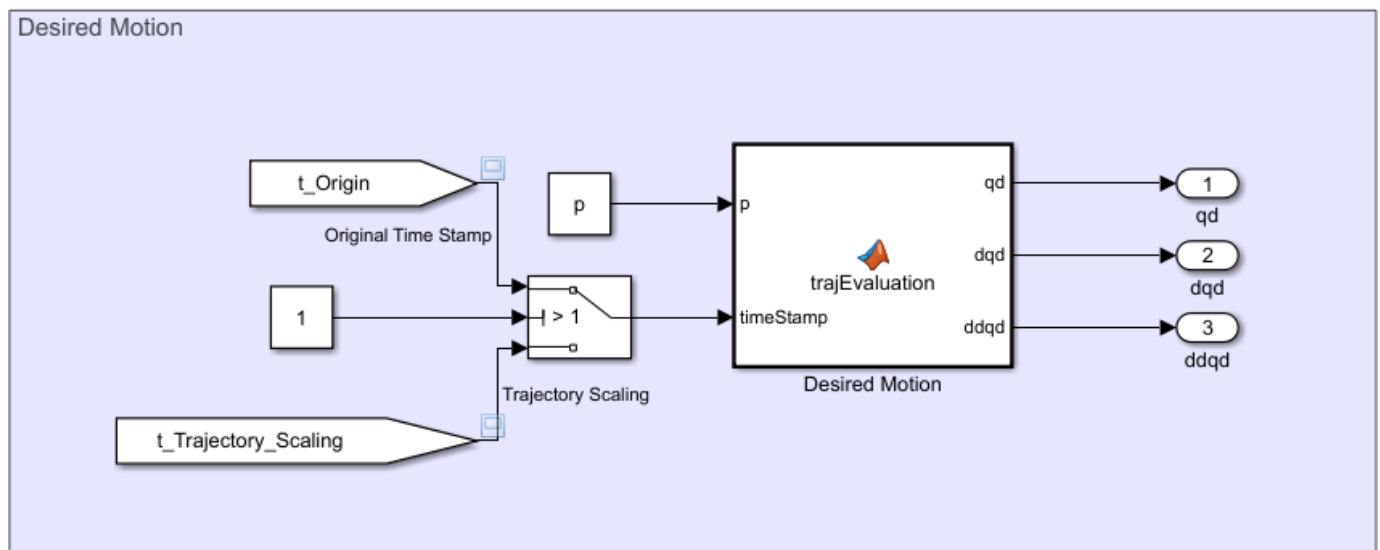
Reference:

[1] S. Haddadin, A. Albu-Schäffer, A. De Luca, and G. Hirzinger, "Collision detection and reaction: A contribution to safe physical human-robot interaction," International Conference on Intelligent Robots and Systems, pp. 3356–3363, 2008.

In the **Trajectory Scaling** block, it is required to estimate the external torque $\hat{\tau}_{ext} = \tau_{mea} - \hat{\tau}$ to calculate $f_s()$, where τ_{mea} is the measured torque from the Simscape model, and $\hat{\tau}$ is the expected torque of the desired motion on the previous time stamp. In the External Torque Observer section of the model, the Inverse Dynamics block calculates the expected torque which is subtracted from the measure torque. Expected torque is: $\hat{\tau} = M(q_d)(\ddot{q}_d) + C(q_d, \dot{q}_d)\dot{q}_d + G(q_d)$.

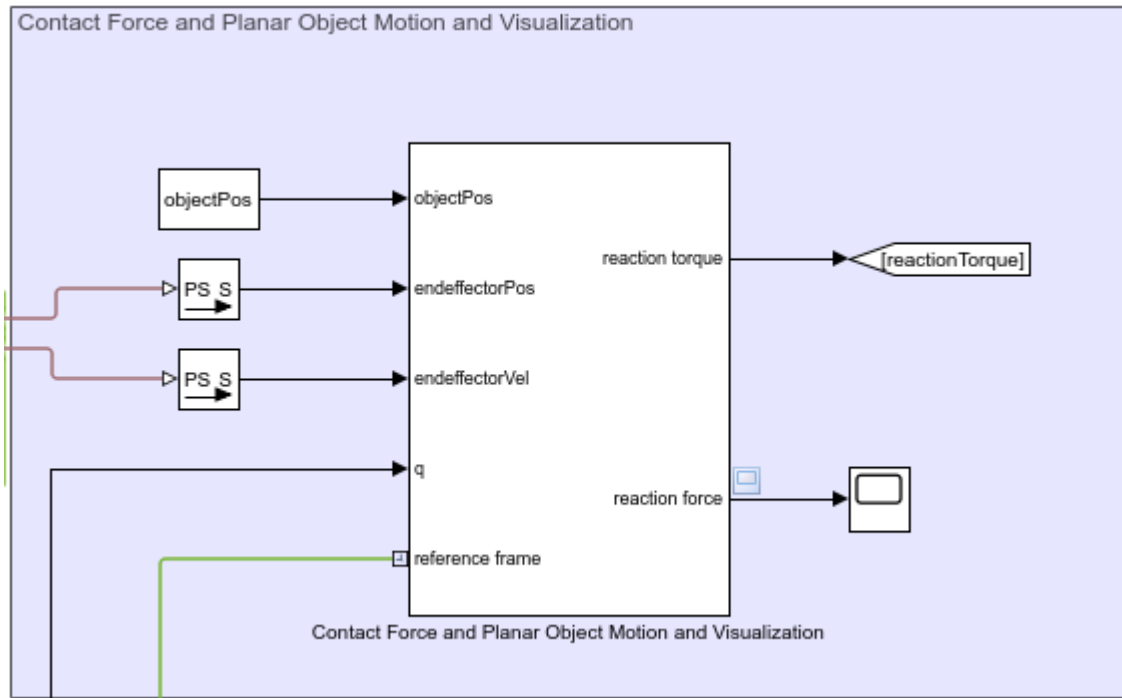


In the **Desired Motion** block, the polynomial coefficients are given to generate the desired trajectory with the given timeStamp input, which can be adjusted based on the trajectory scaling algorithm. The $q_d(t)$, $\dot{q}_d(t)$ and $\ddot{q}_d(t)$ are outputs based on the trajectory polynomial and are fed to the Computed Torque Controller subsystem.



Simscape Multibody Robot Model and Simple Contact Mechanics

The Simscape Multibody Robot Model is imported from the same .urdf file using `smimport`, where a set of torque actuators and sensors for joint torque, joint position and velocity are added. A contact mechanism block as shown below is added to simulate the reaction force between the end effector and the obstacle as a sphere and a plane, where a simple linear spring-damper model is used.

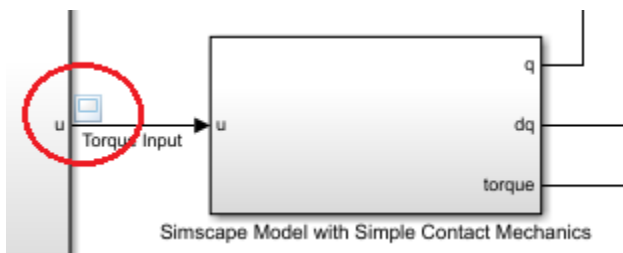


Note: The contact mechanism has only been implemented between the end effector and the planar object. Therefore, other parts of the robot arm may still pass through the obstacle.

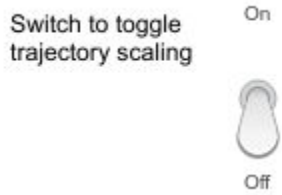
Run the Model

Run the model and observe the behavior of Sawyer in the robot simulator and interact with it.

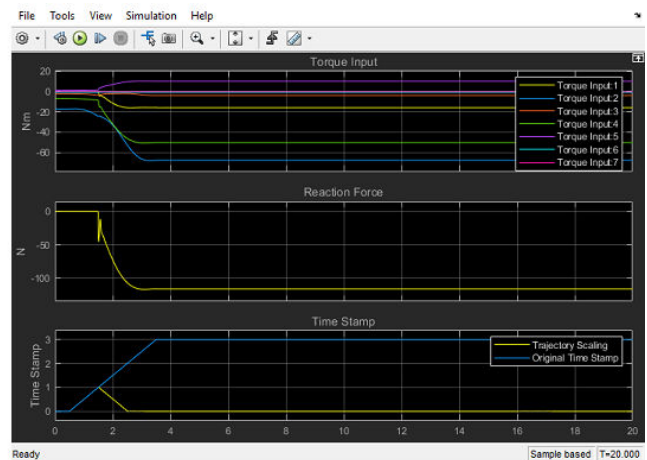
- First, open the viewer by clicking on the scope icon shown below on the left of the Simscape model block. It displays signals including the joint torques, reaction contact force between the end effector and the planar object, and the time stamp for calculating desired motion for trajectory tracking.



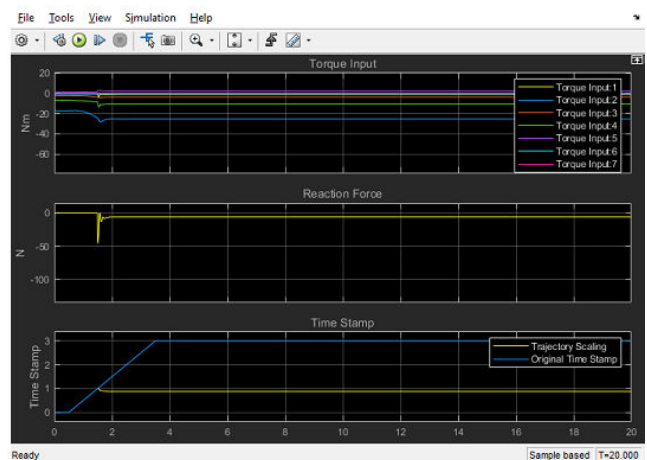
- Toggle the trajectory scaling switch to "Off".



- Click the Play button in Simulink to start the simulation. You should see the arm collide with the object yielding high torque inputs and a large reaction force. Note in this case the original time stamp is used. Stop the simulation afterwards.



- Now, toggle trajectory scaling switch to "On" and rerun the model. Notice the differences in the computed torques and the reduced reaction force after the collision.



- While the simulation is running, adjust the slider to move the object towards or away from the robot. The robot should react to its position while still trying to execute the trajectory safely.
- Click the Stop button in Simulink to stop the simulation.

Summary

This example showed how to use robotics manipulator blocks in Simulink to design a computed torque controller, and integrate it with trajectory scaling and dynamic simulation in Simscape Multibody to achieve safe trajectory tracking. The resultant torque, reaction force and time stamp also demonstrated the capability of trajectory scaling for performing safe trajectory tracking.

Pick and Place Using RRT for Manipulators

Using manipulators to pick and place objects in an environment may require path planning algorithms like the rapidly-exploring random tree planner. The planner explores in the joint-configuration space and searches for a collision-free path between different robot configurations. This example shows how to use the `manipulatorRRT` object to tune the planner parameters and plan a path between two joint configurations based on a `rigidBodyTree` robot model of the Franka Emika™ Panda robot. After tuning the planner parameters, the robot manipulator plans a path to move a can from one place to another.

Load Robot Model and Environment

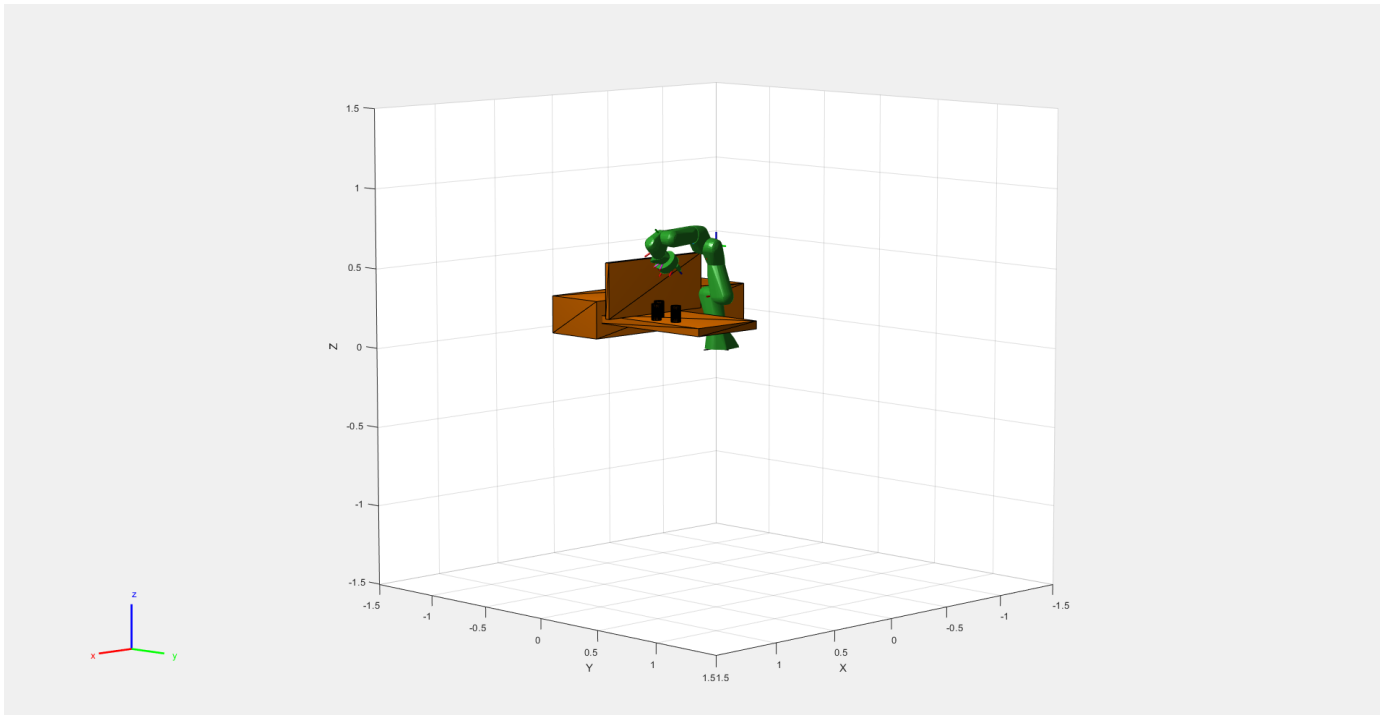
Load the robot and its environment using the `exampleHelperLoadPickAndPlaceRRT` function. The function outputs three variables:

- `franka` — A Franka Emika Panda robot model as a `rigidBodyTree` object. The model has been modified to remove some adjacent collision meshes that are always in collision and adjust position limits based on feasibility.
- `config` — An initial configuration of joint positions for the robot.
- `env` — A set collision objects as a cell array that represent the robot's environment. The path planner checks for self-collisions and collisions with this environment.

```
[franka,config,env] = exampleHelperLoadPickAndPlaceRRT;
```

Visualize the robot model's collision meshes and the environment objects.

```
figure("Name","Pick and Place Using RRT",...
    "Units","normalized",...
    "OuterPosition",[0, 0, 1, 1],...
    "Visible","on");
show(franka,config,"Visuals","off","Collisions","on");
hold on
for i = 1:length(env)
    show(env{i});
end
```

Planner

Create the RRT path planner and specify the robot model and the environment. Define some parameters, which are later tuned, and specify the start and goal configuration for the robot.

```
planner = manipulatorRRT(franka, env);
```

```
planner.MaxConnectionDistance = 0.3;
planner.ValidationDistance = 0.1;
```

```
startConfig = config;
goalConfig = [0.2371  -0.0200  0.0542  -2.2272  0.0013  2.2072  -0.9670  0.0400  0.0400  0.0400];
```

Plan the path between configurations. The RRT planner should generate a rapidly-exploring tree of random configurations to explore the space and eventually returns a collision-free path through the environment. Before planning, reset the MATLAB's random number generator for repeatable results.

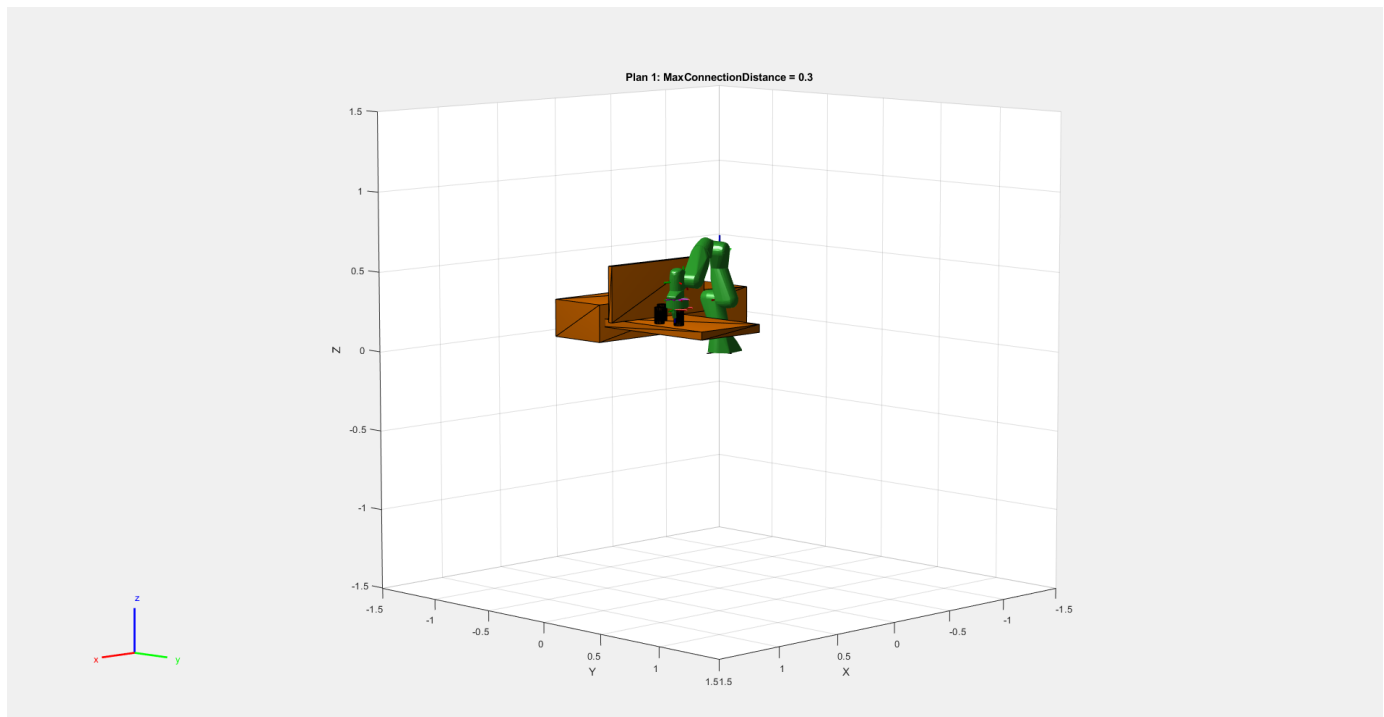
```
rng('default');
path = plan(planner, startConfig, goalConfig);
```

To visualize the entire path, interpolate the path into small steps. By default, the `interpolate` function generates all of the configurations that were checked for feasibility (collision checking) based on the `ValidationDistance` property.

```
interpStates = interpolate(planner, path);

for i = 1:2:size(interpStates,1)
    show(franka, interpStates(i,:), ...
        "PreservePlot", false, ...
        "Visuals", "off", ...
        "Collisions", "on");
    title("Plan 1: MaxConnectionDistance = 0.3")
end
```

```
drawnow;
end
```



Tuning the Planner

Tune the path planner by modifying the `MaxConnectionDistance`, `ValidationDistance`, `EnableConnectHeuristic` properties on the planner object.

Setting the `MaxConnectionDistance` property to a larger value causes longer motions in the planned path, but also enables the planner to greedily explore the space. Use `tic` and `toc` functions to time the `plan` function for reference on how these parameters can affect the execution time.

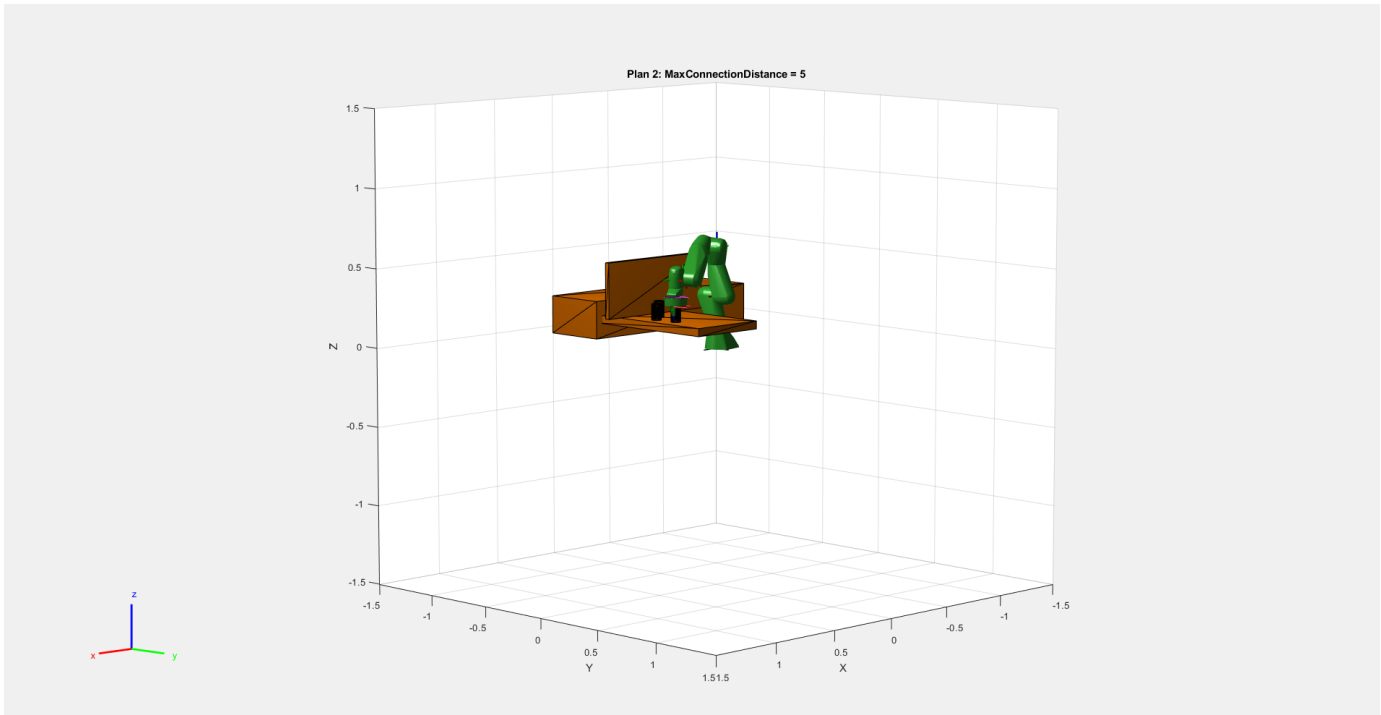
```
planner.MaxConnectionDistance = 5;
tic
path = plan(planner,startConfig,goalConfig);
toc
```

Elapsed time is 13.060740 seconds.

Notice the change in the path. The robot arm swings much higher due to the larger connection distance.

```
interpStates = interpolate(planner, path);

for i = 1:2:size(interpStates, 1)
    show(franka,interpStates(i,:),...
        "PreservePlot",false,...
        "Visuals","off",...
        "Collisions","on");
    title("Plan 2: MaxConnectionDistance = 5")
drawnow;
end
```



Setting the `ValidationDistance` to a smaller value enables finer validation of the motion along an edge in the planned path. Increasing the number of configurations to be validated along a path leads to longer planning times. A smaller value is useful in case of a cluttered environment with a lot of collision objects. Because of the small validation distance, `interpStates` has a larger number of elements. For faster visualization, the `for` loop skips more states in this step for faster visualization.

```

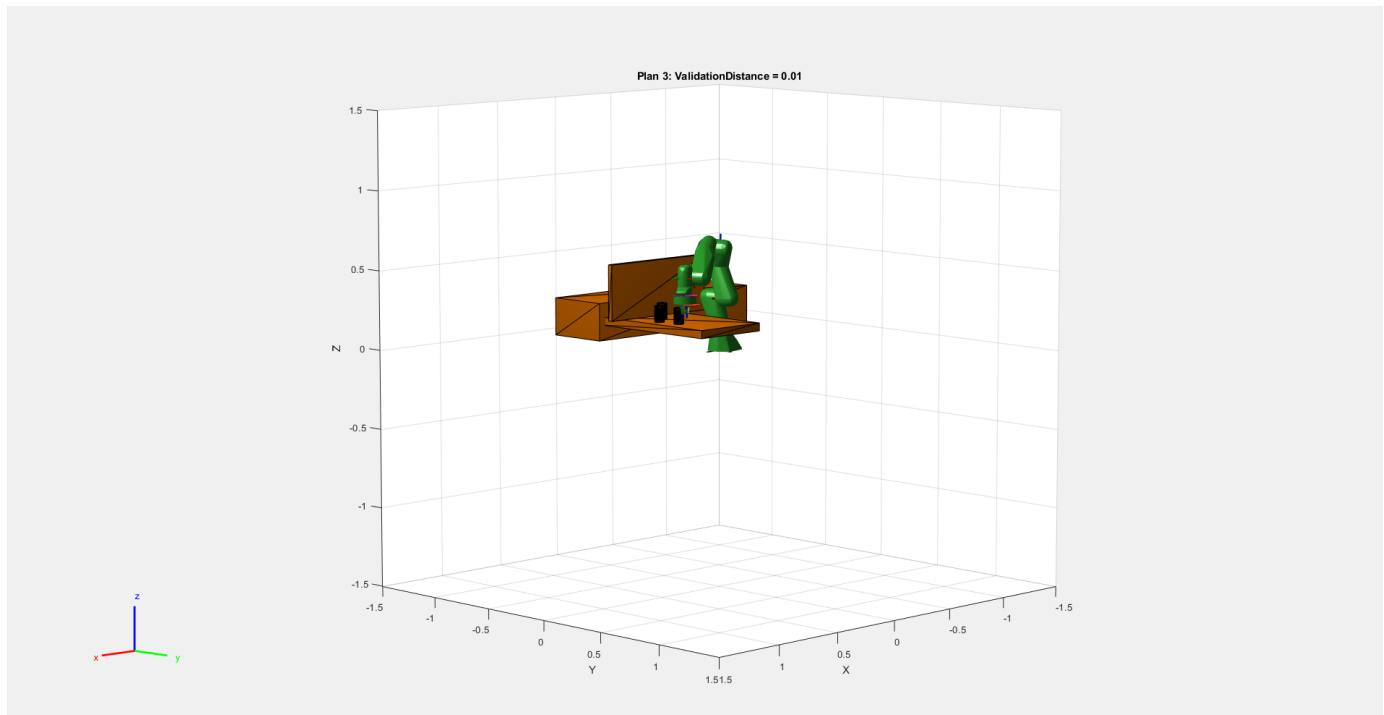
planner.MaxConnectionDistance = 0.3;
planner.ValidationDistance = 0.01;

tic
path = plan(planner,startConfig,goalConfig);
toc

Elapsed time is 12.624720 seconds.

interpStates = interpolate(planner,path);
for i = 1:10:size(interpStates,1)
    show(franka, interpStates(i,:),...
         "PreservePlot",false,...
         "Visuals","off",...
         "Collisions","on");
    title("Plan 3: ValidationDistance = 0.01")
    drawnow;
end

```



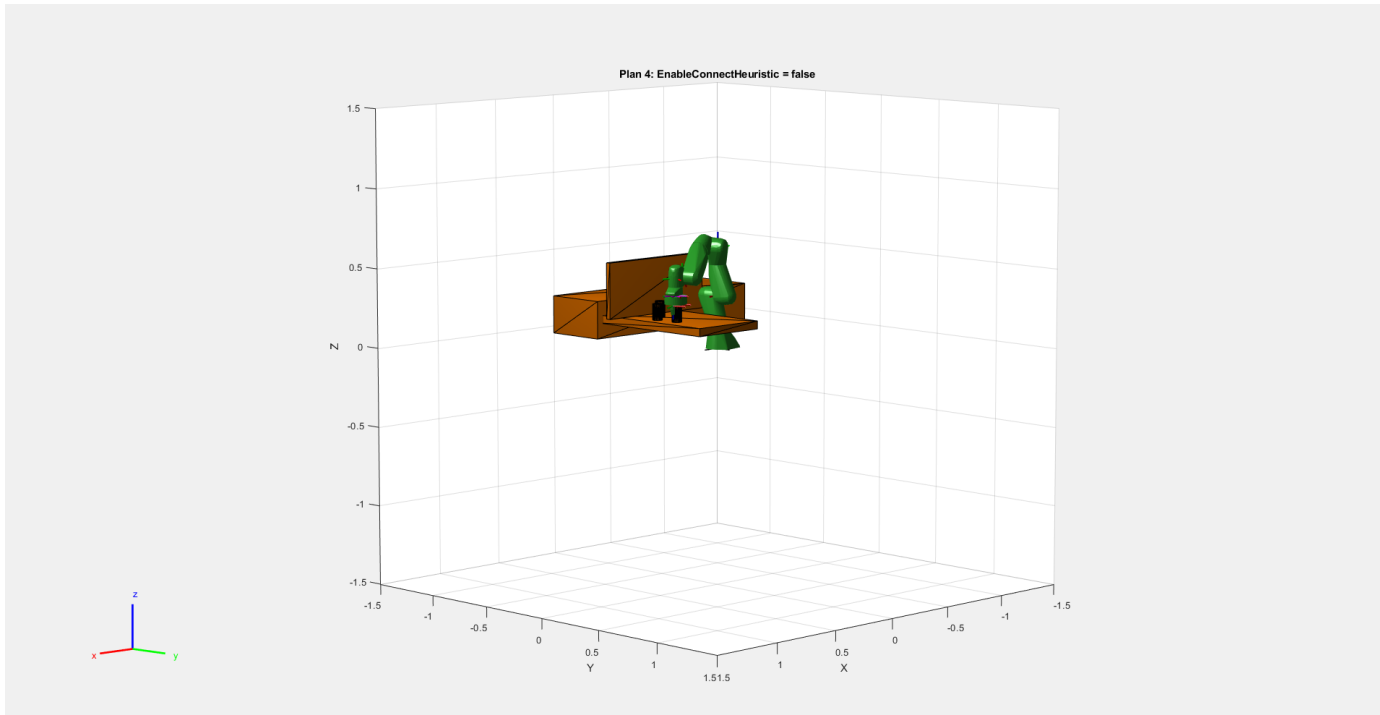
The connect heuristic allows the planner to greedily join the start and goal trees. In places where the environment is less cluttered, this heuristic is useful for shorter planning times. However, a greedy behavior in a cluttered environment leads to wasted connection attempts. Setting the `EnableConnectHeuristic` to `false` gives shorter planning times and higher success rate of finding a valid plan, but may lead to longer paths. The `ValidationDistance` is set back to 0.1 to improve planning time lost from disabling the greedy connect.

```
planner.ValidationDistance = 0.1;
planner.EnableConnectHeuristic = false;
```

```
tic
path = plan(planner,startConfig,goalConfig);
toc
```

Elapsed time is 8.949604 seconds.

```
interpStates = interpolate(planner,path);
for i = 1:2:size(interpStates,1)
    show(franka, interpStates(i,:), ...
         "PreservePlot",false,...
         "Visuals","off",...
         "Collisions","on");
    title("Plan 4: EnableConnectHeuristic = false")
    drawnow;
end
```



Attach the Can to the End-Effector

After tuning the planner for the desired behavior, follow the pick-and-place workflow where the robot moves an object through the environment. This example attaches a cylinder, or can, to the end-effector of the robot and moves it to a new location. For each configuration, the planner checks for collisions with the cylinder mesh as well.

```
% Create can as a rigid body
cylinder1 = env{3};
canBody = rigidBody("myCan");
canJoint = rigidBodyJoint("canJoint");

% Get current pose of the robot hand.
startConfig = path(end, :);
endEffectorPose = getTransform(franka,startConfig,"panda_hand");

% Place can into the end effector gripper.
setFixedTransform(canJoint,endEffectorPose\cylinder1.Pose);

% Add collision geometry to rigid body.
addCollision(canBody,cylinder1,inv(cylinder1.Pose));
canBody.Joint = canJoint;

% Add rigid body to robot model.
addBody(franka,canBody,"panda_hand");

% Remove object from environment.
env(3) = [];
```

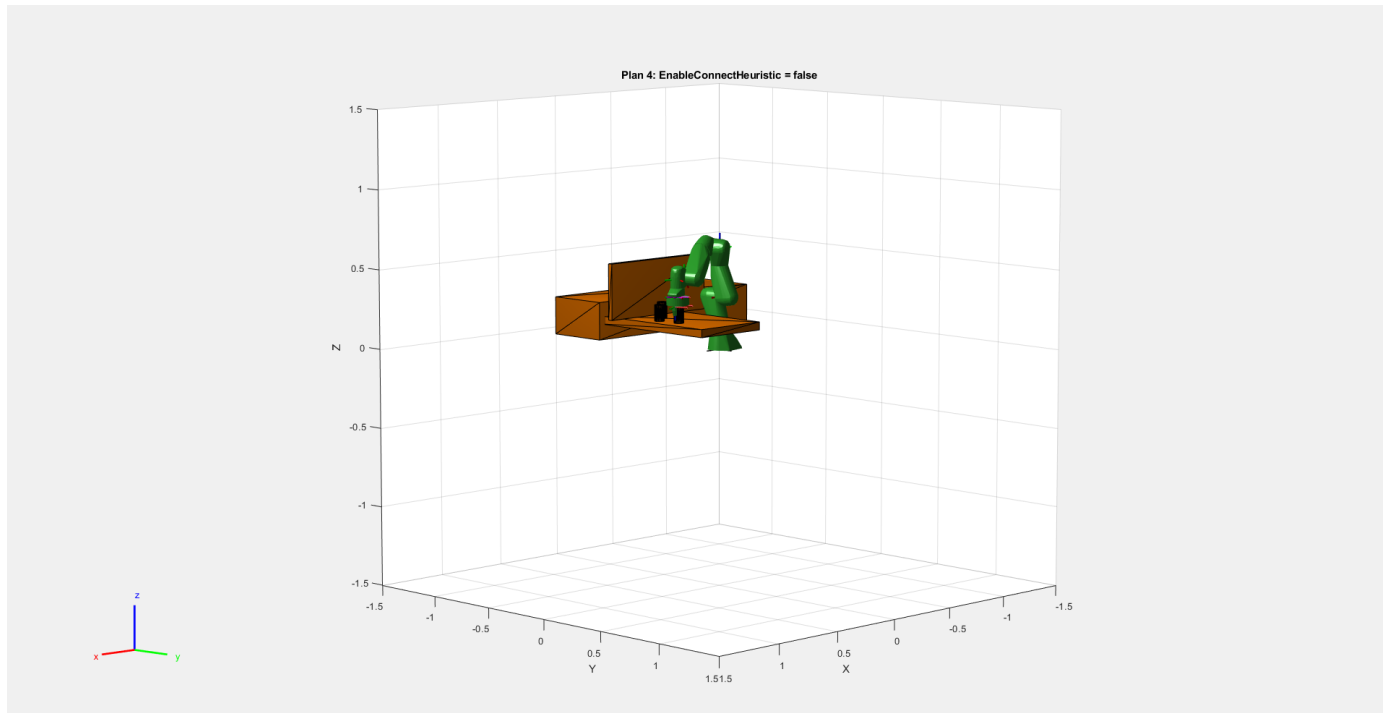
After the can has been attached to the robot arm, specify a goal configuration for placing the object. Modify the planner parameters. Plan a path from start to goal. Visualize the path. Notice the can clears the wall.

```
goalConfig = [-0.6564 0.2885 -0.3187 -1.5941 0.1103 1.8678 -0.2344 0.04 0.04];

planner.MaxConnectionDistance = 1;
planner.ValidationDistance = 0.2;
planner.EnableConnectHeuristic = false;
path = plan(planner,startConfig,goalConfig);

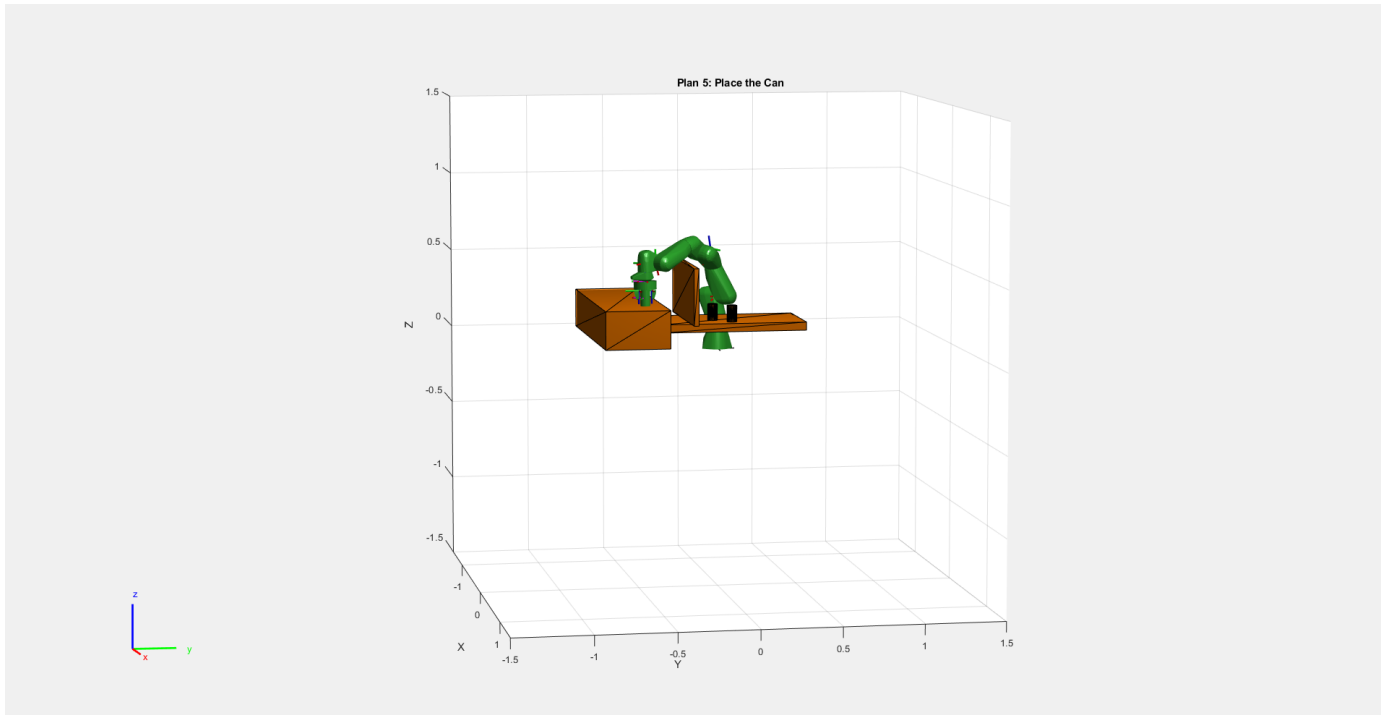
interpStates = interpolate(planner,path);

hold off
```



```
show(franka,config,"Visuals","off","Collisions","on");
hold on
for i = 1:length(env)
    show(env{i});
end

for i = 1:size(interpStates,1)
    show(franka,interpStates(i,:),...
        "PreservePlot", false,...
        "Visuals","off",...
        "Collisions","on");
    title("Plan 5: Place the Can")
    drawnow;
    if i == (size(interpStates,1))
        view([80,7])
    end
end
```

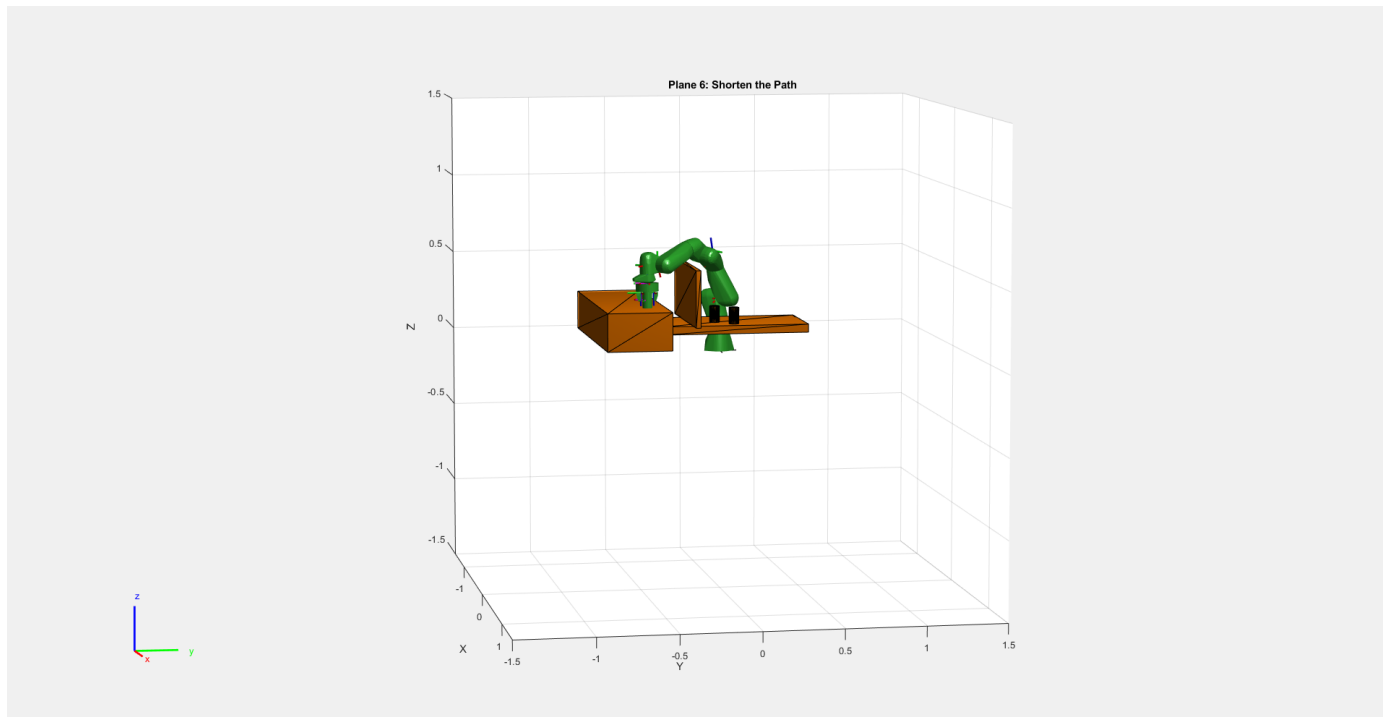


Shorten the Planned Path

To shorten your path, use the `shorten` function and specify a number of iterations. A small value for the `ValidationDistance` property combined with a large number of iterations can result in large computation times.

```
shortenedPath = shorten(planner,path,20);
```

```
interpStates = interpolate(planner,shortenedPath);
for i = 1:size(interpStates,1)
    show(franka, ...
         interpStates(i, :), ...
         "PreservePlot", false, ...
         "Visuals", "off", ...
         "Collisions", "on");
    drawnow;
    title("Plane 6: Shorten the Path")
    if i > (size(interpStates,1)-2)
        view([80,7])
    end
end
end
hold off
```



Pick-and-Place Workflow using Stateflow for MATLAB

This example shows how to setup an end-to-end pick and place workflow for a robotic manipulator like the KINOVA® Gen3.

The pick-and-place workflow implemented in this example can be adapted to different scenarios, planners, simulation platforms, and object detection options. The example shown here uses Model Predictive Control for planning and control, and simulates the robot in MATLAB. For other uses, see:

- “Pick and Place Workflow Using RRT Planner and Stateflow for MATLAB” on page 1-219
- “Pick-and-Place Workflow in Gazebo using ROS” on page 1-228
- “Pick-and-Place Workflow in Gazebo using Point-Cloud Processing and RRT Path Planning” on page 1-237

Overview

This example sorts detected objects and places them on benches using a KINOVA Gen3 manipulator. The example uses tools from four toolboxes:

- **Robotics System Toolbox™** is used to model, simulate, and visualize the manipulator, and for collision-checking.
- **Model Predictive Control Toolbox™** and **Optimization Toolbox™** are used to generate optimized, collision-free trajectories for the manipulator to follow.
- **Stateflow®** is used to schedule the high-level tasks in the example and step from task to task.

This example builds on key concepts from two related examples:

- “Plan and Execute Task- and Joint-space Trajectories using KINOVA Gen3 Manipulator” on page 1-183 shows how to generate and simulate interpolated joint trajectories to move from an initial to a desired end-effector pose.
- “Plan and Execute Collision-Free Trajectories using KINOVA Gen3 Manipulator” on page 1-187 shows how to plan closed-loop collision-free robot trajectories to a desired end-effector pose using nonlinear model predictive control.

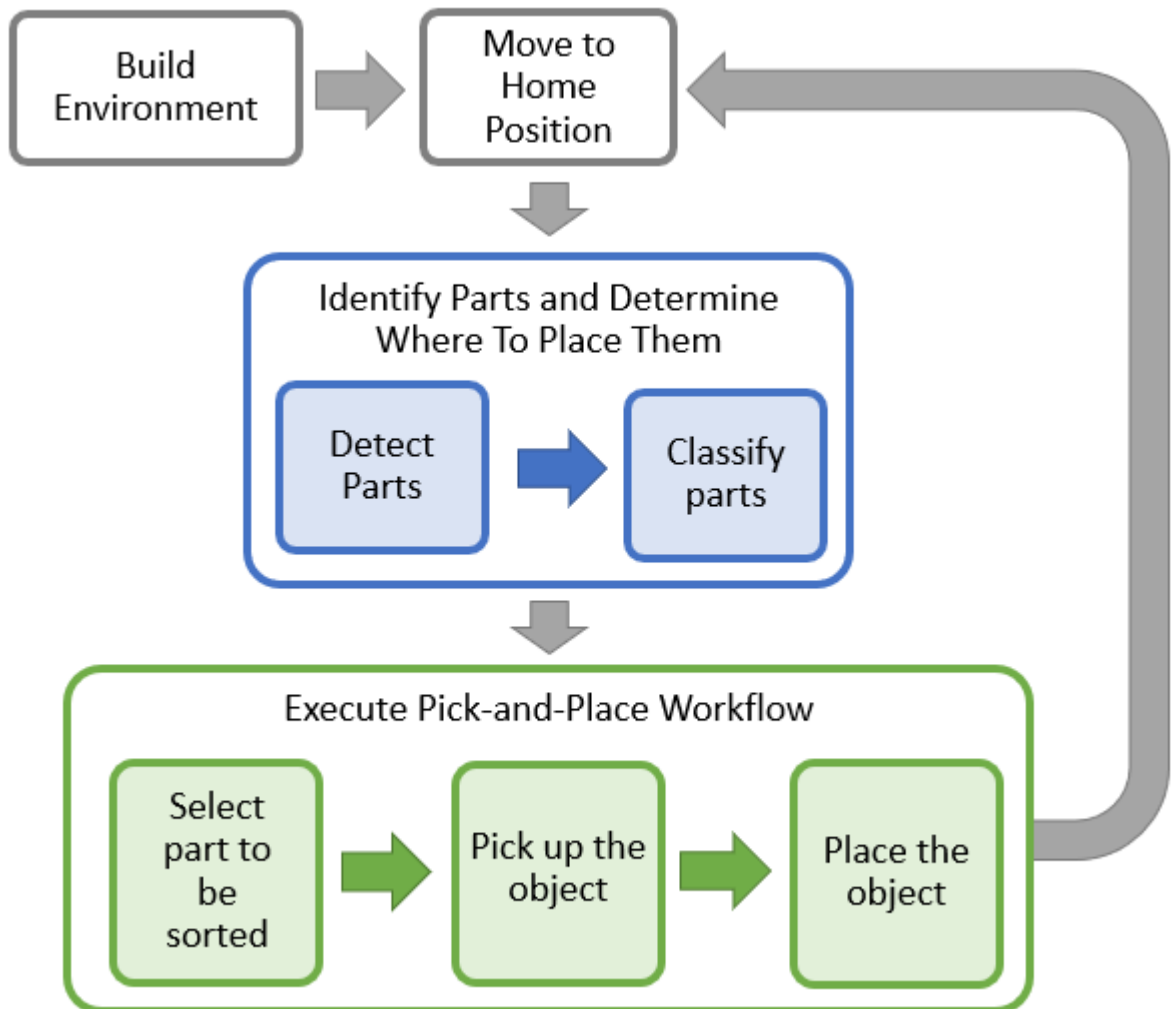
Stateflow Chart

This example uses a Stateflow chart to schedule tasks in the example. Open the chart to examine the contents and follow state transitions during chart execution.

edit [exampleHelperFlowChartPickPlace.sfx](#)

The chart dictates how the manipulator interacts with the objects, or parts. It consists of basic initialization steps, followed by two main sections:

- Identify Parts and Determine Where to Place Them
- Execute Pick-and-Place Workflow



Initialize the Robot and Environment

First, the chart creates an environment consisting of the Kinova Gen3 manipulator, three parts to be sorted, the shelves used for sorting, and a blue obstacle. Next, the robot moves to the home position.

Identify the Parts and Determine Where to Place Them

In the first step of the identification phase, the parts must be detected. The `exampleCommandDetectParts` function directly gives the object poses. Replace this class with your own object detection algorithm based on your sensors or objects.

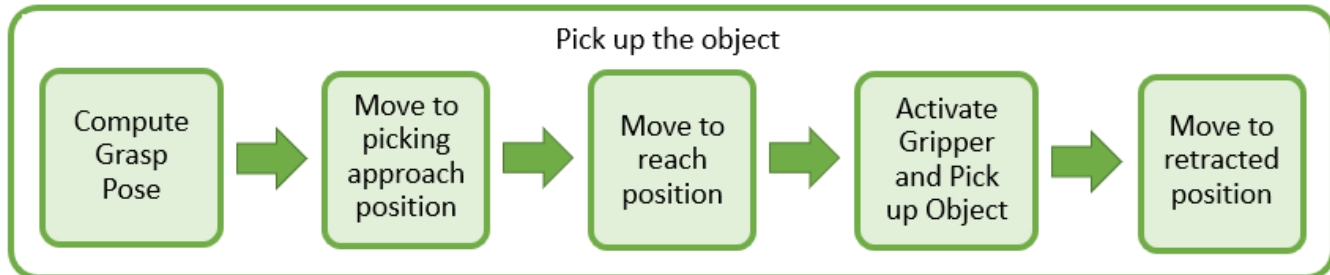
Next, the parts must be classified. The `exampleCommandClassifyParts` function classifies the parts into two types to determine where to place them (top or bottom shelf). Again, you can replace this function with any method for classifying parts.

Execute Pick-and-Place Workflow

Once parts are identified and their destinations have been assigned, the manipulator must iterate through the parts and move them onto the appropriate tables.

Pick up the Object

The picking phase moves the robot to the object, picks it up, and moves to a safe position, as shown in the following diagram:

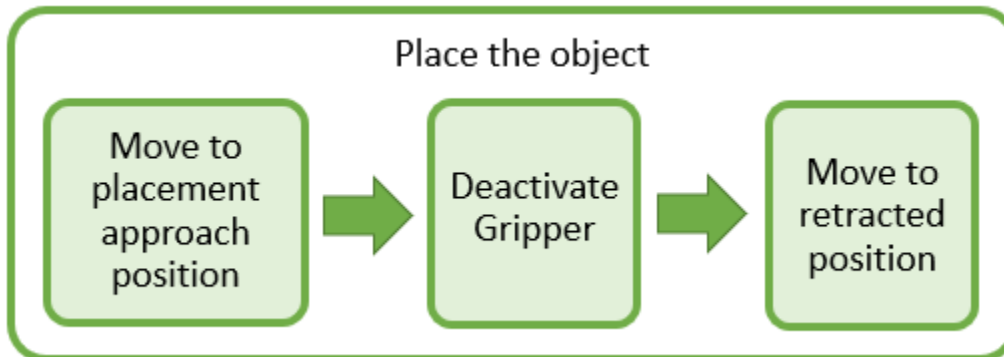


The `exampleCommandComputeGraspPose` function computes the grasp pose. The class computes a task-space grasping position for each part. Intermediate steps for approaching and reaching towards the part are also defined relative to the object.

This robot picks up objects using a simulated gripper. When the gripper is activated, `exampleCommandActivateGripper` adds the collision mesh for the part onto the `rigidBodyTree` representation of the robot, which simulates grabbing it. Collision detection includes this object while it is attached. Then, the robot moves to a retracted position away from the other parts.

Place the Object

The robot then places the object on the appropriate shelf.



As with the picking workflow, the placement approach and retracted positions are computed relative to the known desired placement position. The gripper is deactivated using `exampleCommandActivateGripper`, which removes the part from the robot.

Moving the Manipulator to a Specified Pose

Most of the task execution consists of instructing the robot to move between different specified poses. The `exampleHelperPlanExecuteTrajectoryPickPlace` function defines a solver using a nonlinear model predictive controller (see “Nonlinear MPC” (Model Predictive Control Toolbox)) that computes a feasible, collision-free optimized reference trajectory using `nmpcmove` (Model Predictive Control Toolbox) and `checkCollision`. The obstacles are represented as spheres to ensure the accurate approximation of the constraint Jacobian in the definition of the nonlinear model predictive

control algorithm (see [1]). The helper function then simulates the motion of the manipulator under computed-torque control as it tracks the reference trajectory using the `jointSpaceMotionModel` object, and updates the visualization. The helper function is called from the Stateflow chart via `exampleCommandMoveToTaskConfig`, which defines the correct inputs.

This workflow is examined in detail in “Plan and Execute Collision-Free Trajectories using KINOVA Gen3 Manipulator” on page 1-187. The controller is used to ensure collision-free motion. For simpler trajectories where the paths are known to be obstacle-free, trajectories could be executed using trajectory generation tools and simulated using the manipulator motion models. See “Plan and Execute Task- and Joint-space Trajectories using KINOVA Gen3 Manipulator” on page 1-183.

Task Scheduling in a Stateflow Chart

This example uses a Stateflow chart to direct the workflow in MATLAB®. For more info on creating state flow charts, see “Create Stateflow Charts for Execution as MATLAB Objects” (Stateflow).

The Stateflow chart directs task execution in MATLAB by using command functions. When the command finishes executing, it sends an *input event* to wake up the chart and proceed to the next step of the task execution, see “Execute a Standalone Chart” (Stateflow).

Run and Visualize the Simulation

This simulation uses a KINOVA Gen3 manipulator with a Robotiq gripper. Load the robot model from a `.mat` file as a `rigidBodyTree` object.

```
load('exampleHelperKINOVAGen3GripperColl.mat');
```

Initialize the Pick and Place Coordinator

Set the initial robot configuration. Create the coordinator, which handles the robot control, by giving the robot model, initial configuration, and end-effector name.

```
currentRobotJConfig = homeConfiguration(robot);  
coordinator = exampleHelperCoordinatorPickPlace(robot,currentRobotJConfig, "gripper");
```

Specify the home configuration and two poses for placing objects of different types.

```
coordinator.HomeRobotTaskConfig = trvec2tform([0.4, 0, 0.6])*axang2tform([0 1 0 pi]);  
coordinator.PlacingPose{1} = trvec2tform([0.23 0.62 0.33])*axang2tform([0 1 0 pi]);  
coordinator.PlacingPose{2} = trvec2tform([0.23 -0.62 0.33])*axang2tform([0 1 0 pi]);
```

Run and Visualize the Simulation

Connect the coordinator to the Stateflow Chart. Once started, the Stateflow chart is responsible for continuously going through the states of detecting objects, picking them up and placing them in the correct staging area.

```
coordinator.FlowChart = exampleHelperFlowChartPickPlace('coordinator', coordinator);
```

Use a dialog to start the pick-and-place task execution. Click **Yes** in the dialog to begin the simulation.

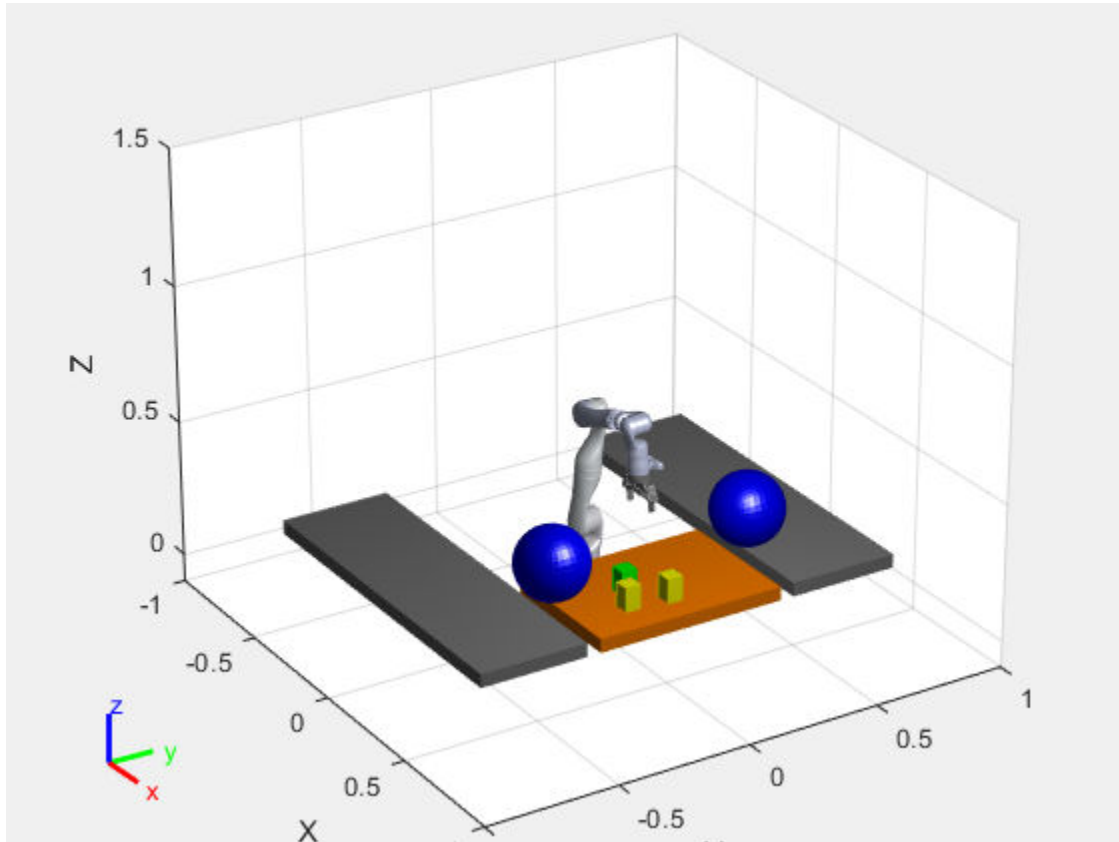
```
answer = questdlg('Do you want to start the pick-and-place job now?', ...  
    'Start job','Yes','No','No');
```

```
switch answer  
    case 'Yes'  
        % Trigger event to start Pick and Place in the Stateflow Chart
```

```

        coordinator.FlowChart.startPickPlace;
    case 'No'
        % End Pick and Place
        coordinator.FlowChart.endPickPlace;
        delete(coordinator.FlowChart);
        delete(coordinator);
    end

```



Ending the Pick-and-Place task

The Stateflow chart will finish executing automatically after 3 failed attempts to detect new objects. To end the pick-and-place task prematurely, uncomment and execute the following lines of code or press Ctrl+C in the command window.

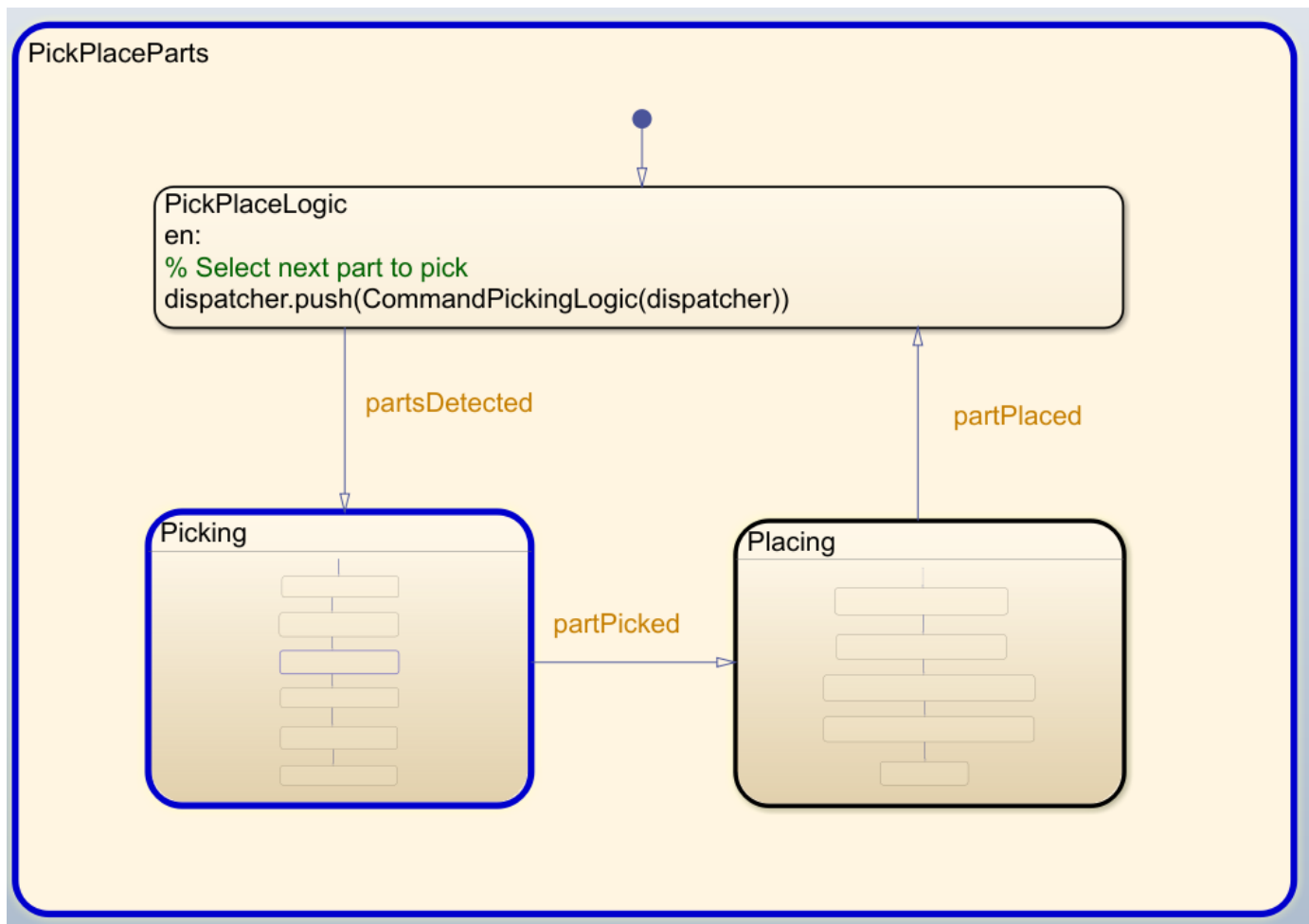
```

% coordinator.FlowChart.endPickPlace;
% delete(coordinator.FlowChart);
% delete(coordinator);

```

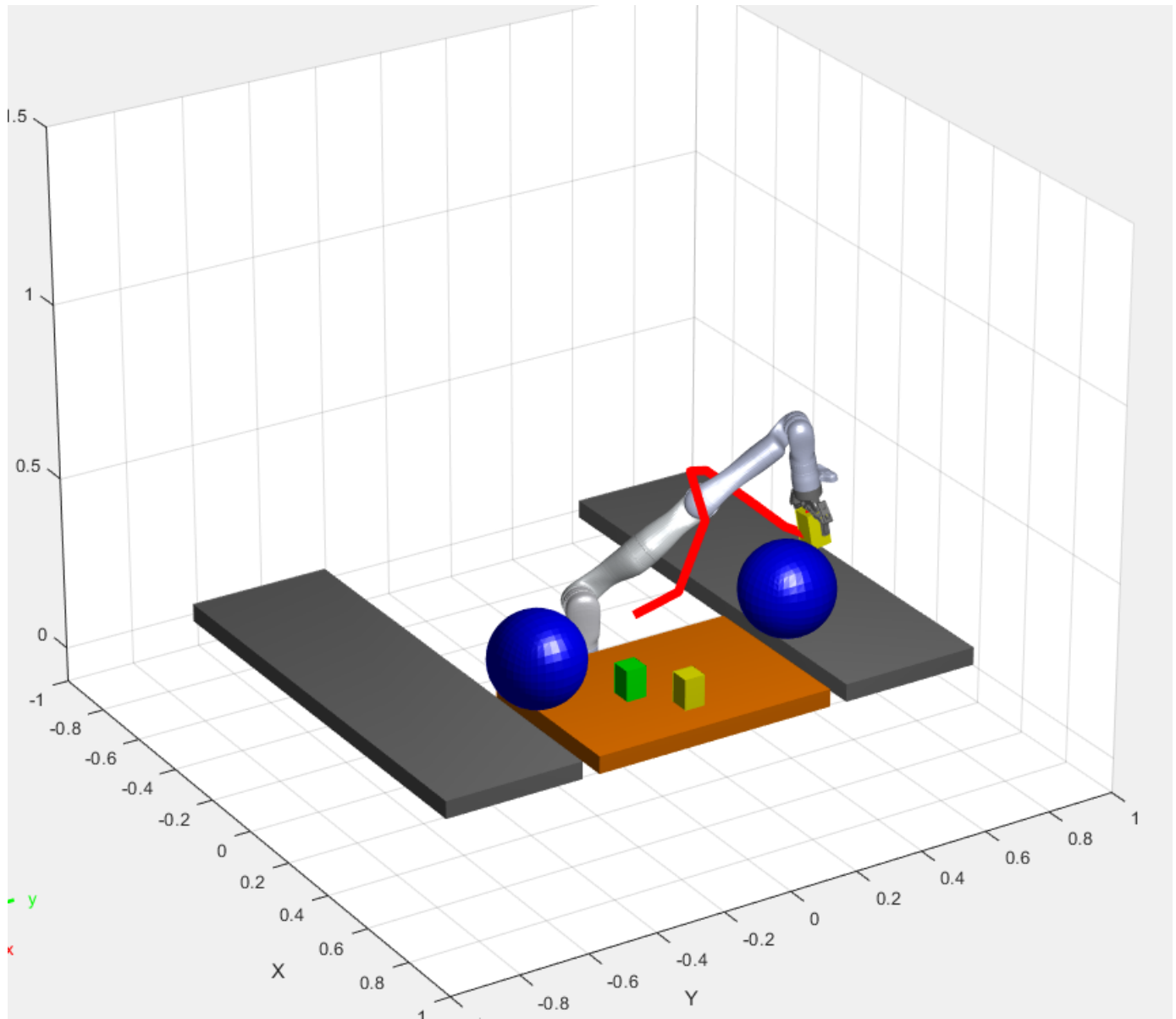
Observe the Simulation States

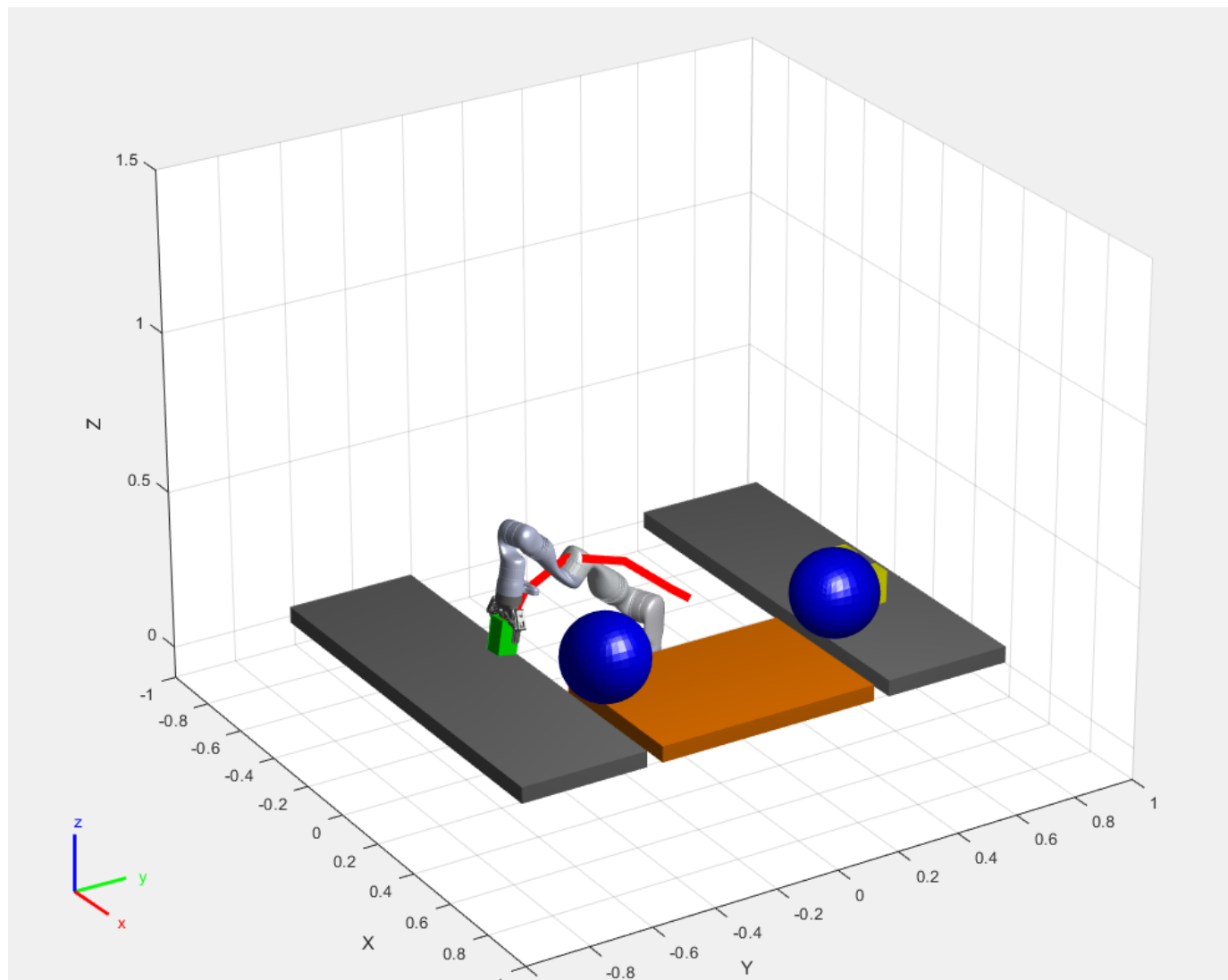
During execution, the active states at each point in time are highlighted in blue in the Stateflow chart. This helps keeping track of what the robot does and when. You can click through the subsystems to see the details of the state in action.



Visualize the Pick-and-Place Action

The example uses `interactiveRigidBodyTree` for robot visualization. The visualization shows the robot in the working area as it moves parts around. The robot avoids obstacles in the environment (blue cylinder) and places objects on top or bottom shelf based on their classification. The robot continues working until all parts have been placed.





References

- [1] Schulman, J., et al. "Motion planning with sequential convex optimization and convex collision checking." *The International Journal of Robotics Research* 33.9 (2014): 1251-1270.

Pick and Place Workflow Using RRT Planner and Stateflow for MATLAB

This example shows how to setup an end-to-end pick-and-place workflow for a robotic manipulator like the KINOVA® Gen3.

The pick-and-place workflow implemented in this example can be adapted to different scenarios, planners, simulation platforms, and object detection options. The example shown here uses the rapidly-exploring random tree (RRT) algorithm for planning, and simulates the robot in MATLAB. For other uses, see:

- “Pick-and-Place Workflow using Stateflow for MATLAB” on page 1-211
- “Pick-and-Place Workflow in Gazebo using ROS” on page 1-228
- “Pick-and-Place Workflow in Gazebo using Point-Cloud Processing and RRT Path Planning” on page 1-237

Overview

This example sorts detected objects onto shelves using a KINOVA Gen3 manipulator. The example uses tools from two toolboxes:

- **Robotics System Toolbox™** is used to model, simulate, and visualize the manipulator, and plan collision-free paths for the manipulator to follow using RRT.
- **Stateflow®** is used to schedule the high-level tasks in the example and step from task to task.

This example uses the RRT algorithm for path planning. For another example that goes into more details about the RRT planner, see “Pick and Place Using RRT for Manipulators” on page 1-202.

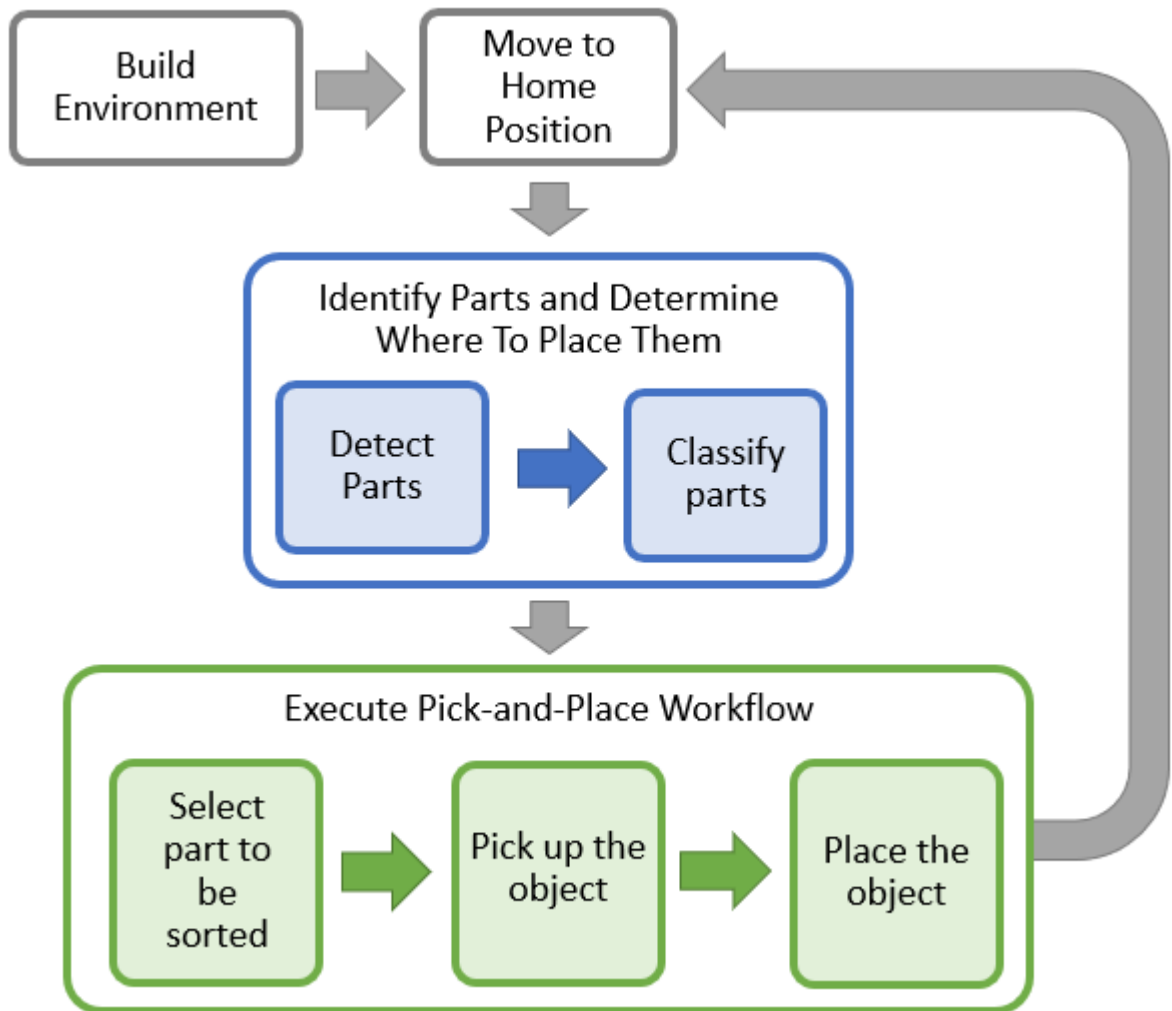
Stateflow Chart

This example uses a Stateflow chart to schedule tasks in the example. Open the chart to examine the contents and follow state transitions during chart execution.

edit [exampleHelperFlowChartPickPlaceRRT.sfx](#)

The chart dictates how the manipulator interacts with the objects, or parts. It consists of basic initialization steps, followed by two main sections:

- Identify Parts and Determine Where to Place Them
- Execute Pick-and-Place Workflow



Initialize the Robot and Environment

First, the chart creates an environment consisting of the Kinova Gen3 manipulator, three parts to be sorted, the shelves used for sorting, and a blue obstacle. Next, the robot moves to the home position.

Identify the Parts and Determine Where to Place Them

In the first step of the identification phase, the parts must be detected. The `exampleCommandDetectParts` function directly gives the object poses. Replace this class with your own object detection algorithm based on your sensors or objects.

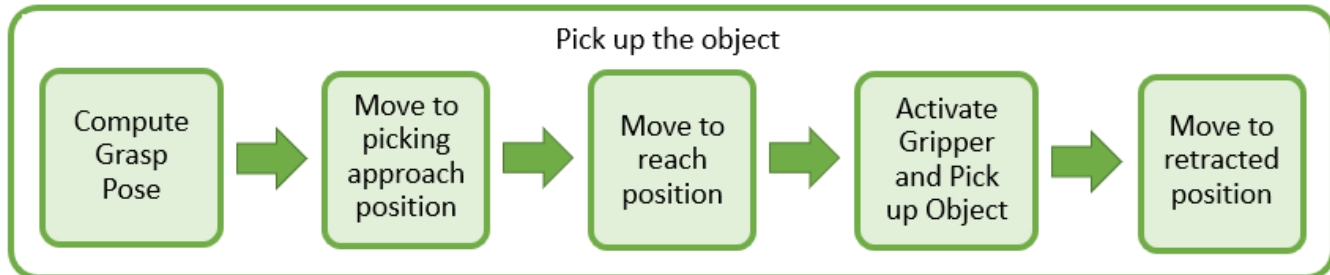
Next, the parts must be classified. The `exampleCommandClassifyParts` function classifies the parts into two types to determine where to place them (top or bottom shelf). Again, you can replace this function with any method for classifying parts.

Execute Pick-and-Place Workflow

Once parts are identified and their destinations have been assigned, the manipulator must iterate through the parts and move them onto the appropriate tables.

Pick up the Object

The picking phase moves the robot to the object, picks it up, and moves to a safe position, as shown in the following diagram:

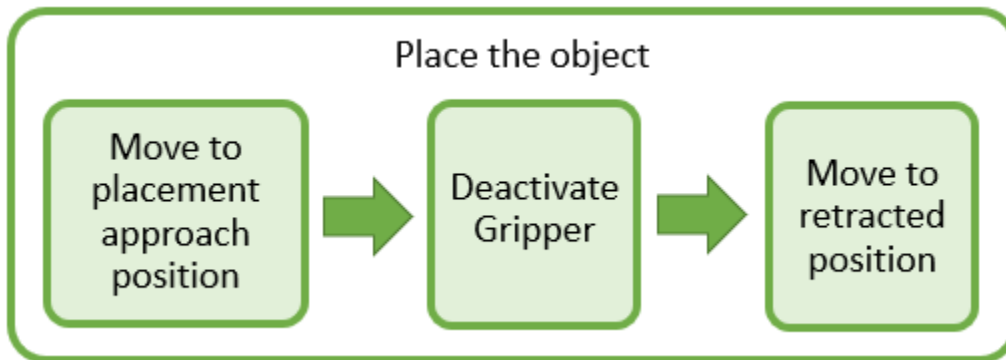


The `exampleCommandComputeGraspPose` function computes the grasp pose. The class computes a task-space grasping position for each part. Intermediate steps for approaching and reaching towards the part are also defined relative to the object.

This robot picks up objects using a simulated pneumatic gripper. When the gripper is activated, `exampleCommandActivateGripper` adds the collision mesh for the part onto the `rigidBodyTree` representation of the robot, by using the `addCollision` object function. Collision detection includes this object while it is attached. Then, the robot moves to a retracted position away from the other parts.

Place the Object

The robot then places the object on the appropriate shelf.

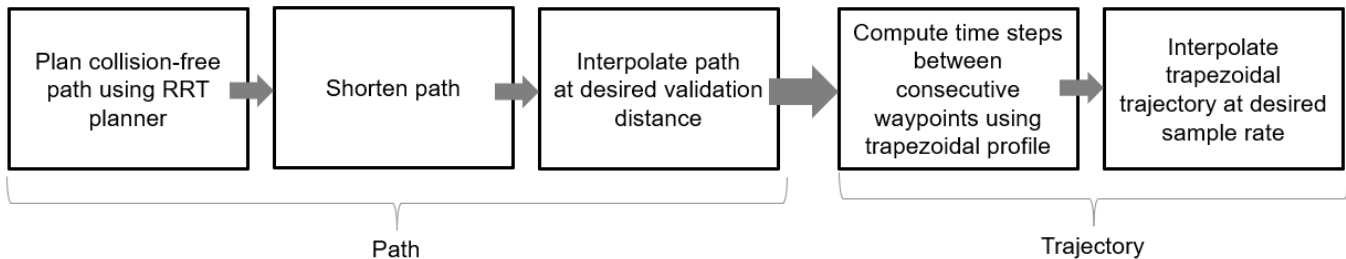


As with the picking workflow, the placement approach and retracted positions are computed relative to the known desired placement position. The gripper is deactivated using `exampleCommandActivateGripper`, which removes the part from the robot, using `clearCollision`. Every time a part of specific type is placed, the placing pose for this object type is updated so that next part of same type is placed next to the placed part.

Moving the Manipulator to a Specified Pose

Most of the task execution consists of instructing the robot to move between different specified poses. The `exampleHelperMoveToTaskConfig` function defines an RRT planner using the `manipulatorRRT` object, which plans paths from an initial to a desired joint configuration by

avoiding collisions with specified collision objects in the scene. The resulting path is first shortened and then interpolated at a desired validation distance. To generate a trajectory, the `trapveltraj` function is used to assign time steps to each of the interpolated waypoints following a trapezoidal profile. Finally, the waypoints with their associated times are interpolated to a desired sample rate (every 0.1 seconds). The generated trajectories ensure that the robot moves slowly at the start and the end of the motion when it is approaching or placing an object.



For another example that goes into more details about the RRT planner, see “Pick and Place Using RRT for Manipulators” on page 1-202.

For simpler trajectories where the paths are known to be obstacle-free, trajectories could be executed using trajectory generation tools and simulated using the manipulator motion models. See the “Plan and Execute Task- and Joint-space Trajectories using KINOVA Gen3 Manipulator” on page 1-183 example.

Task Scheduling in a Stateflow Chart

This example uses a Stateflow chart to direct the workflow in MATLAB®. For more info on creating state flow starts, see “Create Stateflow Charts for Execution as MATLAB Objects” (Stateflow).

The Stateflow chart directs task execution in MATLAB by using command functions. When the command finishes executing, it sends an *input event* to wake up the chart and proceed to the next step of the task execution, see “Execute a Standalone Chart” (Stateflow).

Run and Visualize the Simulation

This simulation uses a KINOVA Gen3 manipulator with a Robotiq gripper. Load the robot model from a `.mat` file as a `rigidBodyTree` object.

```
load('exampleHelperKINOVAGen3GripperCollRRT.mat');
```

Initialize the Pick and Place Coordinator

Set the initial robot configuration. Create the coordinator, which handles the robot control, by giving the robot model, initial configuration, and end-effector name.

```
currentRobotJConfig = homeConfiguration(robot);
coordinator = exampleHelperCoordinatorPickPlaceRRT(robot, currentRobotJConfig, "gripper");
```

Specify the home configuration and two poses for placing objects of two different types. The first pose corresponds to the middle shelf where all parts of type 1 are placed and the second pose corresponds to the top shelf where parts of type 2 are placed. The placing poses are updated in the Stateflow chart every time a new part is placed successfully. Parts of different type are identified by different colors in the visualization.

```

coordinator.HomeRobotTaskConfig = trvec2tform([0.4, 0, 0.5])*axang2tform([0 1 0 pi]);
coordinator.PlacingPose{1} = trvec2tform([-0.15 0.52 0.46])*axang2tform([1 0 0 -pi/2]);
coordinator.PlacingPose{2} = trvec2tform([-0.15 0.52 0.63])*axang2tform([1 0 0 -pi/2]);

```

Run and Visualize the Simulation

Connect the coordinator to the Stateflow Chart. Once started, the Stateflow chart is responsible for continuously going through the states of detecting objects, picking them up and placing them in the correct staging area.

```

coordinator.FlowChart = exampleHelperFlowChartPickPlaceRRT('coordinator', coordinator);

```

Use a dialog to start the pick-and-place task execution. Click **Yes** in the dialog to begin the simulation.

```

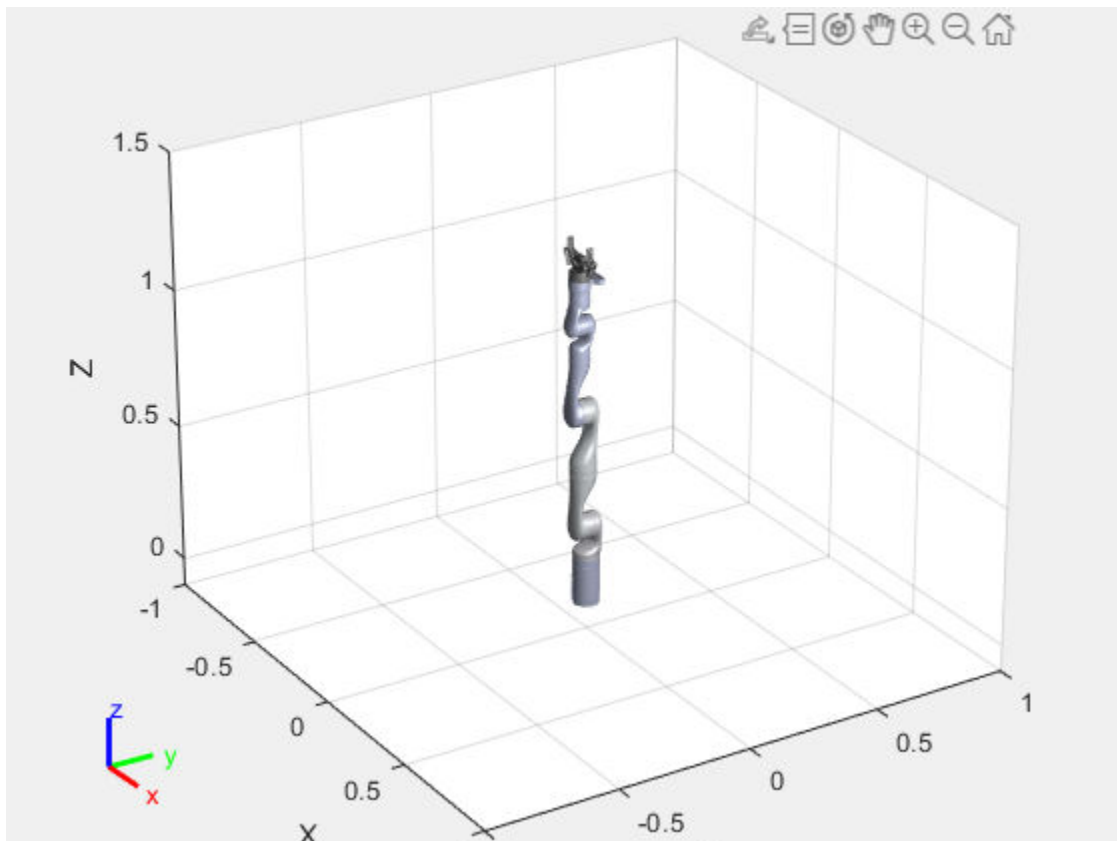
answer = questdlg('Do you want to start the pick-and-place job now?', ...
    'Start job','Yes','No','No');

```

```

switch answer
    case 'Yes'
        % Trigger event to start Pick and Place in the Stateflow Chart
        coordinator.FlowChart.startPickPlace;
    case 'No'
        % End Pick and Place
        coordinator.FlowChart.endPickPlace;
        delete(coordinator.FlowChart);
        delete(coordinator);
end

```



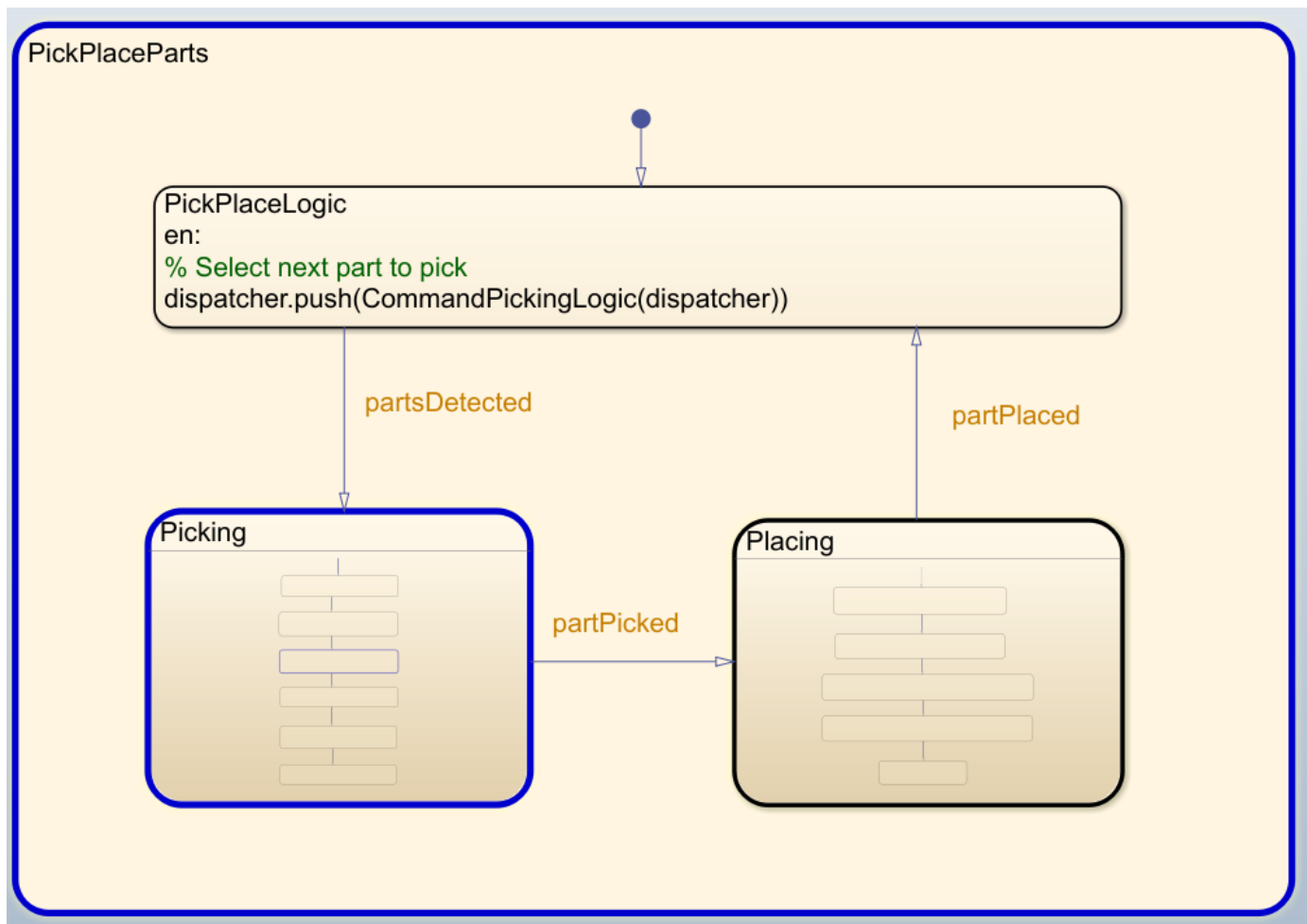
Ending the Pick-and-Place task

The Stateflow chart will finish executing automatically after 3 failed attempts to detect new objects. To end the pick-and-place task prematurely, uncomment and execute the following lines of code or press Ctrl+C in the command window.

```
% coordinator.FlowChart.endPickPlace;
% delete(coordinator.FlowChart);
% delete(coordinator);
```

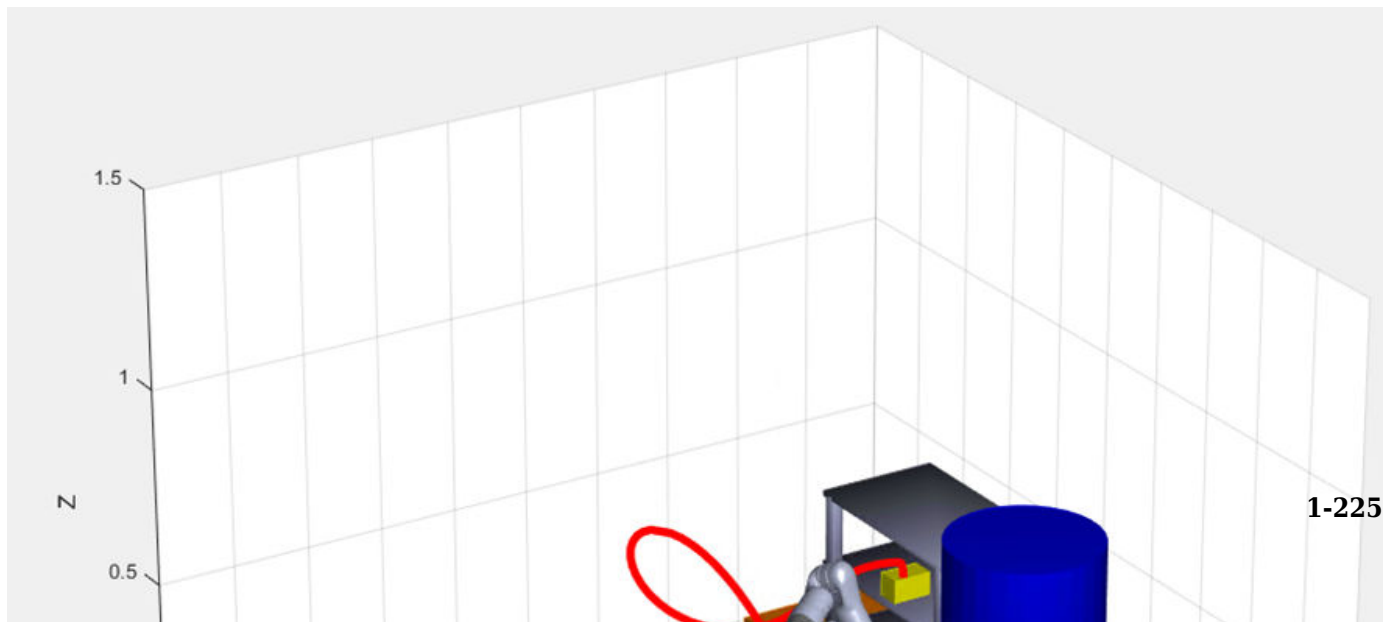
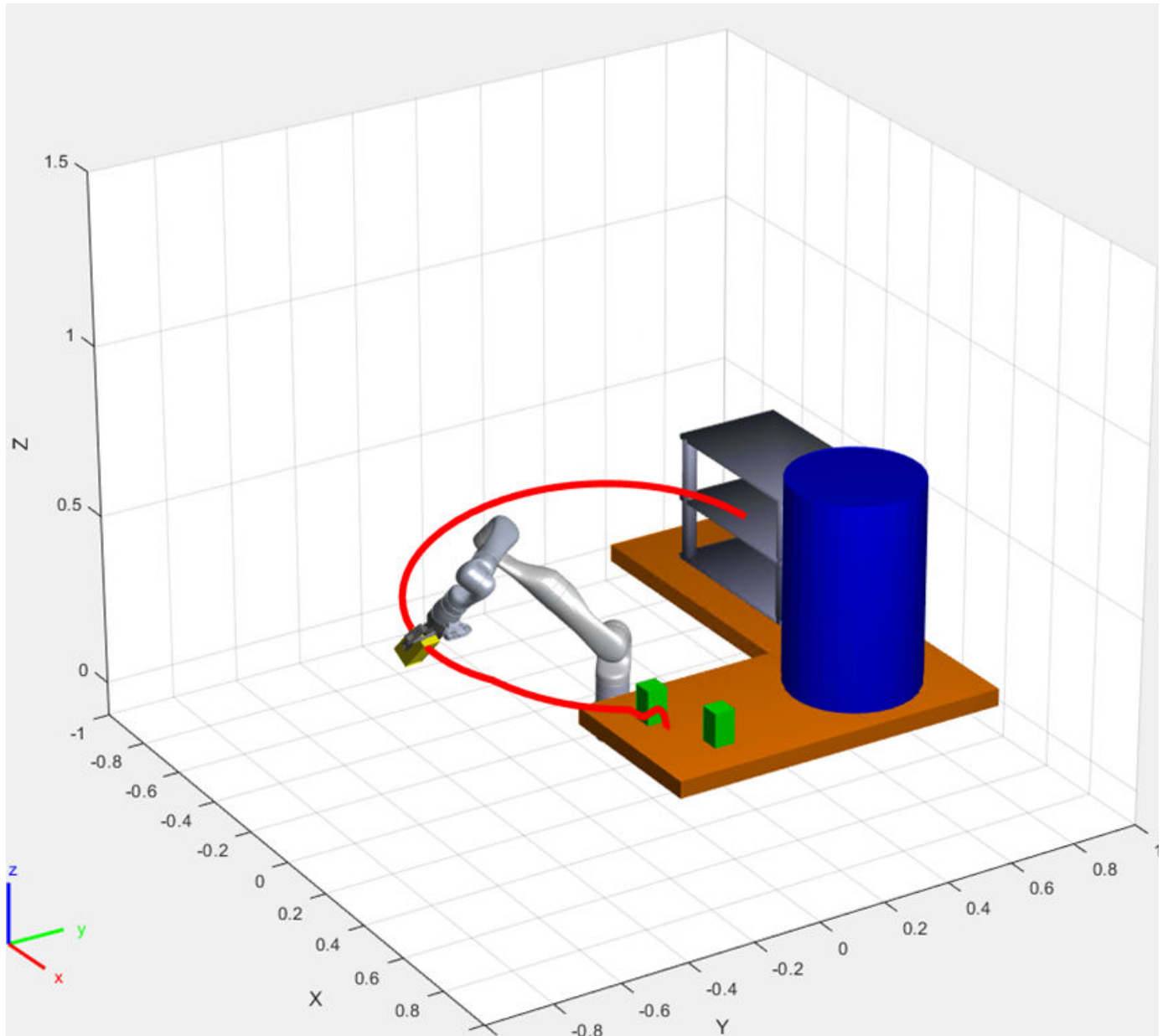
Observe the Simulation States

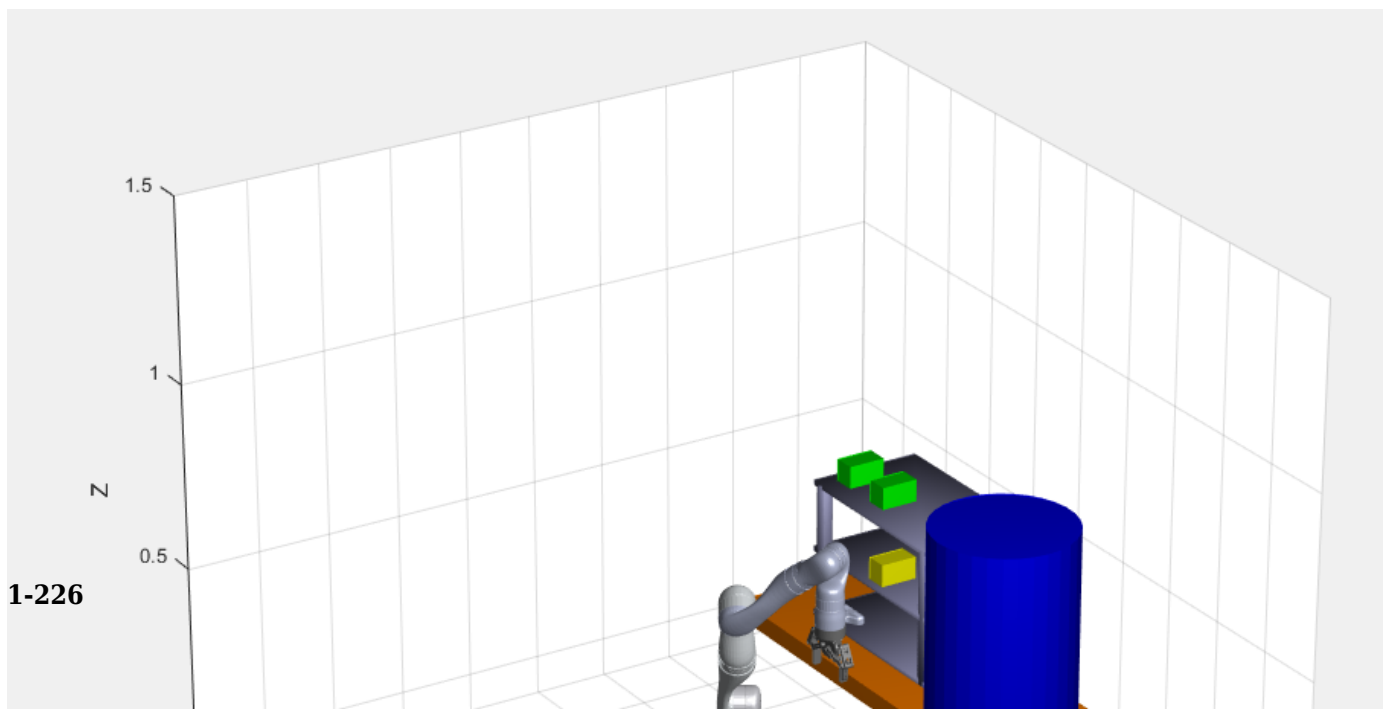
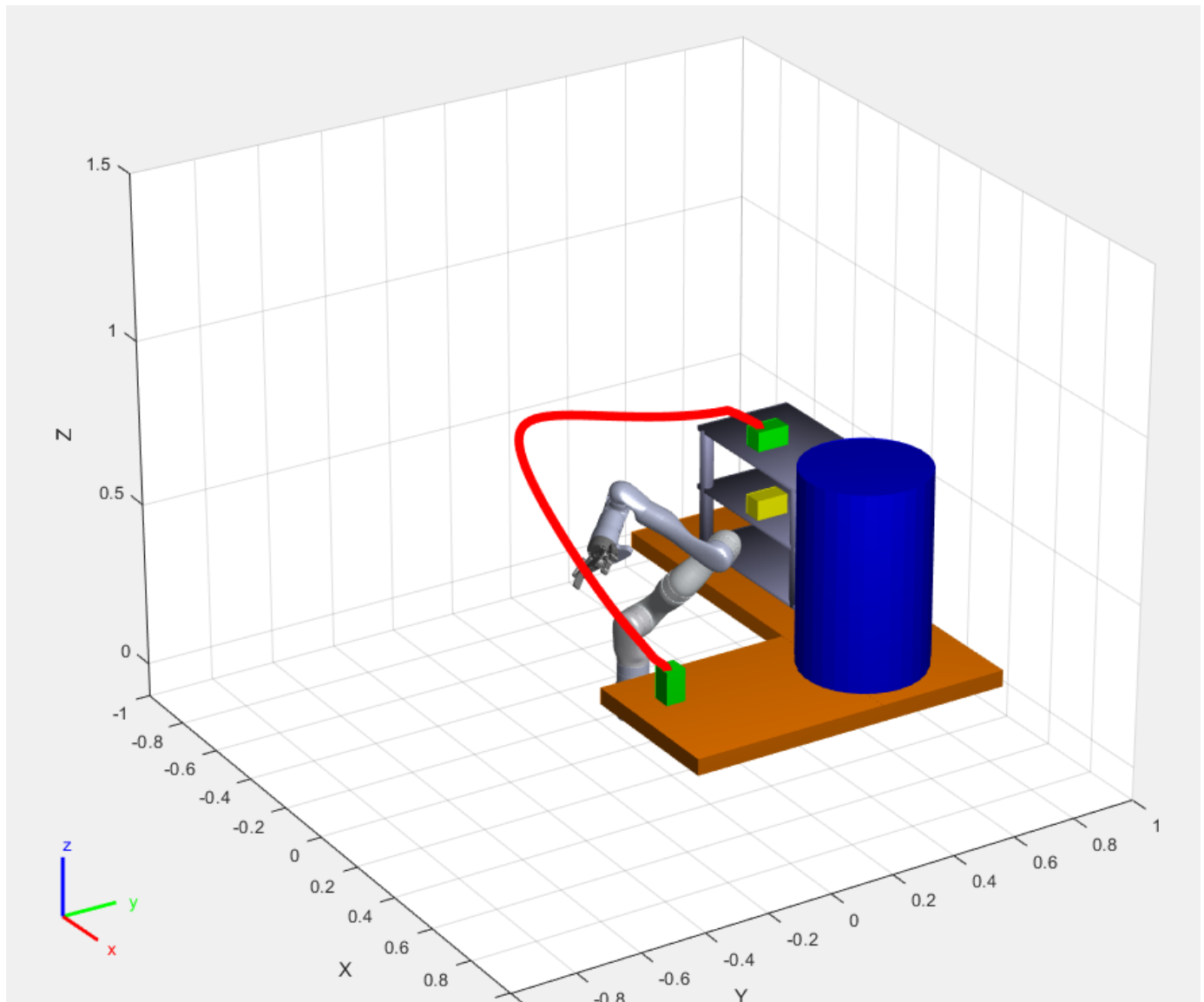
During execution, the active states at each point in time are highlighted in blue in the Stateflow chart. This helps keeping track of what the robot does and when. You can click through the subsystems to see the details of the state in action.



Visualize the Pick-and-Place Action

The example uses the `interactiveRigidBodyTree` object for robot visualization. The visualization shows the robot in the working area as it moves parts around. The robot avoids obstacles in the environment (blue cylinder) and places objects on the top or bottom shelf based on their classification. The robot continues working until all parts have been placed.





Pick-and-Place Workflow in Gazebo using ROS

This example shows how to setup an end-to-end pick and place workflow for a robotic manipulator like the KINOVA® Gen3 and simulate the robot in a physics simulator, Gazebo.

Overview

This example identifies and recycles objects into two bins using a KINOVA Gen3 manipulator. The example uses tools from five toolboxes:

- **Robotics System Toolbox™** is used to model and simulate the manipulator.
- **Stateflow®** is used to schedule the high-level tasks in the example and step from task to task.
- **ROS Toolbox™** is used for connecting MATLAB to Gazebo.
- **Computer Vision Toolbox™** and **Deep Learning Toolbox™** are used for object detection using simulated camera in Gazebo.

This example builds on key concepts from the following related examples:

- “Plan and Execute Task- and Joint-space Trajectories using KINOVA Gen3 Manipulator” on page 1-183 shows how to generate and simulate interpolated joint trajectories to move from an initial to a desired end-effector pose.
- “Pick-and-Place Workflow using Stateflow for MATLAB” on page 1-211
- Computer Vision Toolbox example: “Train YOLO v2 Network for Vehicle Detection” (Computer Vision Toolbox)
- ROS Toolbox example: “Get Started with Gazebo and a Simulated TurtleBot” (ROS Toolbox)

Robot Simulation and Control in Gazebo

Start a ROS-based simulator for a KINOVA Gen3 robot and configure the MATLAB® connection with the robot simulator.

This example uses a virtual machine (VM) available for download. If you have never used it before, see “Get Started with Gazebo and a Simulated TurtleBot” (ROS Toolbox).

- Start the Ubuntu® virtual machine desktop.
- In the Ubuntu desktop, click the **Gazebo Recycling World** icon to start the Gazebo world built for this example.
- Specify the IP address and port number of the ROS master in Gazebo so that MATLAB® can communicate with the robot simulator. For this example, the ROS master in Gazebo uses the IP address of 192.168.203.131 displayed on the Desktop. Adjust the `rosIP` variable based on your VM.
- Start the ROS 1 network using `rosinit`.

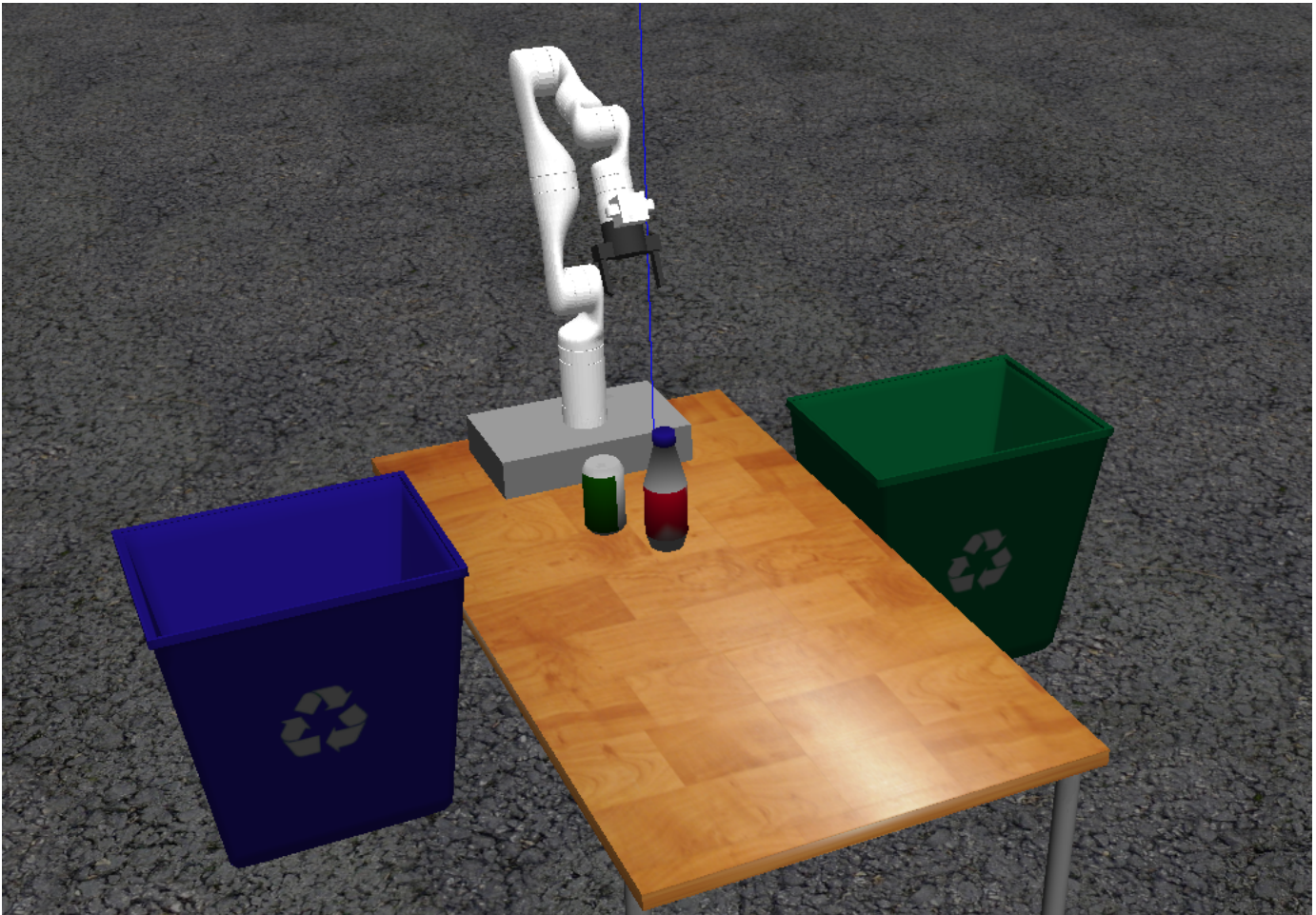
```
rosIP = '192.168.203.131'; % IP address of ROS-enabled machine
```

```
rosinit(rosIP,11311); % Initialize ROS connection
```

The value of the `ROS_IP` environment variable, 192.168.31.1, will be used to set the advertised address. Initializing global node /matlab_global_node_36570 with NodeURI http://192.168.31.1:51073/

After initializing the Gazebo world by click the icon, the VM loads a KINOVA Gen3 Robot arm on a table with one recycling bin on each side. To simulate and control the robot arm in Gazebo, the VM contains the `ros_kortex` ROS package, which are provided by KINOVA.

The packages use `ros_control` to control the joints to desired joint positions. For additional details on using the VM, refer to “Get Started with Gazebo and a Simulated TurtleBot” (ROS Toolbox)



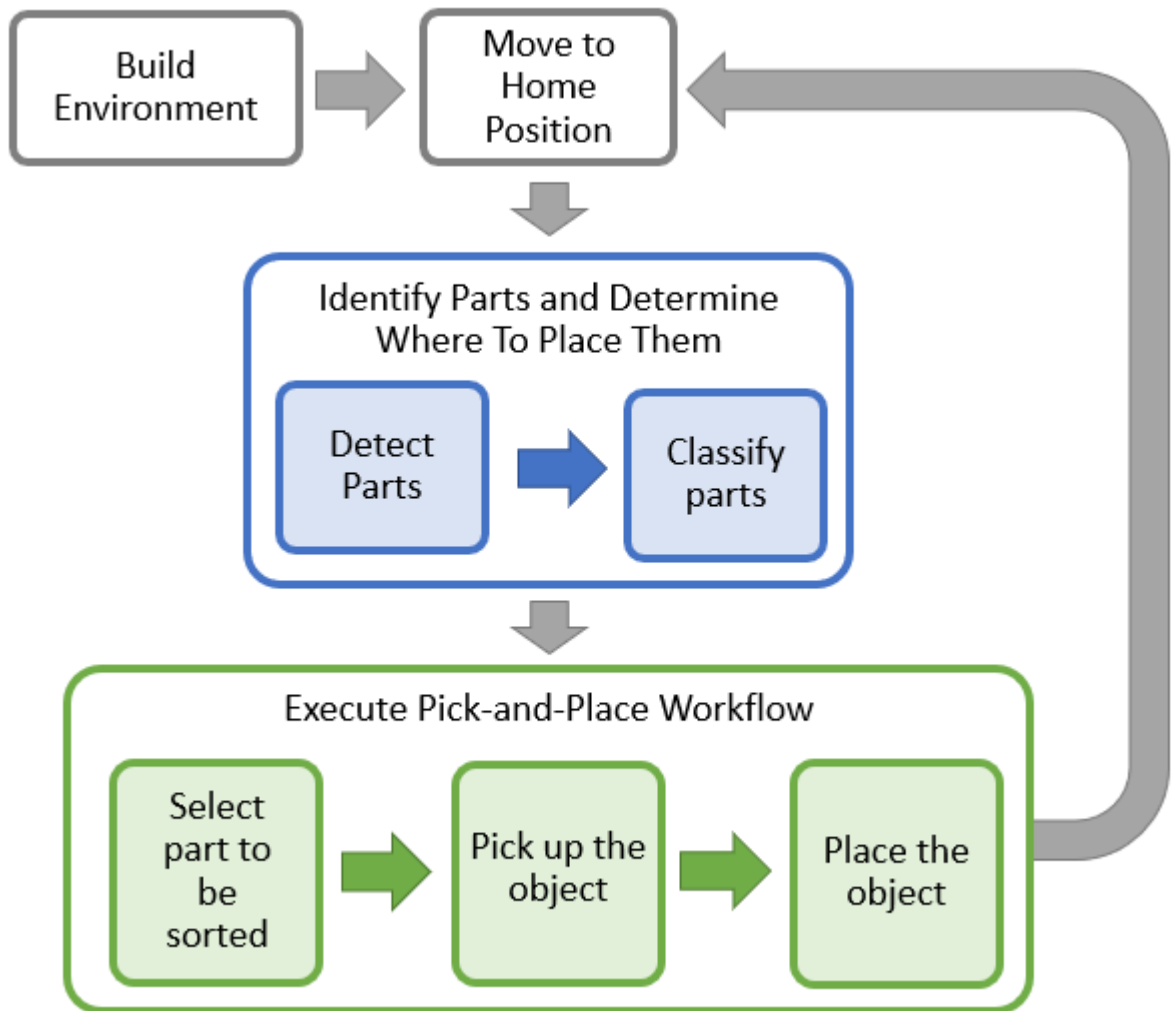
Stateflow Chart

This example uses a Stateflow chart to schedule tasks in the example. Open the chart to examine the contents and follow state transitions during chart execution.

```
edit exampleHelperFlowChartPickPlaceROSgazebo.sfx
```

The chart dictates how the manipulator interacts with the objects, or parts. It consists of basic initialization steps, followed by two main sections:

- Identify Parts and Determine Where to Place Them
- Execute Pick-and-Place Workflow



For a high-level description of the pick-and-place steps, see “Pick-and-Place Workflow using Stateflow for MATLAB” on page 1-211.

Opening and closing the gripper

The command for activating the gripper, `exampleCommandActivateGripperROSGazebo`, sends an action request to open and close the gripper implemented in Gazebo. To send a request to open the gripper, the following code is used. **Note:** The example code shown just illustrates what the command does. Do not run.

```
[gripAct,gripGoal] = rosactionclient('/my_gen3/custom_gripper_controller/gripper_cmd');
gripperCommand = rosmessage('control_msgs/GripperCommand');
gripperCommand.Position = 0.0;
gripGoal.Command = gripperCommand;
sendGoal(gripAct,gripGoal);
```

Moving the Manipulator to a Specified Pose

The `commandMoveToTaskConfig` command function is used to move the manipulator to specified poses.

Planning

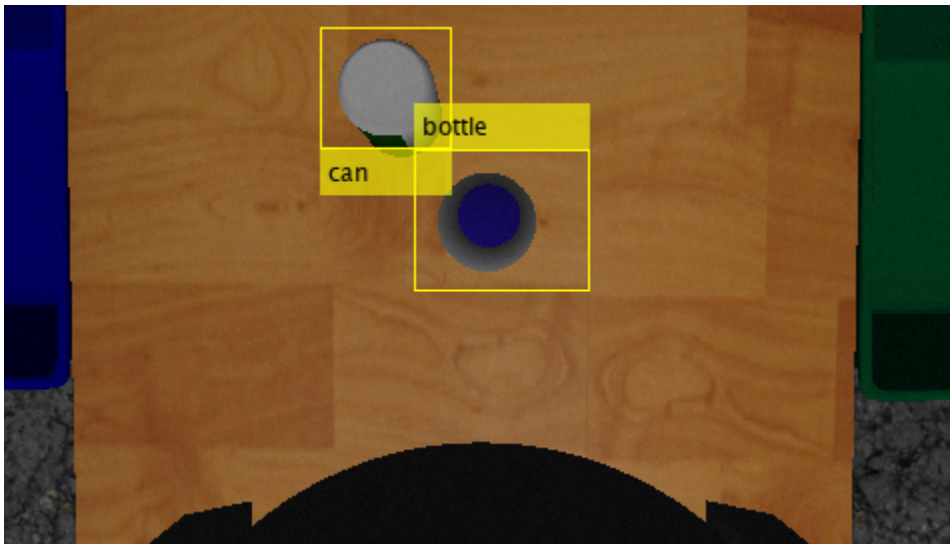
The path planning generates simple task-space trajectories from an initial to a desired task configuration using `trapveltraj` and `transformtraj`. For more details on planning and executing trajectories, see “Plan and Execute Task- and Joint-space Trajectories using KINOVA Gen3 Manipulator” on page 1-183.

Joint Trajectory Controller in ROS

After generating a joint trajectory for the robot to follow, `commandMoveToTaskConfig` samples the trajectory at the desired sample rate, packages it into joint-trajectory ROS messages and sends an action request to the joint-trajectory controller implemented in the KINOVA ROS package.

Detecting and classifying objects in the scene

The functions `commandDetectParts` and `commandClassifyParts` use the simulated end-effector camera feed from the robot and apply a pretrained deep-learning model to detect the recyclable parts. The model takes a camera frame as input and outputs the 2D location of the object (pixel position) and the type of recycling it requires (blue or green bin). The 2D location on the image frame is mapped to the robot base frame.



Deep-Learning Model Training: Acquiring and Labeling Gazebo Images

The detection model was trained using a set of images acquired in the simulated environment within the Gazebo world with the two classes of objects (bottle, can) placed on different locations of the table. The images are acquired from the simulated camera on-board the robot, which is moved along the horizontal and vertical planes to get images of the objects from many different camera perspectives.

The images are then labeled using the Image Labeler (Computer Vision Toolbox) app, creating the training dataset for the YOLO v2 detection model. `trainYOLOv2ObjectDetector` (Computer Vision

Toolbox) trains the model. To see how to train a YOLO v2 network in MATLAB, see “Train YOLO v2 Network for Vehicle Detection” (Computer Vision Toolbox).

The trained model is deployed for online inference on the single image acquired by the on-board camera when the robot is in the home position. The `detect` (Computer Vision Toolbox) function returns the image position of the bounding boxes of the detected objects, along with their classes, that is then used to find the position of the center of the top part of the objects. Using a simple camera projection approach, assuming the height of the objects is known, the object position is projected into the world and finally used as reference position for picking the object. The class associated with the bounding boxed decides which bin to place the object.

Start the Pick-and-Place Task

This simulation uses a KINOVA Gen3 manipulator with a Robotiq gripper attached. Load the robot model from a `.mat` file as a `rigidBodyTree` object.

```
load('exampleHelperKINOVAGen3GripperROSGazebo.mat');
```

Initialize the Pick and Place Coordinator

Set the initial robot configuration. Create the coordinator, which handles the robot control, by giving the robot model, initial configuration, and end-effector name.

```
initialRobotJConfig = [3.5797 -0.6562 -1.2507 -0.7008 0.7303 -2.0500 -1.9053];
endEffectorFrame = "gripper";
```

Initialize the coordinator by giving the robot model, initial configuration, and end-effector name.

```
coordinator = exampleHelperCoordinatorPickPlaceROSGazebo(robot,initialRobotJConfig, endEffectorFrame);
```

Specify the home configuration and two poses for placing objects.

```
coordinator.HomeRobotTaskConfig = getTransform(robot, initialRobotJConfig, endEffectorFrame);
coordinator.PlacingPose{1} = trvec2tform([[0.2 0.55 0.26]])*axang2tform([0 0 1 pi/2])*axang2tform([0 0 1 pi/2]);
coordinator.PlacingPose{2} = trvec2tform([[0.2 -0.55 0.26]])*axang2tform([0 0 1 pi/2])*axang2tform([0 0 1 pi/2]);
```

Run and Visualize the Simulation

Connect the coordinator to the Stateflow Chart. Once started, the Stateflow chart is responsible for continuously going through the states of detecting objects, picking them up and placing them in the correct staging area.

```
coordinator.FlowChart = exampleHelperFlowChartPickPlaceROSGazebo('coordinator', coordinator);
```

Use a dialog to start the pick-and-place task execution. Click **Yes** in the dialog to begin the simulation.

```
answer = questdlg('Do you want to start the pick-and-place job now?', ...
    'Start job','Yes','No','No');
```

```
switch answer
    case 'Yes'
        % Trigger event to start Pick and Place in the Stateflow Chart
        coordinator.FlowChart.startPickPlace;
    case 'No'
        coordinator.FlowChart.endPickPlace;
        delete(coordinator.FlowChart)
        delete(coordinator);
end
```

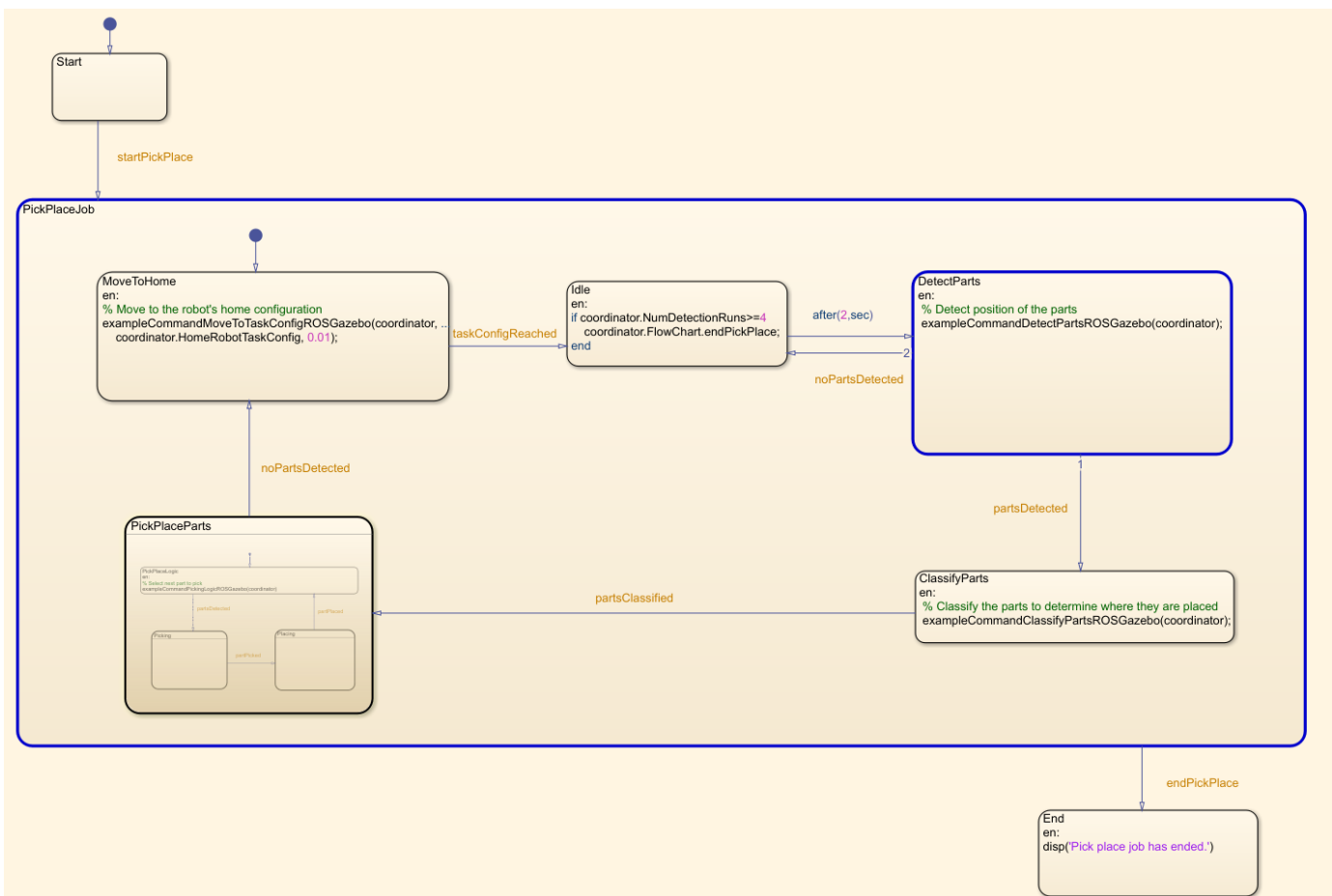
Ending the pick-and-place task

The Stateflow chart will finish executing automatically after 3 failed attempts to detect new objects. To end the pick-and-place task prematurely, uncomment and execute the following lines of code or press Ctrl+C in the command window.

```
% coordinator.FlowChart.endPickPlace;
% delete(coordinator.FlowChart);
% delete(coordinator);
```

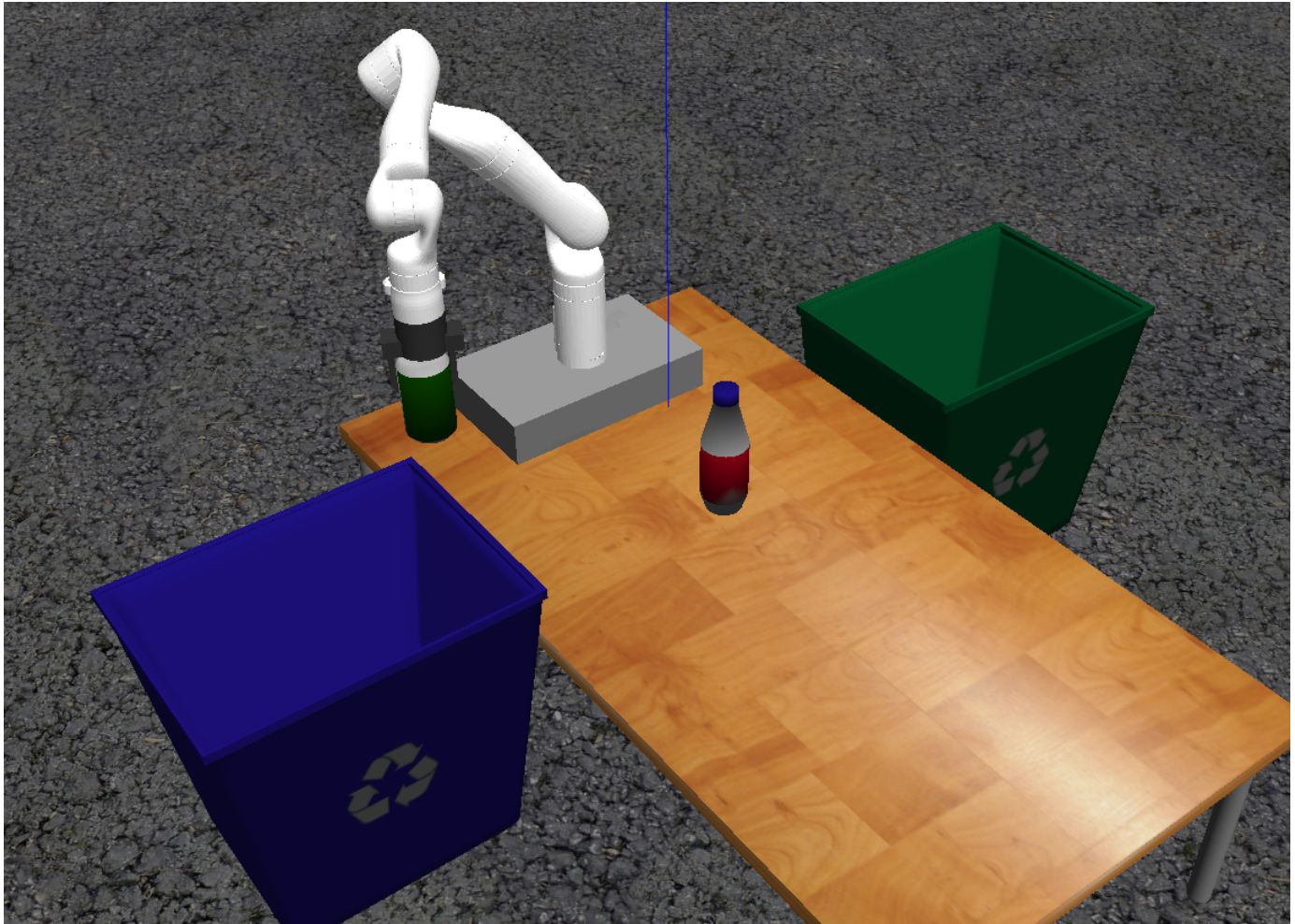
Observe the Simulation States

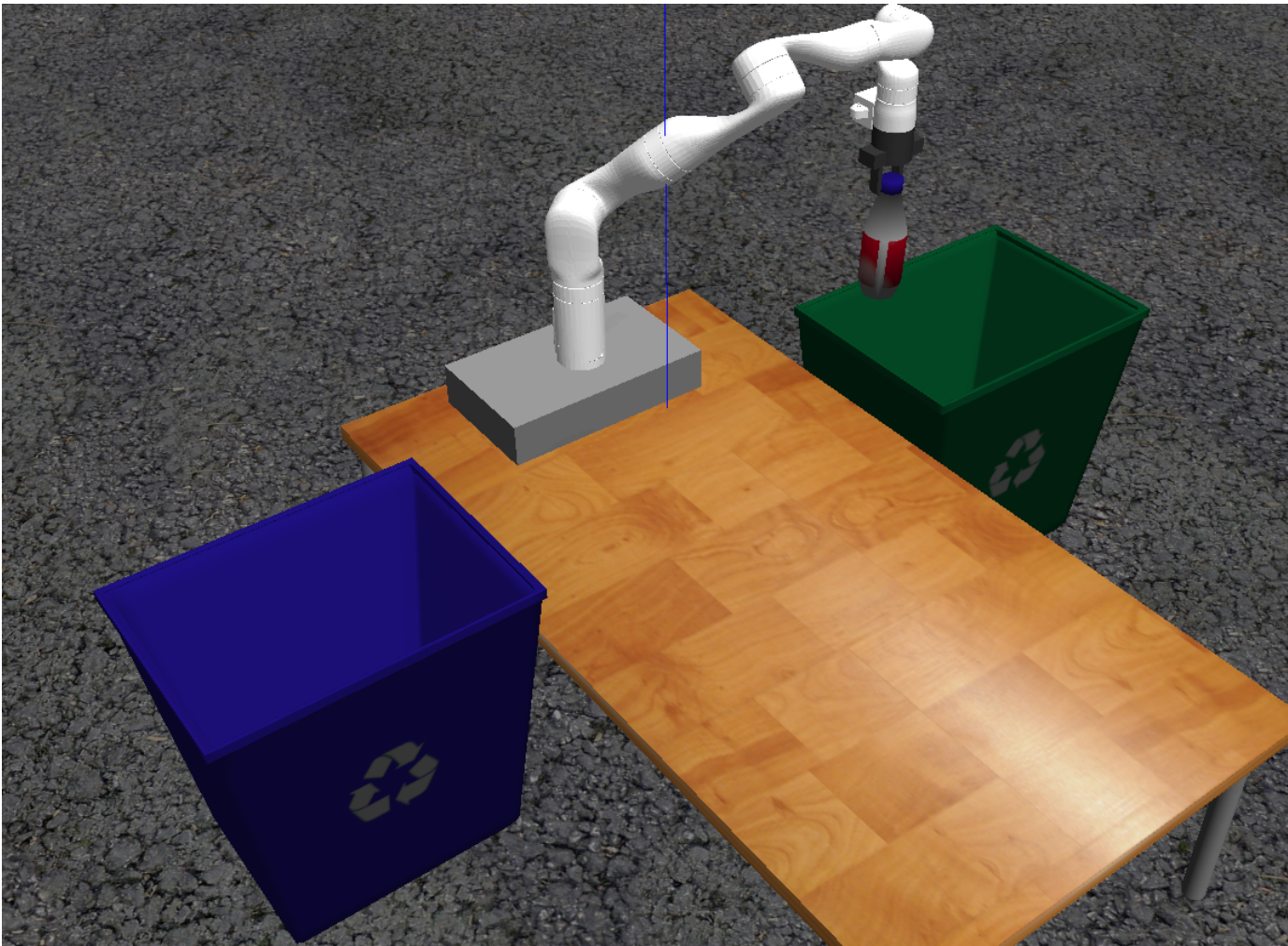
During execution, the active states at each point in time are highlighted in blue in the Stateflow chart. This helps keeping track of what the robot does and when. You can click through the subsystems to see the details of the state in action.

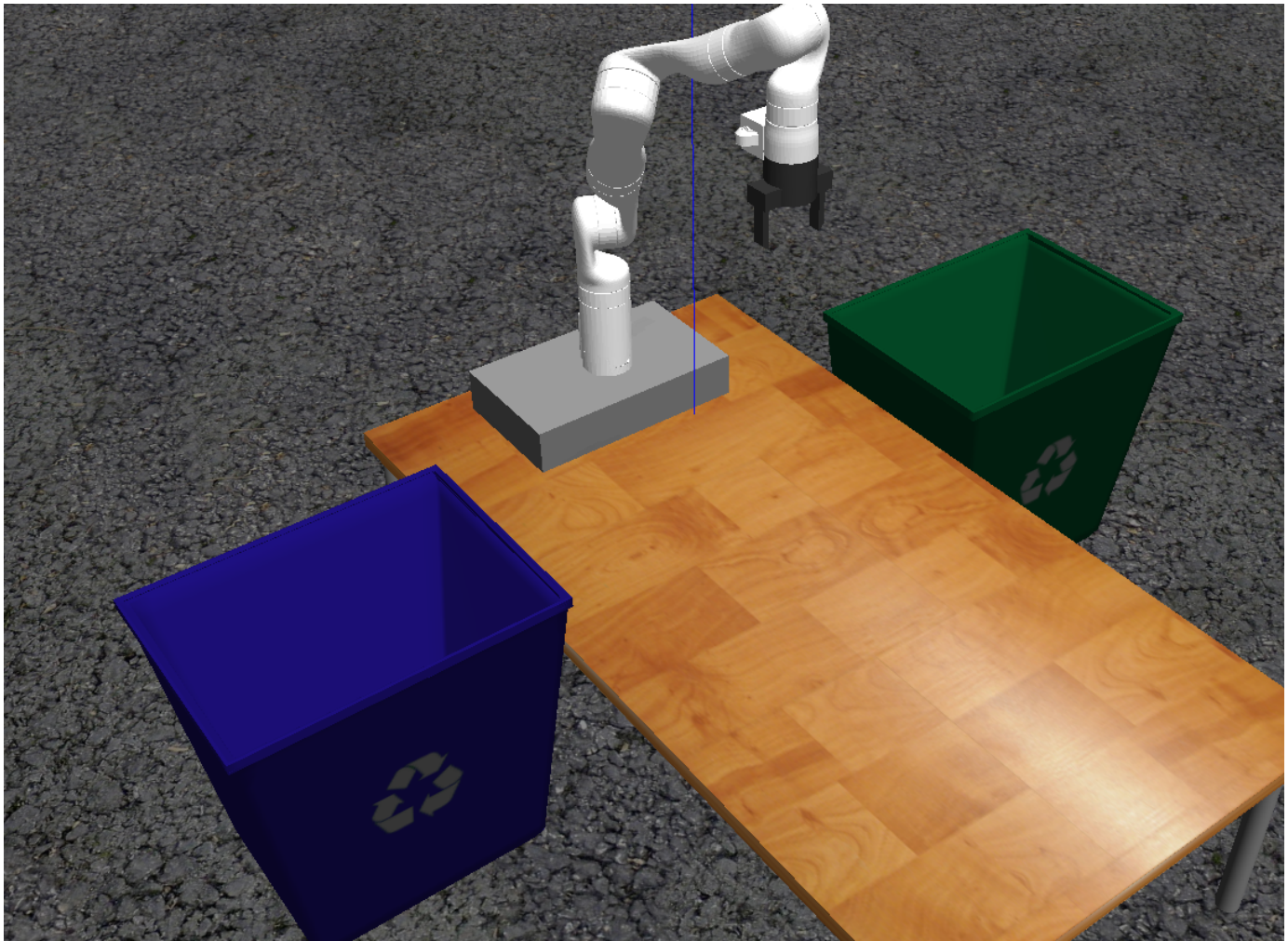


Visualize the Pick-and-Place Action in Gazebo

The Gazebo world shows the robot in the working area as it moves parts to the recycling bins. The robot continues working until all parts have been placed. When the detection step doesn't find any more parts four times, the Stateflow chart exists.







```
if strcmp(answer, 'Yes')
    while coordinator.NumDetectionRuns < 4
        % Wait for no parts to be detected.
    end
end
```

Shutdown the ROS network after finishing the example.

```
roshutdown
```

```
Shutting down global node /matlab_global_node_36570 with NodeURI http://192.168.31.1:51073/
```

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Pick-and-Place Workflow in Gazebo using Point-Cloud Processing and RRT Path Planning

Setup an end-to-end pick and place workflow for a robotic manipulator like the KINOVA® Gen3.

The pick-and-place workflow implemented in this example can be adapted to different scenarios, planners, simulation platforms, and object detection options. The example shown here uses RRT for planning and simulates the robot in Gazebo using the Robot Operating System (ROS). For other pick-and-place workflows, see:

- “Pick-and-Place Workflow using Stateflow for MATLAB” on page 1-211
- “Pick and Place Workflow Using RRT Planner and Stateflow for MATLAB” on page 1-219
- “Pick-and-Place Workflow in Gazebo using ROS” on page 1-228

Overview

This example identifies and recycles objects into two bins using a KINOVA Gen3 manipulator. The example uses tools from five toolboxes:

- **Robotics System Toolbox™** is used to model and simulate the manipulator.
- **ROS Toolbox™** is used for connecting MATLAB to Gazebo.
- **Image Processing Toolbox™** and **Computer Vision Toolbox™** are used for object detection using point cloud processing and simulated depth camera in Gazebo.

This example builds on key concepts from the following related examples:

- “Pick and Place Using RRT for Manipulators” on page 1-202
- “Get Started with Gazebo and a Simulated TurtleBot” (ROS Toolbox) (ROS Toolbox)
- “3-D Point Cloud Registration and Stitching” (Computer Vision Toolbox) (Computer Vision Toolbox)

Robot Simulation and Control in Gazebo

Start a ROS-based simulator for a KINOVA Gen3 robot and configure the MATLAB® connection with the robot simulator.

This example uses a virtual machine (VM) available for download. See the “Get Started with Gazebo and a Simulated TurtleBot” (ROS Toolbox) (ROS Toolbox) example.

- Start the Ubuntu® virtual machine desktop.
- In the Ubuntu desktop, click the **Gazebo Recycling World - Depth Sensing** icon to start the Gazebo world built for this example.
- Specify the IP address and port number of the ROS master in Gazebo so that MATLAB® can communicate with the robot simulator. For this example, the ROS master in Gazebo uses the IP address of 192.168.203.131 displayed on the Desktop. Adjust the `rosIP` variable based on your VM.
- Start the ROS 1 network using `rosinit`.

```
rosIP = '192.168.203.132'; % IP address of ROS-enabled machine
```

```
rosshutdown;
```

```
rosinit(rosIP,11311); % Initialize ROS connection
```

Initializing global node /matlab_global_node_52545 with NodeURI http://192.168.203.1:53426/

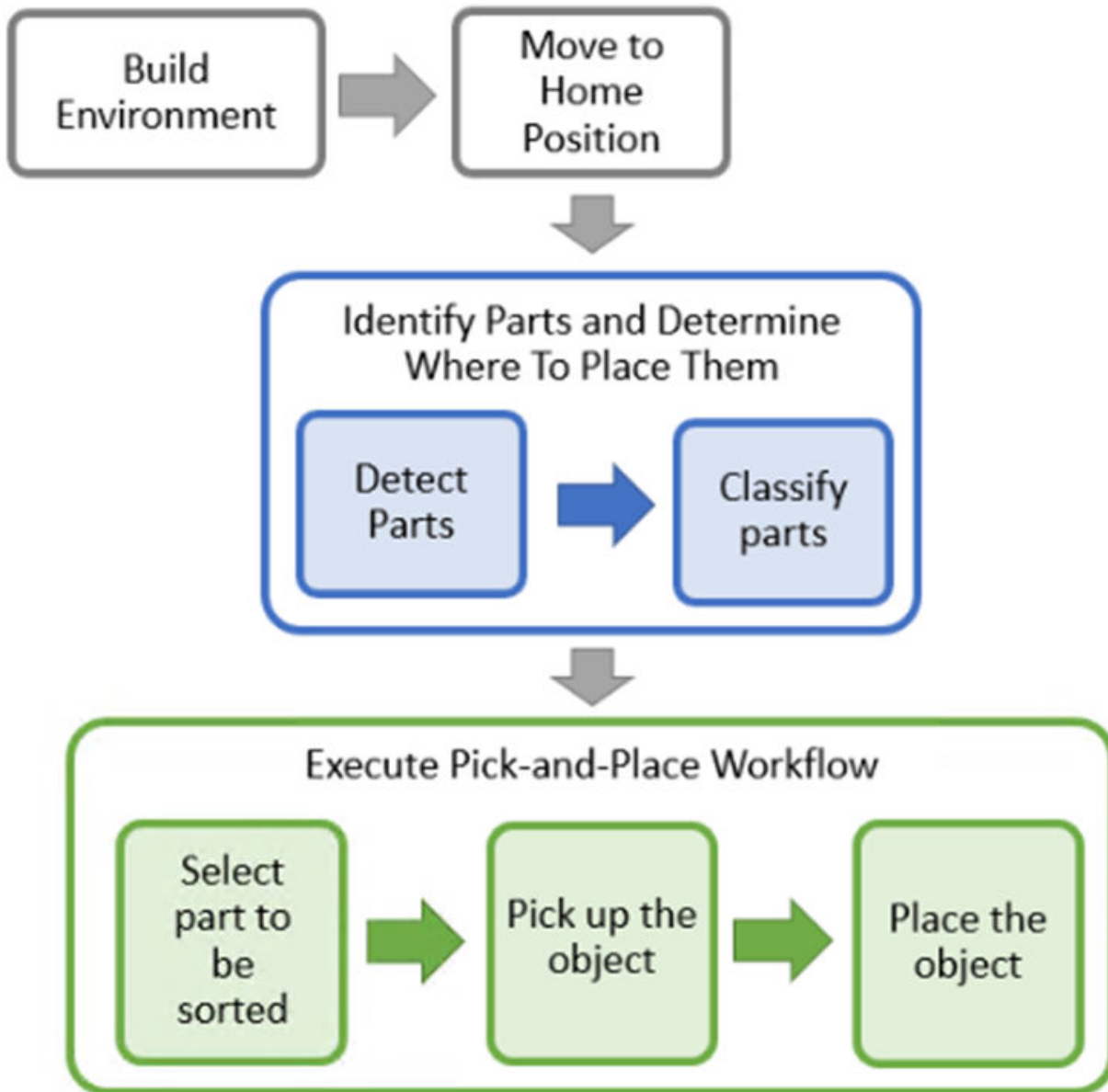
After initializing the Gazebo world by click the icon, the VM loads a KINOVA Gen3 Robot arm on a table with one recycling bin on each side. To simulate and control the robot arm in Gazebo, the VM contains the `ros_kortex` ROS package, which are provided by KINOVA.

The packages use `ros_control` to control the joints to desired joint positions. For additional details on using the VM, refer to “Get Started with Gazebo and a Simulated TurtleBot” (ROS Toolbox)

Pick-and-Place Tasks

The Pick-and-Place workflow is implemented in MATLAB and consists of basic initialization steps, followed by two main sections:

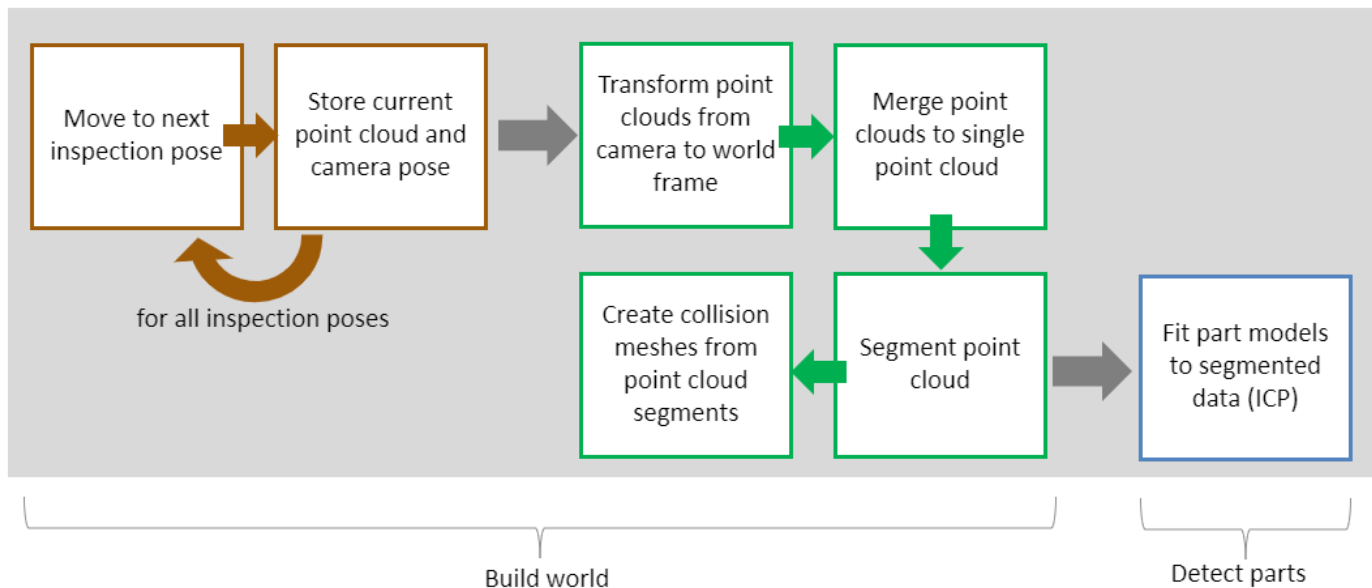
- Identify Parts and Determine Where to Place Them
- Execute Pick-and-Place Workflow



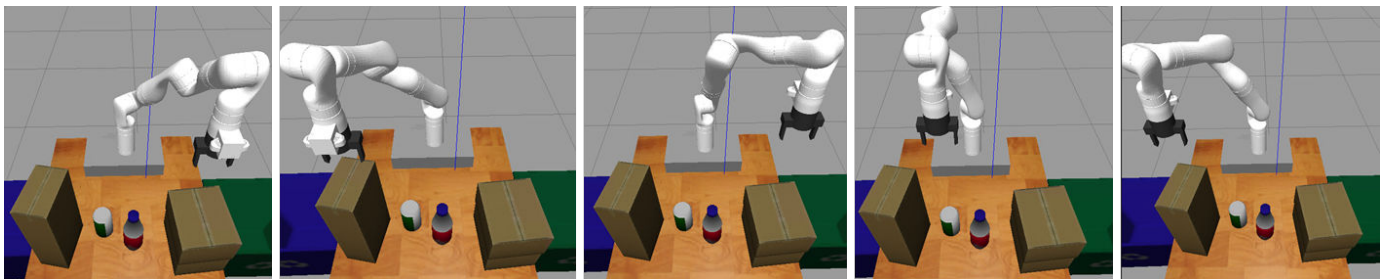
For an implementation that uses Stateflow to schedule the tasks, see “Pick-and-Place Workflow using Stateflow for MATLAB” on page 1-211.

Scanning the environment to build planning scene for RRT path planner

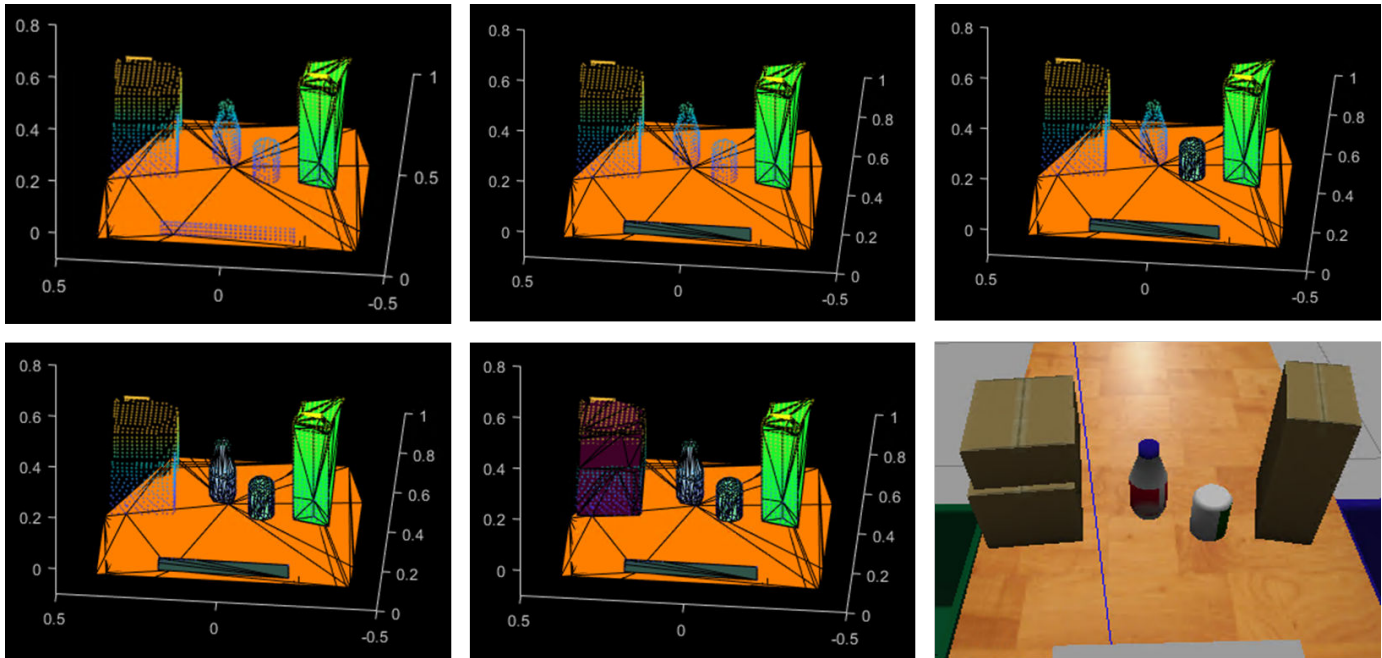
Before starting the pick-and-place job, the robot goes through a set of tasks to identify the planning scene in the `exampleCommandBuildWorld` function and detects the objects to pick using the `exampleCommandDetectParts` function.



First, the robot moves to predefined scanning poses one by one and captures a set of point clouds of the scene using an onboard depth sensor. At each of the scanning poses, the current camera pose is retrieved by reading the corresponding ROS transformation using `rosterf` (ROS Toolbox) and `getTransform` (ROS Toolbox). The scanning poses are visualized below:



Once the robot has visited all the scanning poses, the captured point clouds are transformed from camera to world frame using `pcttransform` (Computer Vision Toolbox) and merged to a single point cloud using `pcmerge` (Computer Vision Toolbox). The final point cloud is segmented based on Euclidean distance using `pcsegdist` (Computer Vision Toolbox). The resulting point cloud segments are then encoded as collision meshes (see `collisionMesh`) to be easily identified as obstacles during RRT path planning. The process from point cloud to collision meshes is shown one mesh at a time below.



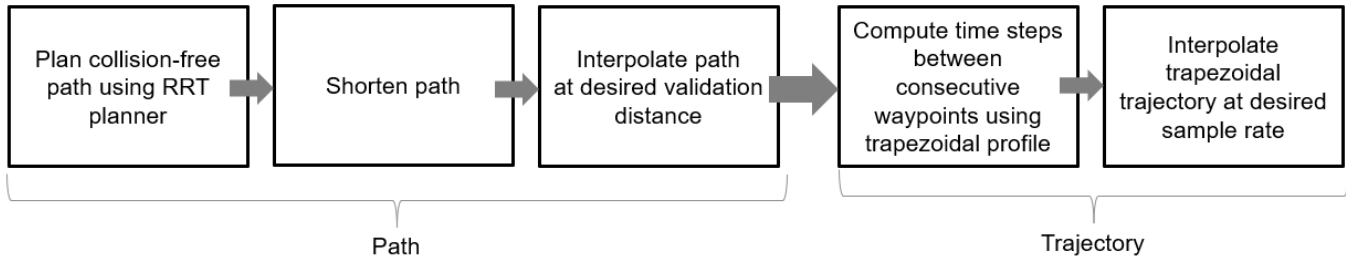
Opening and closing the gripper

The command for activating the gripper, `exampleCommandActivateGripper`, sends an action request to open and close the gripper implemented in Gazebo. For example, to send a request to open the gripper, the following code is used.

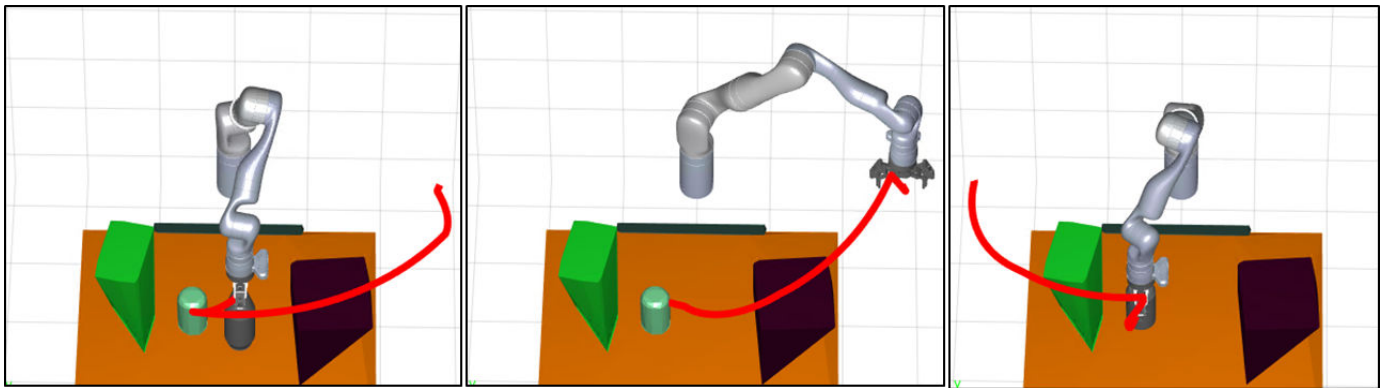
```
[gripAct,gripGoal] = rosactionclient('/my_gen3/custom_gripper_controller/gripper_cmd');
gripperCommand = rosmessage('control_msgs/GripperCommand');
gripperCommand.Position = 0.0;
gripGoal.Command = gripperCommand;
sendGoal(gripAct,gripGoal);
```

Moving the manipulator to a specified pose

Most of the task execution consists of instructing the robot to move between different specified poses. The `exampleHelperMoveToTaskConfig` function defines an RRT planner using the `manipulatorRRT` object, which plans paths from an initial to a desired joint configuration by avoiding collisions with specified collision objects in the scene. The resulting path is first shortened and then interpolated at a desired validation distance. To generate a trajectory, the `trapveltraj` function is used to assign time steps to each of the interpolated waypoints following a trapezoidal profile. Finally, the waypoints with their associated times are interpolated to a desired sample rate (every 0.1 seconds). The generated trajectories ensure that the robot moves slowly at the start and the end of the motion when it is approaching or placing an object.



The planned paths are visualized in MATLAB along with the planning scene.



This workflow is examined in detail in the “Pick and Place Workflow Using RRT Planner and Stateflow for MATLAB” on page 1-219 example. For more information about the RRT planner, see “Pick and Place Using RRT for Manipulators” on page 1-202. For simpler trajectories where the paths are known to be obstacle-free, trajectories could be executed using trajectory generation tools and simulated using the manipulator motion models. See “Plan and Execute Task- and Joint-space Trajectories using KINOVA Gen3 Manipulator” on page 1-183.

Joint Trajectory Controller in ROS

After generating a joint trajectory for the robot to follow, the `exampleCommandMoveToTaskConfig` function samples the trajectory at the desired sample rate, packages it into joint-trajectory ROS messages and sends an action request to the joint-trajectory controller implemented in the KINOVA ROS package.

Detecting and classifying objects in the scene

The functions `exampleCommandDetectParts` and `exampleCommandClassifyParts` use the simulated end-effector depth camera feed from the robot to detect the recyclable parts. Since a complete point cloud of the scene is available from the **Build Environment** step, the iterative closest point (ICP) registration algorithm implemented in `pregistericp` (Computer Vision Toolbox) identifies which of the segmented point clouds match the geometries of objects that should be picked.

Start the Pick-and-Place Workflow

This simulation uses a KINOVA Gen3 manipulator with a gripper attached.

```
load('exampleHelperKINOVAGen3GripperGazeboRRTScene.mat');
rng(0)
```


Initialize the Pick-and-Place Application

Set the initial robot configuration and name of the end-effector body.

```
initialRobotJConfig = [3.5797  -0.6562  -1.2507  -0.7008  0.7303  -2.0500  -1.9053];
endEffectorFrame = "gripper";
```

Initialize the coordinator by giving the robot model, initial configuration, and end-effector name.

```
coordinator = exampleHelperCoordinatorPickPlaceROSGazeboScene(robot,initialRobotJConfig, endEffectorFrame);
```

Specify pick-and-place coordinator properties.

```
coordinator.HomeRobotTaskConfig = getTransform(robot, initialRobotJConfig, endEffectorFrame);
coordinator.PlacingPose{1} = trvec2tform([[0.2 0.55 0.26]])*axang2tform([0 0 1 pi/2])*axang2tform([0 0 1 pi/2]);
coordinator.PlacingPose{2} = trvec2tform([[0.2 -0.55 0.26]])*axang2tform([0 0 1 pi/2])*axang2tform([0 0 1 pi/2]);
```

Run the Pick-and-Place Application Step by Step

```
% Task 1: Build world
```

```
exampleCommandBuildWorldROSGazeboScene(coordinator);
```

```
Moving to scanning pose 1
Now planning...
```

```
Waiting until robot reaches the desired configuration
```

```
Capturing point cloud 1
Getting camera pose 1
Moving to scanning pose 2
Now planning...
```

```
Waiting until robot reaches the desired configuration
```

```
Capturing point cloud 2
Getting camera pose 2
Moving to scanning pose 3
Now planning...
```

```
Waiting until robot reaches the desired configuration
```

```
Capturing point cloud 3
Getting camera pose 3
Moving to scanning pose 4
Now planning...
```

```
Waiting until robot reaches the desired configuration
```

```
Capturing point cloud 4
Getting camera pose 4
Moving to scanning pose 5
Now planning...
```

```
Waiting until robot reaches the desired configuration
```

```
Capturing point cloud 5
Getting camera pose 5
```

```
% Task 2: Move to home position
```

```
exampleCommandMoveToTaskConfigROSGazeboScene(coordinator,coordinator.HomeRobotTaskConfig);
```

Now planning...

Waiting until robot reaches the desired configuration

```
% Task 3: Detect objects in the scene to pick
exampleCommandDetectPartsROSGazeboScene(coordinator);
```

Bottle detected...

Can detected...

```
% Task 4: Select next part to pick
remainingParts = exampleCommandPickingLogicROSGazeboScene(coordinator);
```

1

```
while remainingParts==true
    % Task 5: [PICKING] Compute grasp pose
    exampleCommandComputeGraspPoseROSGazeboScene(coordinator);

    % Task 6: [PICKING] Move to picking pose
    exampleCommandMoveToTaskConfigROSGazeboScene(coordinator, coordinator.GraspPose);

    % Task 7: [PICKING] Activate gripper
    exampleCommandActivateGripperROSGazeboScene(coordinator, 'on');

    % Part has been picked

    % Task 8: [PLACING] Move to placing pose
    exampleCommandMoveToTaskConfigROSGazeboScene(coordinator, ...
        coordinator.PlacingPose{coordinator.DetectedParts{coordinator.NextPart}.placingBelt});

    % Task 9: [PLACING] Deactivate gripper
    exampleCommandActivateGripperROSGazeboScene(coordinator, 'off');

    % Part has been placed

    % Select next part to pick
    remainingParts = exampleCommandPickingLogicROSGazeboScene(coordinator);
end
```

Now planning...

Waiting until robot reaches the desired configuration

Gripper closed...

Now planning...

Waiting until robot reaches the desired configuration

Gripper open...

2

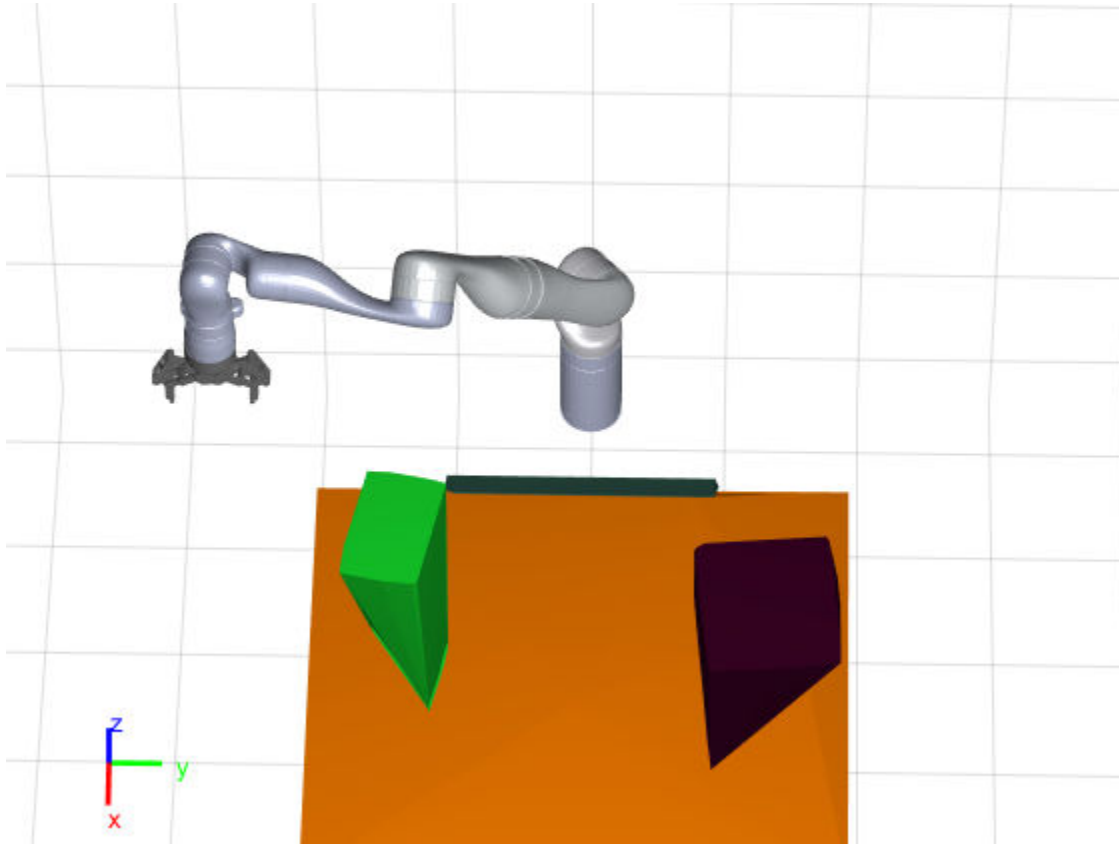
Now planning...

Waiting until robot reaches the desired configuration

Gripper closed...

Now planning...

Waiting until robot reaches the desired configuration



Gripper open...

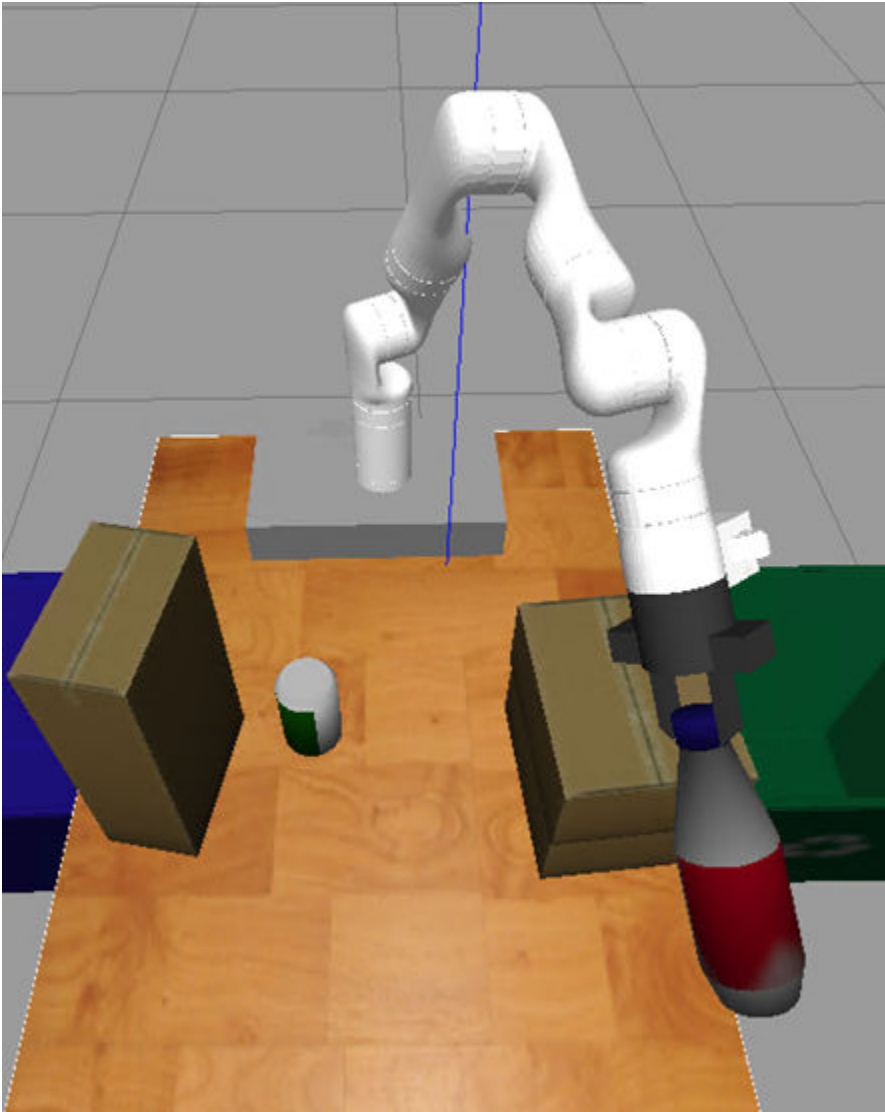
```
% Shut down ros when the pick-and-place application is done  
roshutdown;
```

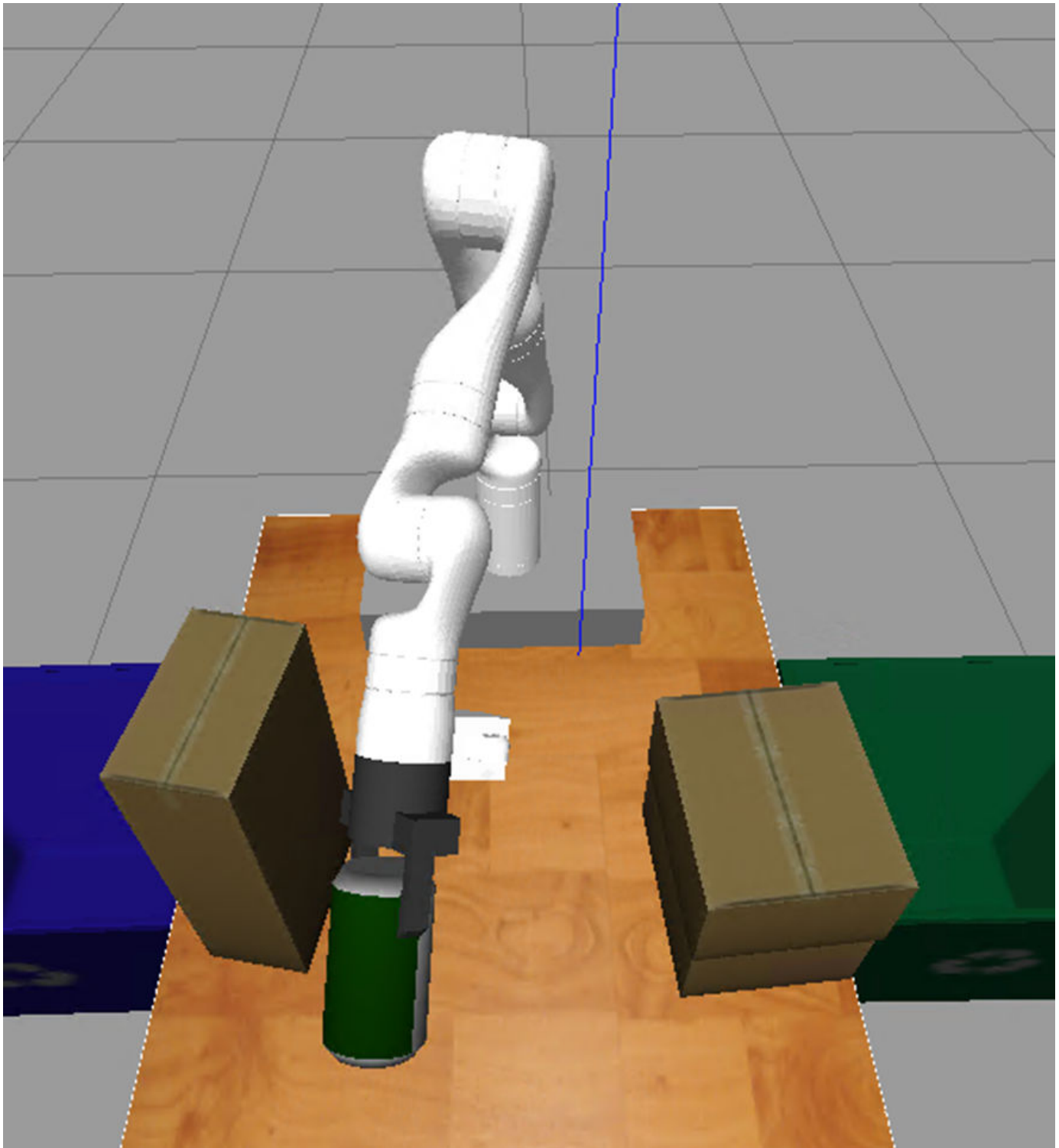
```
Shutting down global node /matlab_global_node_52545 with NodeURI http://192.168.203.1:53426/
```

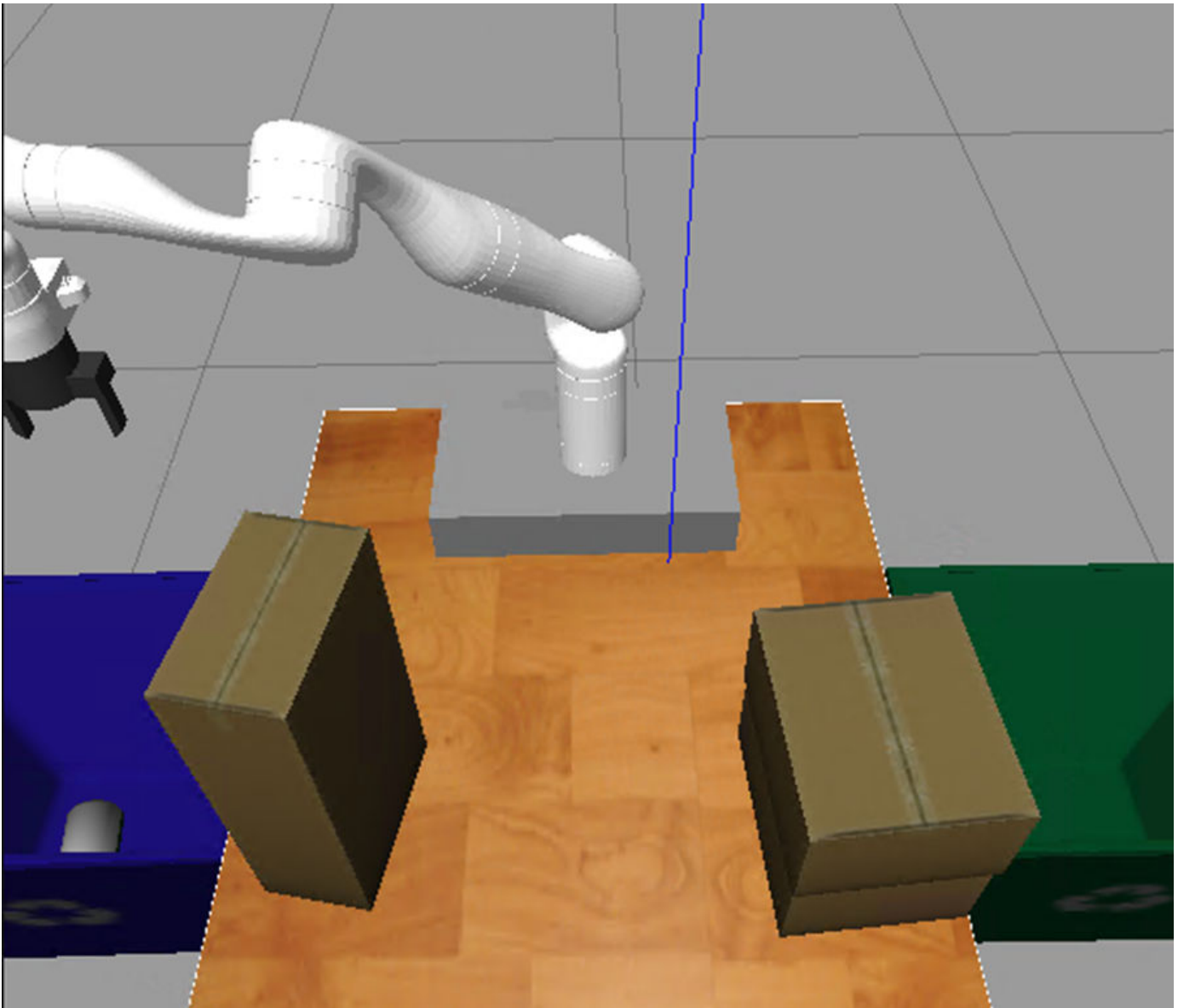
Visualize the Pick-and-Place Action in Gazebo

The Gazebo world shows the robot in the working area as it moves parts to the recycling bins. The robot continues working until all parts have been placed.









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Manipulator Shape Tracing in MATLAB and Simulink

This example shows how to trace a predefined 3-D shape in space. Following a smooth, distinct path is useful in many robotics applications such as welding, manufacturing, or inspection. A 3-D trajectory is solved in the task space for tracing the MATLAB® membrane and is executed using the Sawyer robot from Rethink Robotics®. The goal is to generate a smooth path for the end effector for the robot to follow based.

The “Manipulator Shape Tracing in MATLAB and Simulink” on page 1-250 example shows how to generate a closely discretized set of segments that can then be passed to an inverse kinematics solver to be solved using an iterative solution. However, this example offers an alternate approach to reduce computational complexity. This example splits paths segments into just a few discrete points and uses smoothing functions to interpolate between the waypoints. This approach should generate a smoother trajectory and improve run-time efficiency.

Load the Robot

This example uses the Sawyer robot from Rethink Robotics®. Import the URDF file that specifies the rigid body dynamics. Set the `DataFormat` to use column vectors to define robot configurations. Simulink® uses column vectors. The task space limits are defined based on empirical data.

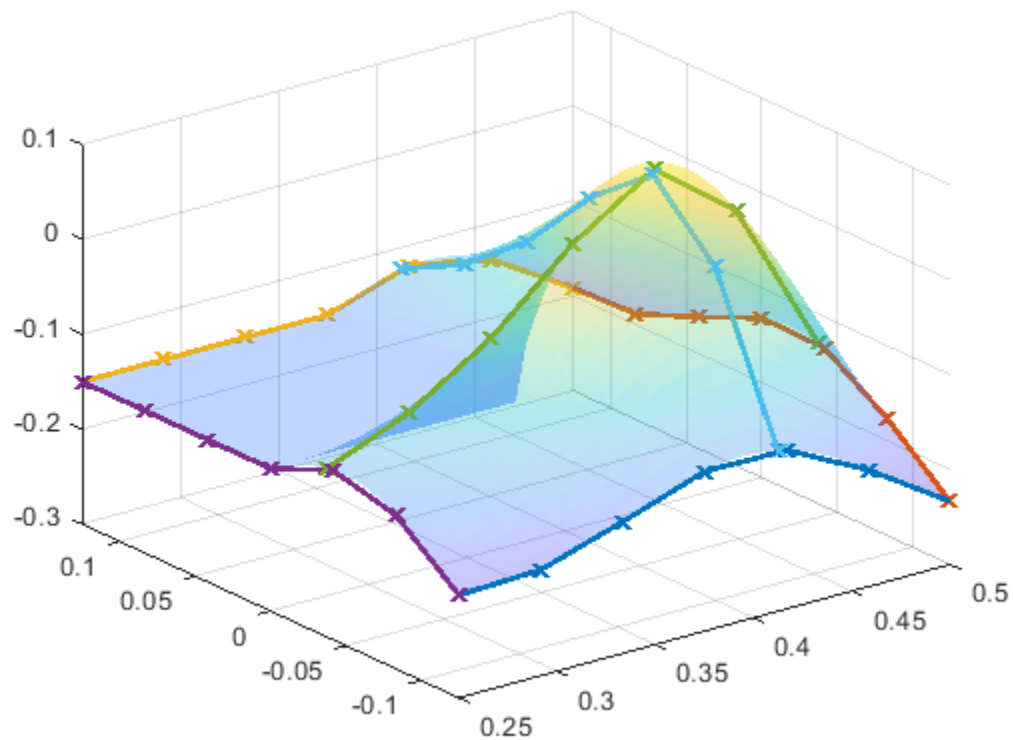
```
sawyer = importrobot('sawyer.urdf');
sawyer.DataFormat = 'column';
taskSpaceLimits = [0.25 0.5; -0.125 0.125; -0.15 0.1];
numJoints = 8; % Number of joints in robot
```

Generate a Set of Task-Space Waypoints

For this example, the goal is to get a set of path segments that trace the MATLAB® membrane logo. The membrane surface and the path segments are generated as cell arrays using the helper function `generateMembranePaths`. To visualize the paths overlaid on the surface, plot the surface using `surf` and the path segments by iterating through the path segment cell array. You can increase `numSamples` to sample more finely across the surface.

```
numSamples = 7;
[pathSegments, surface] = generateMembranePaths(numSamples, taskSpaceLimits);

% Visualize the output
figure
surf(surface{:}, 'FaceAlpha', 0.3, 'EdgeColor', 'none');
hold all
for i=1:numel(pathSegments)
    segment = pathSegments{i};
    plot3(segment(:,1), segment(:,2), segment(:,3), 'x-', 'LineWidth', 2);
end
hold off
```

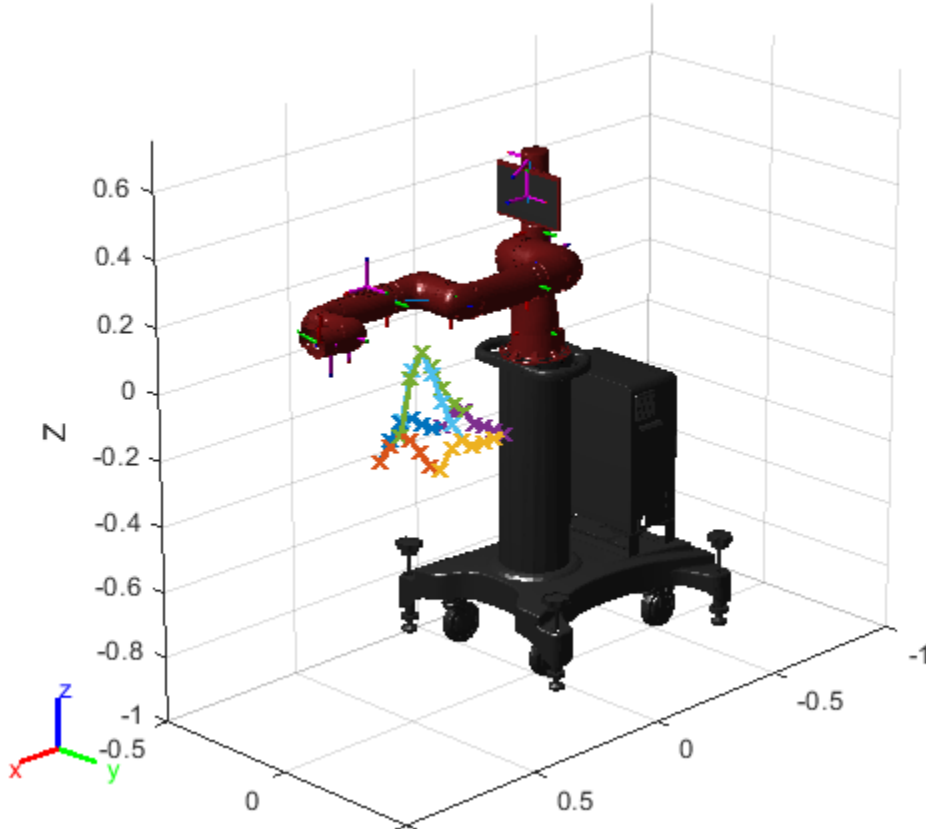



To ensure that the robot can trace the output, visualize the shape in the robot workspace. Show the sawyer robot and plot the line segments in the same figure.

```
figure
show(sawyer);
hold all

for i=1:numel(pathSegments)
    segment = pathSegments{i};
    plot3(segment(:,1),segment(:,2),segment(:,3),'x-','LineWidth',2);
end

view(135,20)
axis([-1 1 -.5 .5 -1 .75])
hold off
```



Create an Inverse Kinematics Solver

Create an inverse kinematics (IK) using the loaded sawyer rigid body tree . It is initially configured with a uniform set of weights, using the home configuration as the initial guess. Set the initial guess to the home configuration and the pose tolerances with uniform weights. The end effector for IK solver is the 'right_hand' body of the robot.

```
ik = inverseKinematics('RigidBodyTree', sawyer);
initialGuess = sawyer.homeConfiguration;
weights = [1 1 1 1 1 1];
eeName = 'right_hand';
```

Convert Task-Space Waypoints to Joint-Space Using Inverse Kinematics

Use the inverse kinematics solver to generate a set of joint space waypoints, which give the joint configurations for the robot at each point of the generated pathSegments. Each joint-space segment is filed into a matrix, jointPathSegmentMatrix, which is passed to the Simulink model as an input.

```
% Initialize the output matrix
jointPathSegmentMatrix = zeros(length(pathSegments), numJoints, numSamples);

% Define the orientation so that the end effector is oriented down
sawyerOrientation = axang2rotm([0 1 0 pi]);

% Compute IK at each waypoint along each segment
for i = 1:length(pathSegments)
    currentTaskSpaceSegment = pathSegments{i};
```

```

currentJointSegment = zeros(numJoints, length(currentTaskSpaceSegment));
for j = 1:length(currentTaskSpaceSegment)
    pose = [sawyerOrientation currentTaskSpaceSegment(j,:)' ; 0 0 0 1];
    currentJointSegment(:,j) = ik(eeName,pose,weights,initialGuess);
    initialGuess = currentJointSegment(:,j);
end

jointPathSegmentMatrix(i, :, :) = (currentJointSegment);
end

```

Load Simulink Model

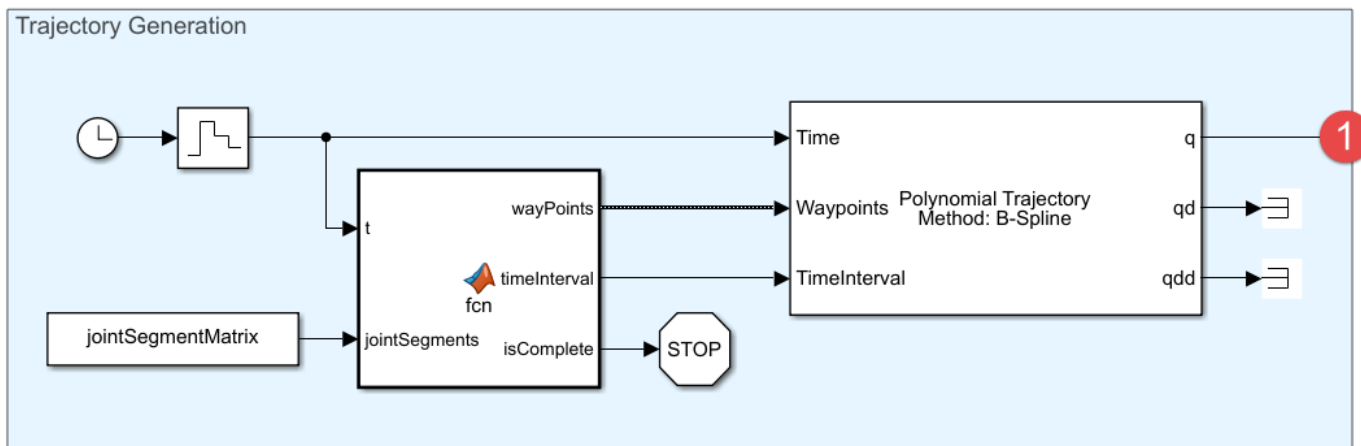
Use the `shapeTracingSawyer` model to execute the trajectories and simulate them on a kinematic model of the robot.

```
open_system("shapeTracingSawyer.slx")
```

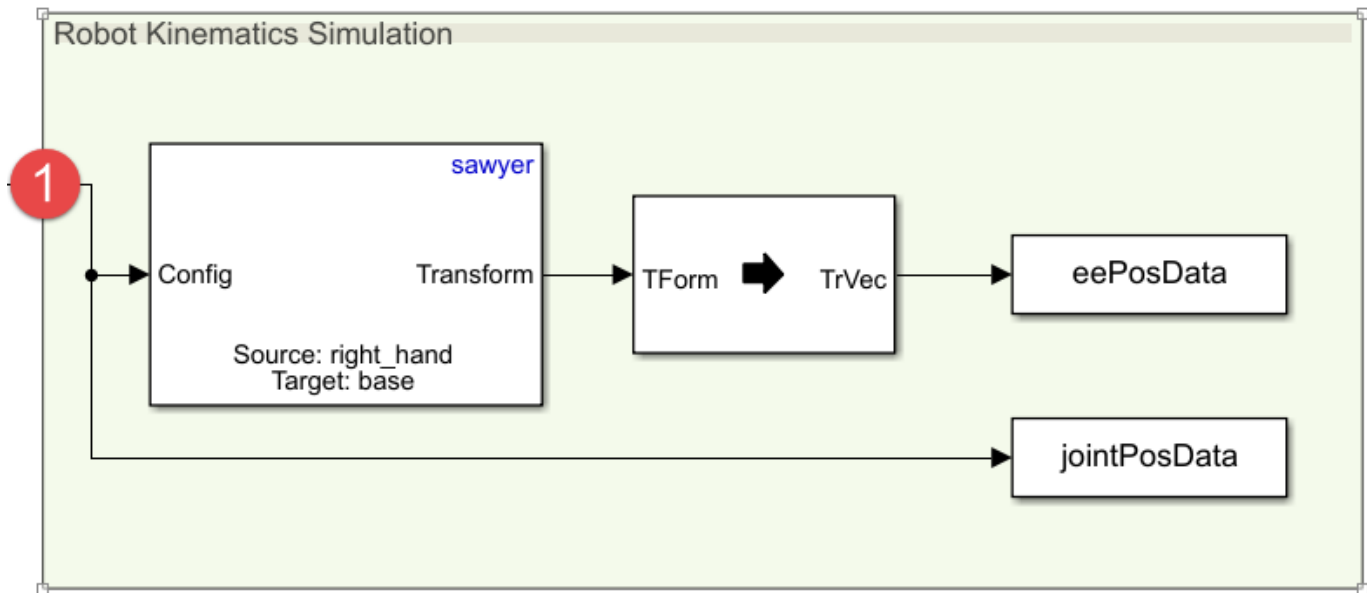
The Simulink model has two main parts:

- 1 The **Trajectory Generation** section takes the matrix of joint-space path segments, `jointPathSegmentMatrix`, and converts the segments to a set of discretized joint-space waypoints (joint configurations) at each time step in the simulation using a MATLAB function block. The **Polynomial Trajectory Block** converts the set of joint configurations to a smoothed joint space B-spline trajectory in time.
- 2 The **Robot Kinematics Simulation** section accepts the joint-space waypoints from the smoothed trajectory and computes the resulting end-effector position for the robot.

Trajectory Generation



Robot Kinematics Simulation



Execute Joint-Space Trajectories in Simulink

Simulate the model to execute the generate trajectories.

```
sim("shapeTracingSawyer.slx")
```

View Trajectory Generation Results

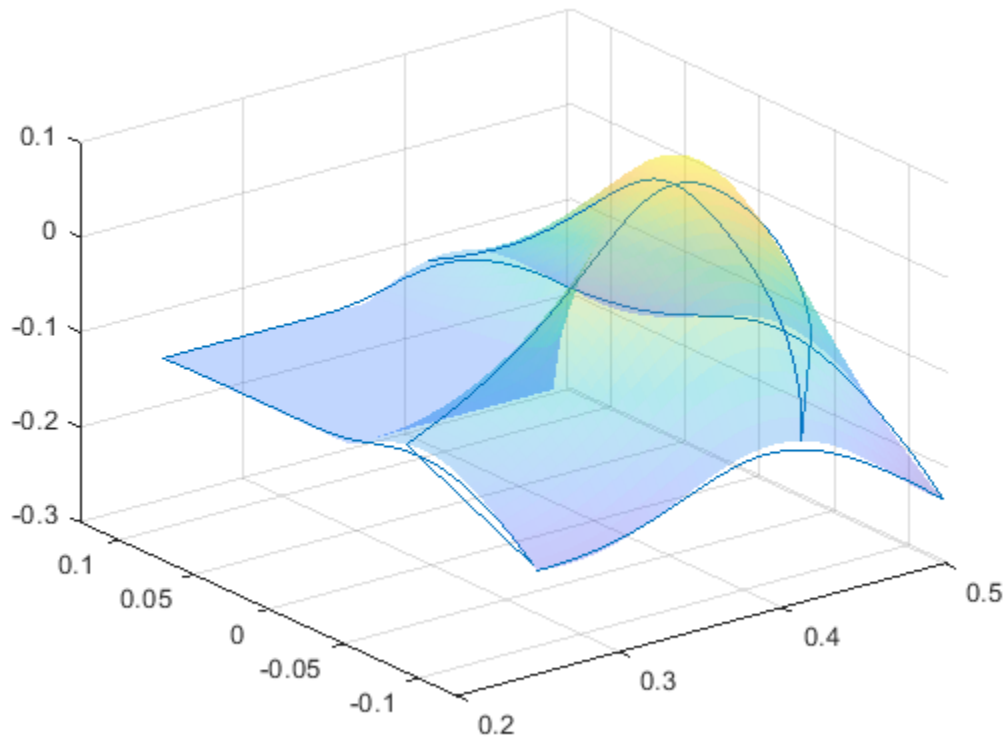
The model outputs the robot joint configurations and the end-effector positions along each smoothed path trajectory. To work easily with MATLAB plotting tools, reshape the data.

```
% End effector positions
xPositionsEE = reshape(eePosData.Data(1,:,:),1,size(eePosData.Data,3));
yPositionsEE = reshape(eePosData.Data(2,:,:),1,size(eePosData.Data,3));
zPositionsEE = reshape(eePosData.Data(3,:,:),1,size(eePosData.Data,3));

% Extract joint-space results
jointConfigurationData = reshape(jointPosData.Data, numJoints, size(eePosData.Data,3));
```

Plot the new end-effector positions on the original membrane surface.

```
figure
surf(surface{:},'FaceAlpha',0.3,'EdgeColor','none');
hold all
plot3(xPositionsEE,yPositionsEE,zPositionsEE)
grid on
hold off
```



Visualize Robot Motion

In addition to the visualization above, the tracing behavior can be recreated using the Sawyer robot model. Iterate through the joint configurations in `jointConfigurationData` to visualize the robot using `show` and continuously plot the end-effector position in 3-D space.

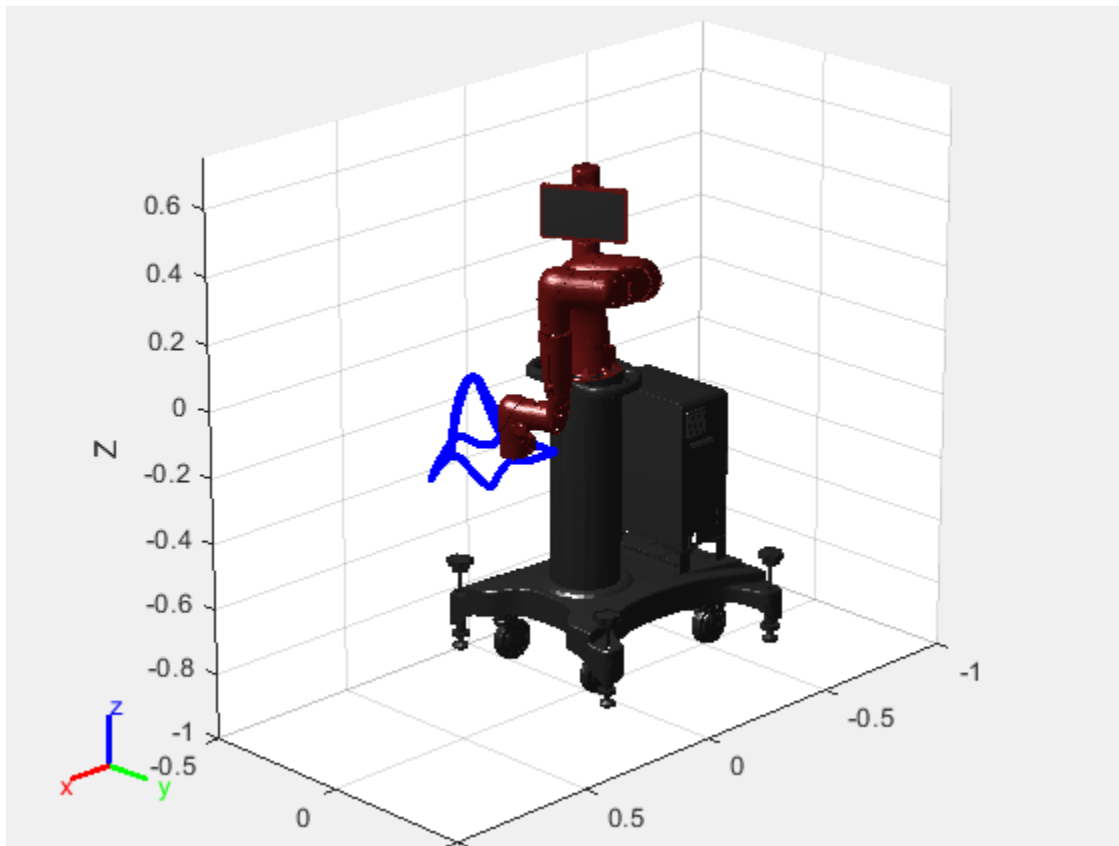
```
% For faster visualization, only display every few steps
vizStep = 5;

% Initialize a new figure window
figure
set(gcf, 'Visible', 'on');

% Iterate through all joint configurations and end-effector positions
for i = 1:vizStep:length(xPositionsEE)
    show(sawyer, jointConfigurationData(:,i), 'Frames', 'off', 'PreservePlot', false);
    hold on
    plot3(xPositionsEE(1:i), yPositionsEE(1:i), zPositionsEE(1:i), 'b', 'LineWidth', 3)

    view(135, 20)
    axis([-1 1 -0.5 0.5 -1 0.75])

    drawnow
end
hold off
```



Perform Co-Simulation between Simulink and Gazebo

This example shows how to setup synchronized simulation between Simulink and Gazebo, how to receive data from Gazebo, and send commands to Gazebo.

Setup Gazebo simulation environment

For this example, use your own Linux environment with Gazebo or download the provided [Virtual Machine with ROS and Gazebo](#). In the virtual machine (VM), the required Gazebo plugin is located in `/home/user/src/GazeboPlugin`.

The software requirements (included in VM) are:

Operating System: Ubuntu Xenial Xerus or Ubuntu Bionic Beaver

Software dependency: cmake 2.8, gazebo9, and libgazebo9-dev

If using your own Linux environment, follow the steps in **Install Gazebo Plugin Manually**.

Install Gazebo Plugin Manually

Obtain the plugin source code as a zip package. This function creates a folder called `GazeboPlugin` in your current working directory and compresses it as `GazeboPlugin.zip`.

```
packageGazeboPlugin
```

Copy the `GazeboPlugin.zip` to your Linux machine that meets the following requirement:

Unzip the package on your Linux platform, for this example we unpack to `/home/user/src/GazeboPlugin`.

Run the following commands in the terminal to compile the plugin to `/home/user/src/GazeboPlugin/export/lib/libGazeboCoSimPlugin.so`.

```
cd /home/user/src/GazeboPlugin
mkdir build
cd build
cmake ..
make
```

Remove the generated plugin from host computer.

```
if exist('GazeboPlugin', 'dir')
    rmdir('GazeboPlugin', 's');
end

if exist('GazeboPlugin.zip', 'file')
    delete('GazeboPlugin.zip');
end
```

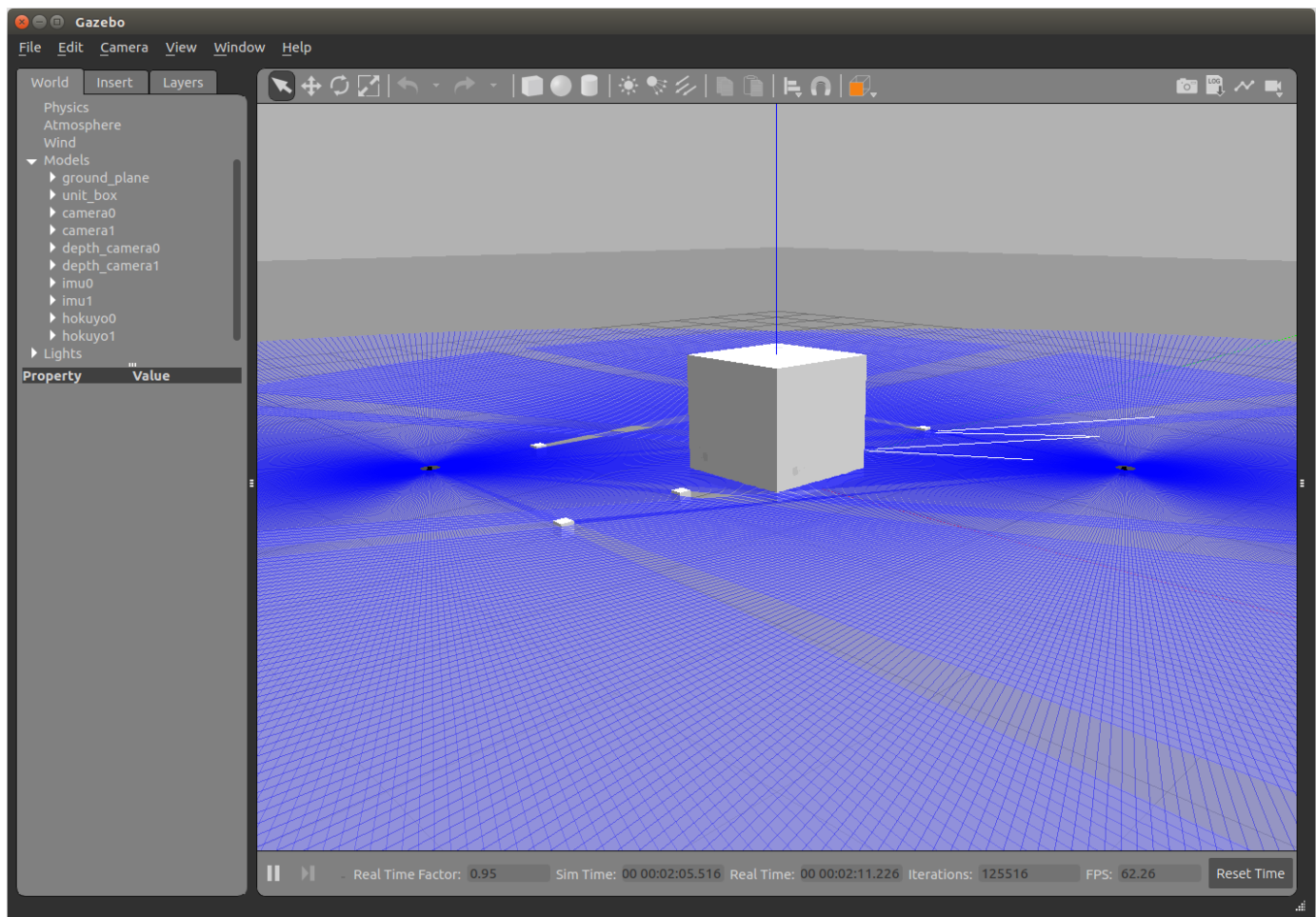
Launch Gazebo Simulation Environment

Open a terminal in the VM or your own Linux operating system, run the following commands to launch the Gazebo simulator.

```
cd /home/user/src/GazeboPlugin/export
export SVGA_VGPU10=0
gazebo ../world/multiSensorPluginTest.world --verbose
```

These commands launch a Gazebo simulator with:

- Two laser range finders: hokuyo0 and hokuyo1
- Two RGB cameras: camera0 and camera1
- Two depth cameras: depth_camera0 and depth_camera1
- Two IMU sensors: imu0 and imu1
- Unit box model: unit_box



The `multiSensorPluginTest.world` is located in `/home/user/src/GazeboPlugin/world` folder. This world file includes the Gazebo plugin for co-simulation with Simulink using the following lines in its `.xml` body:

```
<plugin name="GazeboPlugin" filename="lib/libGazeboCoSimPlugin.so"><portNumber>14581</portNumber>
```

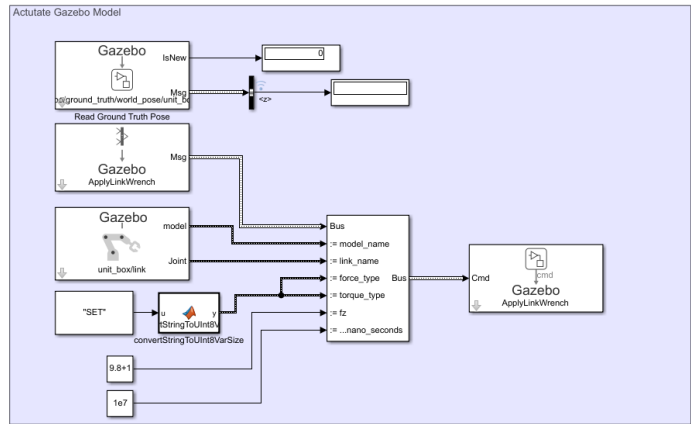
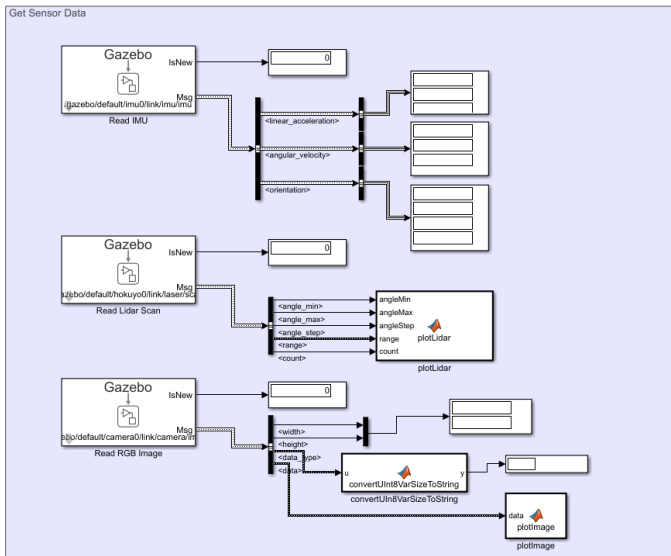
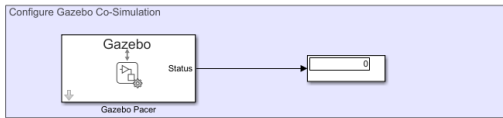
The filename field must be pointing to the location of the compiled Gazebo plugin. This path can be relative to the location Gazebo itself is launched, or you could add it to the Gazebo plugin search path by running:


```
export GAZEBO_PLUGIN_PATH=${GAZEBO_PLUGIN_PATH}:/home/user/src/GazeboPlugin/export
```

Configure Gazebo Co-Simulation

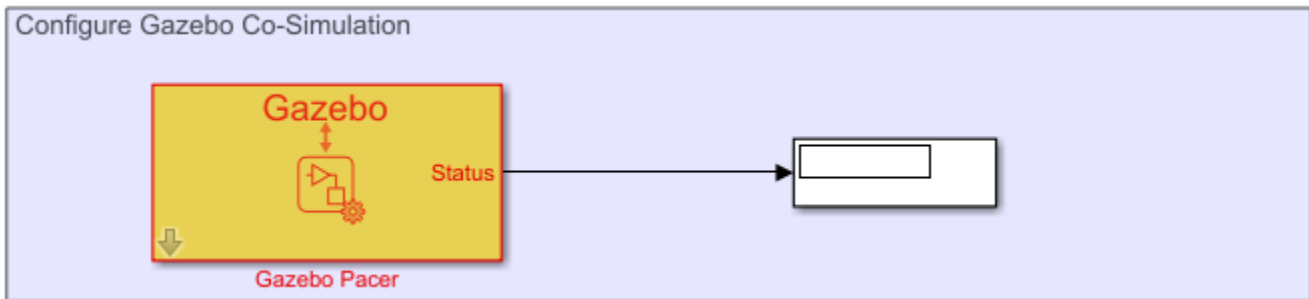
Open the performCoSimulationWithGazebo model, which demonstrates how to receive sensor data from these simulated sensors and how to actuate the unit box model from Simulink.

```
open_system("performCoSimulationWithGazebo")
```



Before simulating the model, configure Gazebo Co-Simulation using **Gazebo Pacer** block:

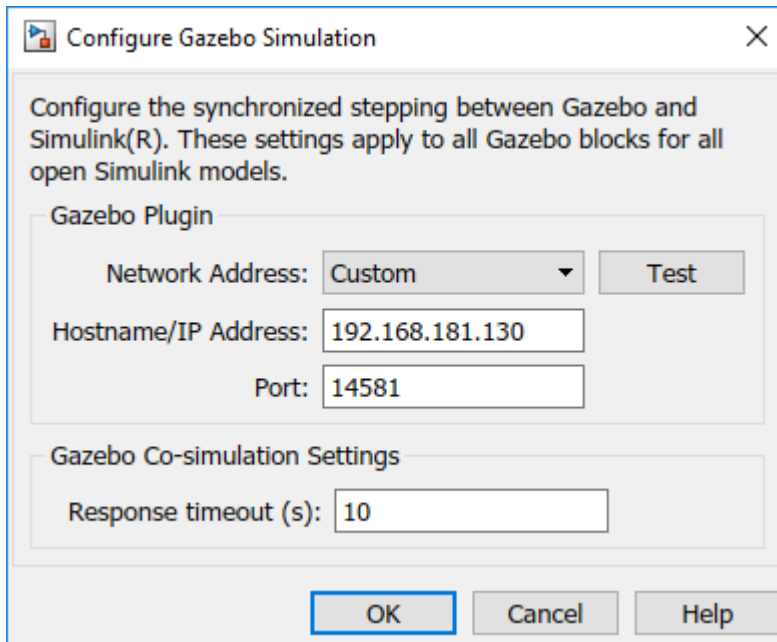
```
hilite_system('performCoSimulationWithGazebo/Gazebo Pacer')
```



Open the block and click the **Configure Gazebo network and simulation settings** link.

```
open_system('performCoSimulationWithGazebo/Gazebo Pacer')
```

In the **Network Address** drop down, select Custom. Enter the IP address of your Linux machine. The default **Port** for Gazebo is 14581. Set **Response timeout** to 10 seconds.



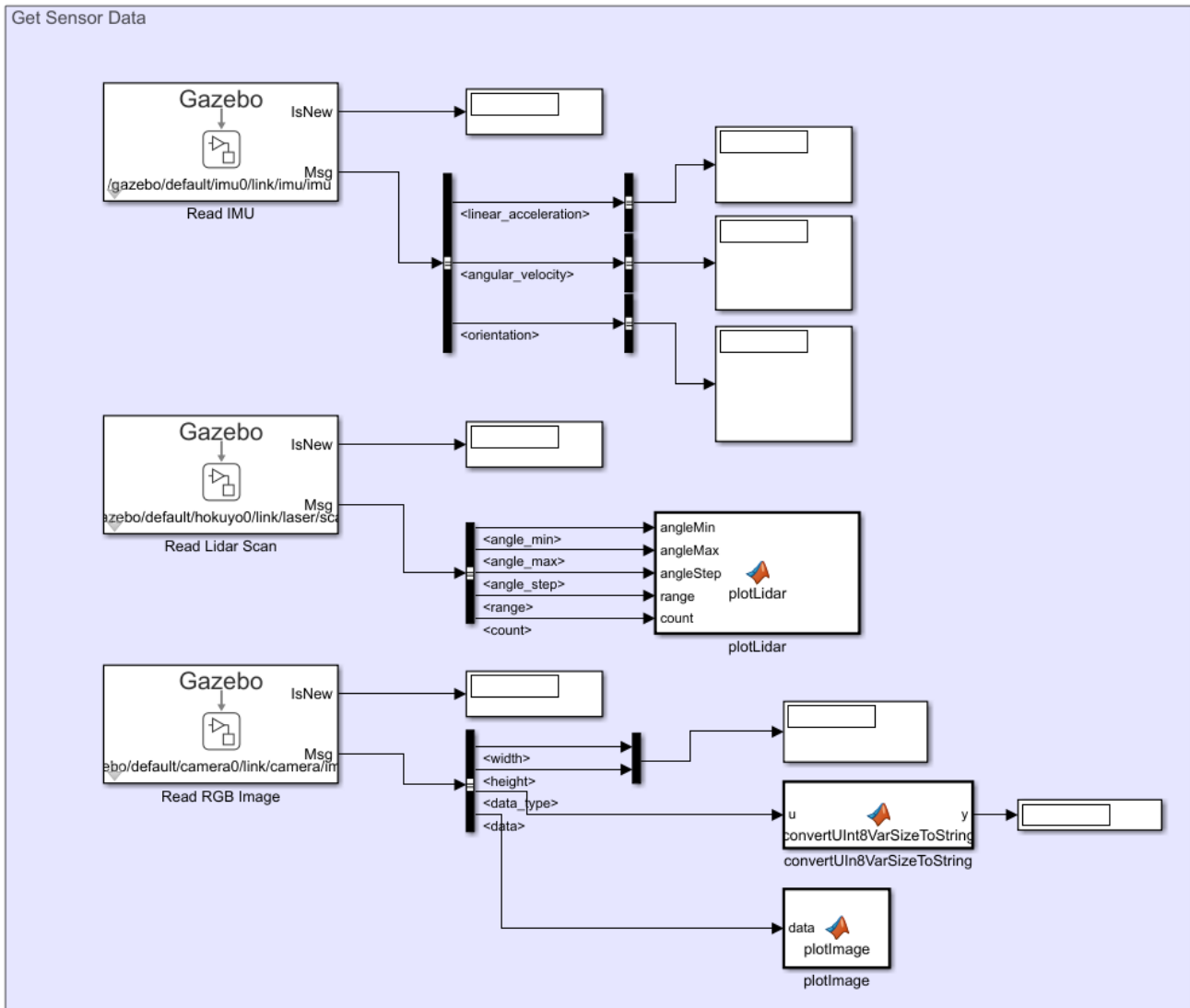
Click the **Test** button to test the connection to the running Gazebo simulator.

Get Sensor Data

Use the **Gazebo Read** block to obtain data on specific topics from three sensors:

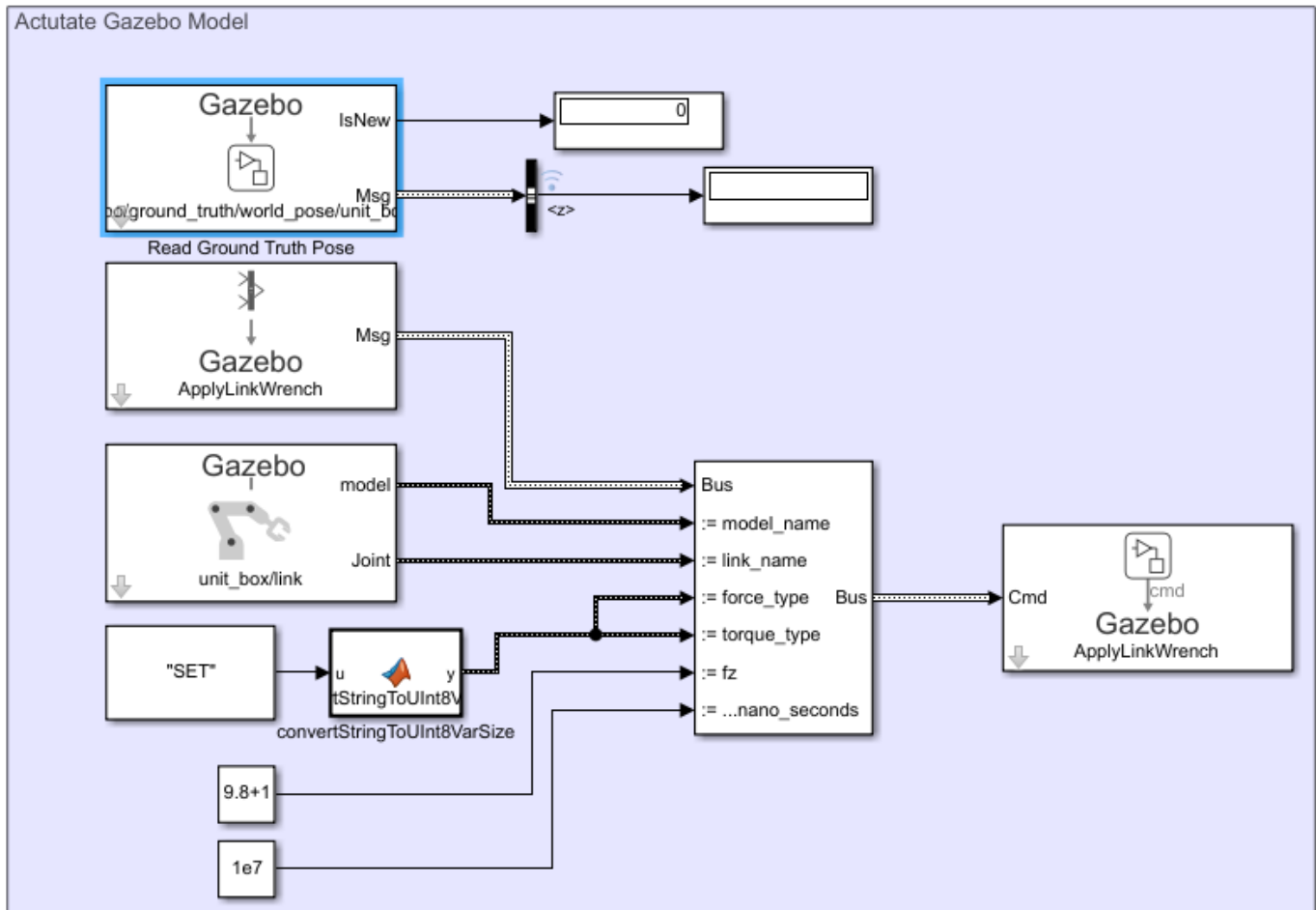
- IMU, /gazebo/default/imu0/link/imu/imu
- Lidar Scan, /gazebo/default/hokuyo0/link/laser/scan
- RGB camera, /gazebo/default/camera0/link/camera/image

Display the IMU readings and visualize the Lidar Scan and RGB Image using MATLAB® function blocks.



Actuate Gazebo Model

Use the **Gazebo Apply Command** block to apply a constant force in the z-direction to the unit box that results in an acceleration of 1 m/s^2 . Create a blank **ApplyLinkWrench** message using **Gazebo Blank Message**. Specify elements of the message to apply the force to the `unit_box/link` entity using the **Bus Assignment** block. Use **Gazebo Read** to output the ground truth pose of the box. The displacement of the box over a 1 second period should be close to 0.5 meters.



Perform Co-Simulation

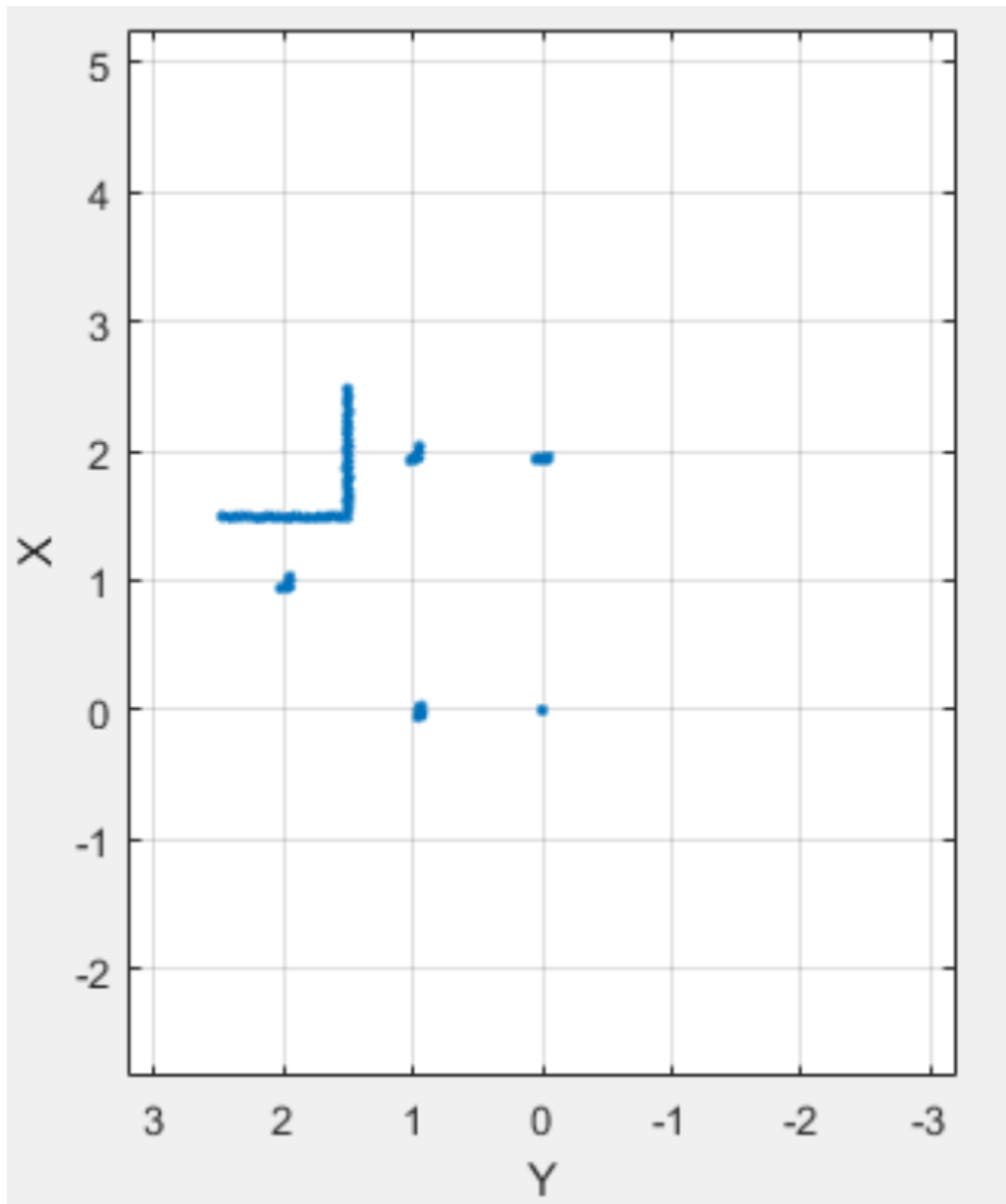
To start co-simulation, click **Run**. You can also step the simulation using **Step Forward**. **Step Back** is not supported during co-simulation.

While the simulation is running, notice that Gazebo simulator and Simulink time are synchronized.

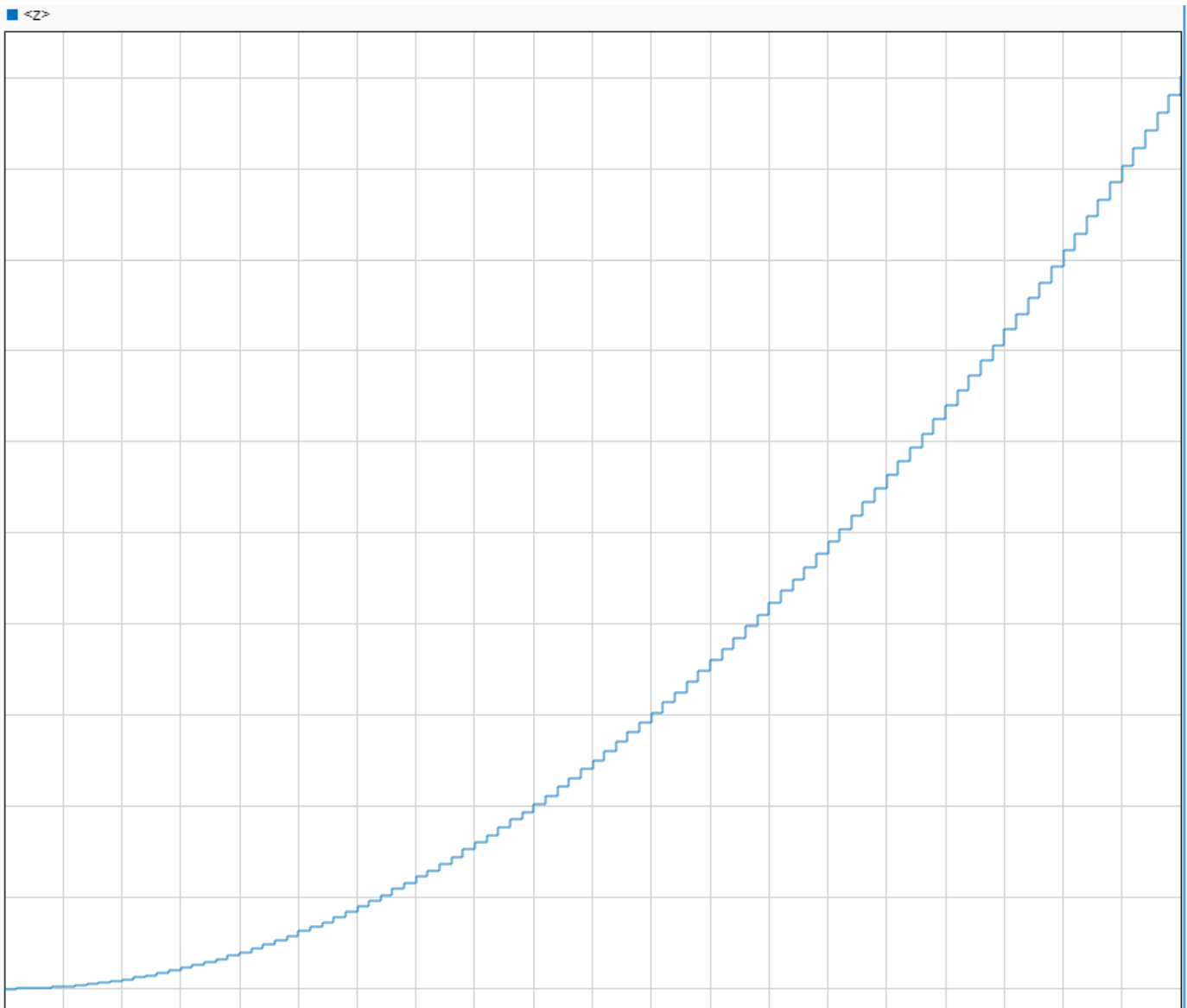
This model visualizes the Gazebo sensor data using MATLAB function block and MATLAB plotting functionalities. Here is a snapshot of the image data obtained from Gazebo camera:



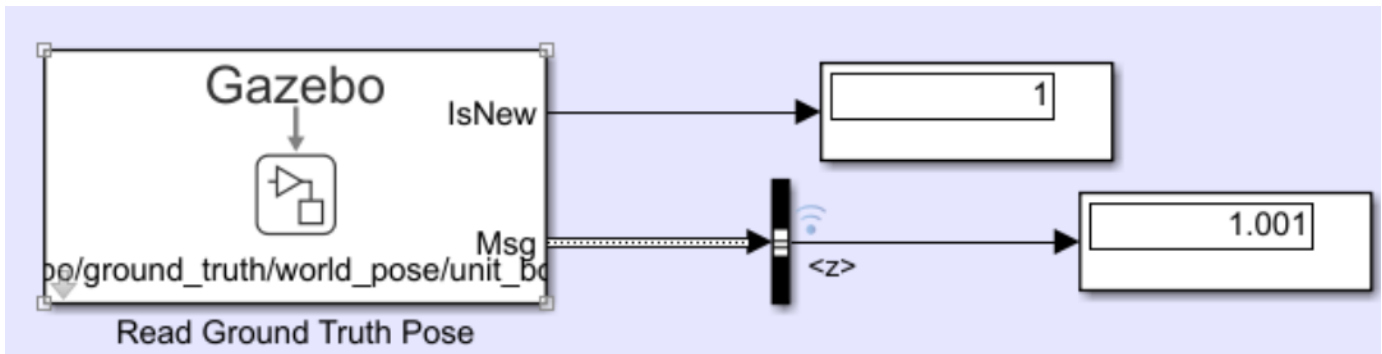
Here is a snapshot of the lidar scan image:



The time-plot of the position of the unit box block in z-direction can be viewed using **Data Inspector**. The block tracks a parabolic shape due to the constant acceleration over time.



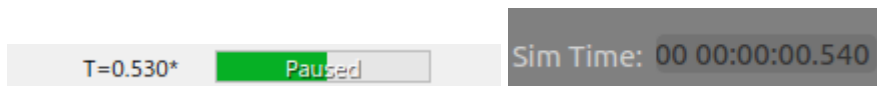
The position of the unit box at the end of simulation is 1.001, leading to a 0.5001 displacement, which is slightly different from the expected value of 0.5. This is due to the error of the Gazebo physics engine. Make the max step size in the Gazebo physics engine smaller to reduce this error.



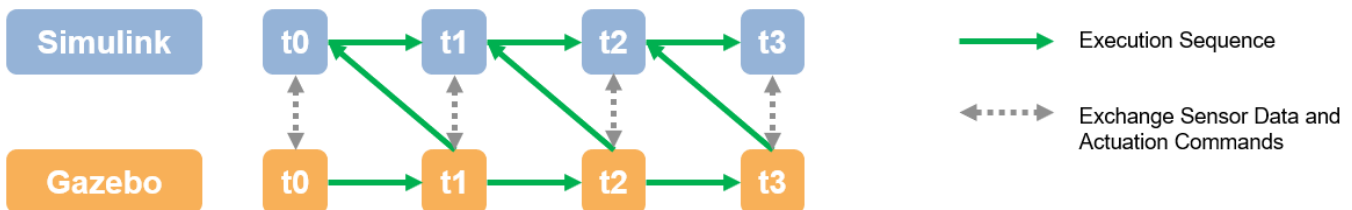
Time Synchronization

During co-simulation, you can pause Simulink and the Gazebo Simulator at any time using **Pause**

Note: Gazebo pauses one time step ahead of the simulation.



This is due to the following co-simulation time sequence:



Sensor data and actuation commands are exchanged at the correct time step. The execution chooses to step Gazebo first, then Simulink. The simulation execution is still on the $t+1$, Simulink just stays on the previous step time until you resume the model.

Next Steps

- “Control A Differential-Drive Robot in Gazebo With Simulink” on page 1-70

Robotics System Toolbox Topics

- “Rigid Body Tree Robot Model” on page 2-2
- “Build a Robot Step by Step” on page 2-6
- “Inverse Kinematics Algorithms” on page 2-10
- “2-D Path Tracing With Inverse Kinematics” on page 2-14
- “Solve Inverse Kinematics for a Four-Bar Linkage” on page 2-18
- “Robot Dynamics” on page 2-21
- “Occupancy Grids” on page 2-23
- “Probabilistic Roadmaps (PRM)” on page 2-27
- “Pure Pursuit Controller” on page 2-36
- “Particle Filter Parameters” on page 2-38
- “Particle Filter Workflow” on page 2-43
- “Standard Units for Robotics System Toolbox” on page 2-47
- “Coordinate Transformations in Robotics” on page 2-48
- “Execute Code at a Fixed-Rate” on page 2-52
- “Accelerate Robotics Algorithms with Code Generation” on page 2-55
- “Install Robotics System Toolbox Add-ons” on page 2-59
- “Code Generation from MATLAB Code” on page 2-60
- “Code Generation Support” on page 2-61

Rigid Body Tree Robot Model

In this section...
“Rigid Body Tree Components” on page 2-2
“Robot Configurations” on page 2-4

The rigid body tree model is a representation of a robot structure. You can use it to represent robots such as manipulators or other kinematic trees. Use `rigidBodyTree` objects to create these models.

A rigid body tree is made up of rigid bodies (`rigidBody`) that are attached via joints (`rigidBodyJoint`). Each rigid body has a joint that defines how that body moves relative to its parent in the tree. Specify the transformation from one body to the next by setting the fixed transformation on each joint (`setFixedTransform`).

You can add, replace, or remove bodies from the rigid body tree model. You can also replace joints for specific bodies. The `rigidBodyTree` object maintains the relationships and updates the `rigidBody` object properties to reflect this relationship. You can also get transformations between different body frames using `getTransform`.

Rigid Body Tree Components

Base

Every rigid body tree has a base. The base defines the world coordinate frame and is the first attachment point for a rigid body. The base cannot be modified, except for the `Name` property. You can do so by modifying the `BaseName` property of the rigid body tree.

Rigid Body

The rigid body is the basic building block of rigid body tree model and is created using `rigidBody`. A rigid body, sometimes called a link, represents a solid body that cannot deform. The distance between any two points on a single rigid body remains constant.



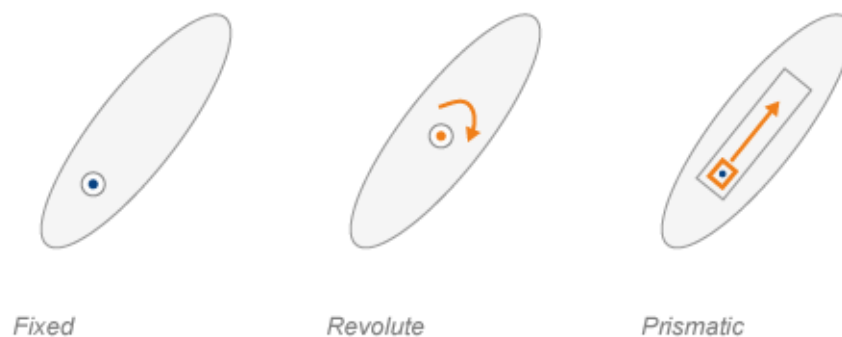
When added to a rigid body tree with multiple bodies, rigid bodies have parent or children bodies associated with them (`Parent` or `Children` properties). The parent is the body that this rigid body is attached to, which can be the robot base. The children are all the bodies attached to this body downstream from the base of the rigid body tree.

Each rigid body has a coordinate frame associated with them, and contains a `rigidBodyJoint` object.

Joint

Each rigid body has one joint, which defines the motion of that rigid body relative to its parent. It is the attachment point that connects two rigid bodies in a robot model. To represent a single physical body with multiple joints or different axes of motion, use multiple `rigidBody` objects.

The `rigidBodyJoint` object supports fixed, revolute, and prismatic joints.



These joints allow the following motion, depending on their type:

- 'fixed' — No motion. Body is rigidly connected to its parent.
- 'revolute' — Rotational motion only. Body rotates around this joint relative to its parent. Position limits define the minimum and maximum angular position in radians around the axis of motion.
- 'prismatic' — Translational motion only. The body moves linearly relative to its parent along the axis of motion.

Each joint has an axis of motion defined by the `JointAxis` property. The joint axis is a 3-D unit vector that either defines the axis of rotation (revolute joints) or axis of translation (prismatic joints). The `HomePosition` property defines the home position for that specific joint, which is a point within the position limits. Use `homeConfiguration` to return the home configuration for the robot, which is a collection of all the joints home positions in the model.

Joints also have properties that define the fixed transformation between parent and children body coordinate frames. These properties can only be set using the `setFixedTransform` method. Depending on your method of inputting transformation parameters, either the `JointToParentTransform` or `ChildToJointTransform` property is set using this method. The other property is set to the identity matrix. The following images depict what each property signifies.



- The `JointToParentTransform` defines where the joint of the child body is in relationship to the parent body frame. When `JointToParentTransform` is an identity matrix, the parent body and joint frames coincide.
- The `ChildToJointTransform` defines where the joint of the child body is in relationship to the child body frame. When `ChildToJointTransform` is an identity matrix, the child body and joint frames coincide.

Note The actual joint positions are not part of this `Joint` object. The robot model is stateless. There is an intermediate transformation between the parent and child joint frames that defines the position of the joint along the axis of motion. This transformation is defined in the robot configuration. See “Robot Configurations” on page 2-4.

Robot Configurations

After fully assembling your robot and defining transformations between different bodies, you can create robot configurations. A configuration defines all the joint positions of the robot by their joint names.

Use `homeConfiguration` to get the `HomePosition` property of each joint and create the home configuration.

Robot configurations are given as an array of structures.

```
config = homeConfiguration(robot)
```

```
config =
```

```
1x6 struct array with fields:
```

```
JointName  
JointPosition
```

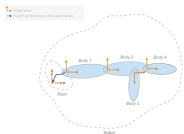
Each element in the array is a structure that contains the name and position of one of the robot joints.

```
config(1)
```

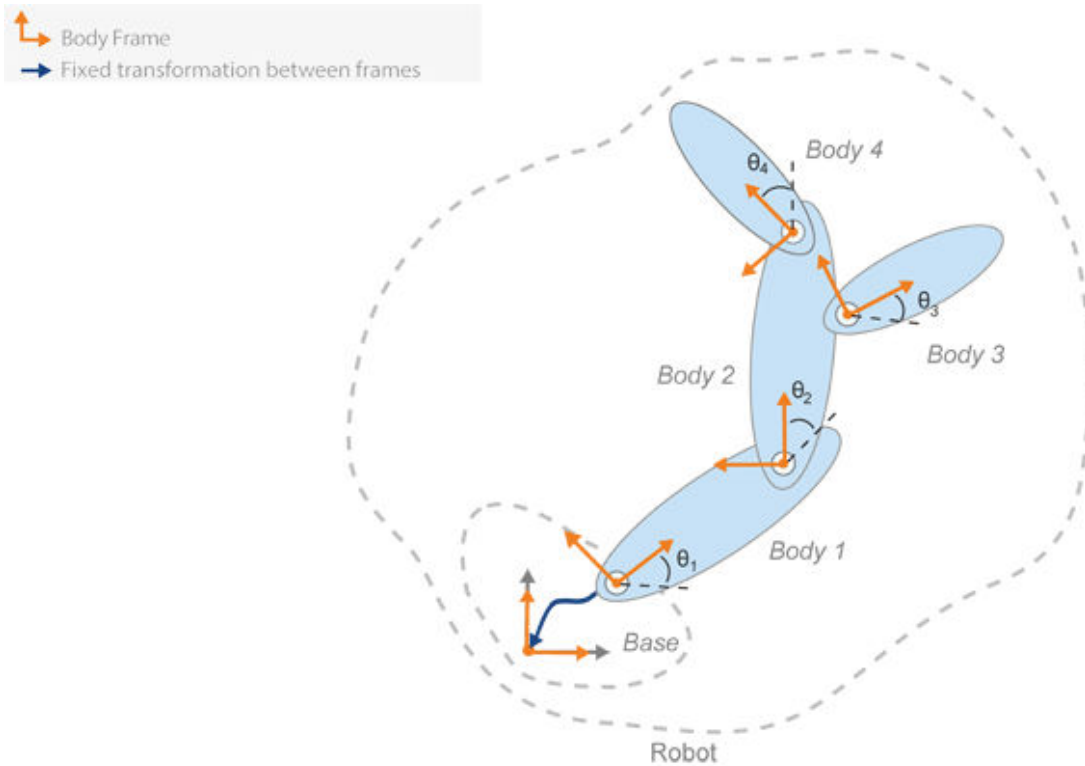
```
ans =
```

```
struct with fields:
```

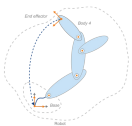
```
JointName: 'jnt1'  
JointPosition: 0
```



You can also generate a random configuration that obeys all the joint limits using `randomConfiguration`.



Use robot configurations when you want to plot a robot in a figure using `show`. Also, you can get the transformation between two body frames with a specific configuration using `getTransform`.



To get the robot configuration with a specified end-effector pose, use `inverseKinematics`. This algorithm solves for the required joint angles to achieve a specific pose for a specified rigid body.

See Also

`inverseKinematics` | `rigidBodyTree`

Related Examples

- “Build a Robot Step by Step” on page 2-6
- “Inverse Kinematics Algorithms” on page 2-10

Build a Robot Step by Step

This example goes through the process of building a robot step by step, showing you the different robot components and how functions are called to build it. Code sections are shown, but actual values for dimensions and transformations depend on your robot.

- 1 Create a rigid body object.

```
body1 = rigidBody('body1');
```



- 2 Create a joint and assign it to the rigid body. Define the home position property of the joint, HomePosition. Set the joint-to-parent transform using a homogeneous transformation, tform. Use the trvec2tform function to convert from a translation vector to a homogenous transformation. ChildToJointTransform is set to an identity matrix.

```
jnt1 = rigidBodyJoint('jnt1','revolute');
jnt1.HomePosition = pi/4;
tform = trvec2tform([0.25, 0.25, 0]); % User defined
setFixedTransform(jnt1,tform);
body1.Joint = jnt1;
```



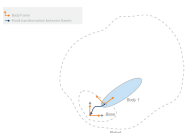
- 3 Create a rigid body tree. This tree is initialized with a base coordinate frame to attach bodies to.

```
robot = rigidBodyTree;
```



- 4 Add the first body to the tree. Specify that you are attaching it to the base of the tree. The fixed transform defined previously is from the base (parent) to the first body.

```
addBody(robot, body1, 'base')
```

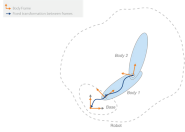


- 5 Create a second body. Define properties of this body and attach it to the first rigid body. Define the transformation relative to the previous body frame.

```

body2 = rigidBody('body2');
jnt2 = rigidBodyJoint('jnt2','revolute');
jnt2.HomePosition = pi/6; % User defined
tform2 = trvec2tform([1, 0, 0]); % User defined
setFixedTransform(jnt2,tform2);
body2.Joint = jnt2;
addBody(robot,body2,'body1'); % Add body2 to body1

```

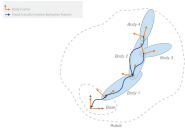


- 6** Add other bodies. Attach body 3 and 4 to body 2.

```

body3 = rigidBody('body3');
body4 = rigidBody('body4');
jnt3 = rigidBodyJoint('jnt3','revolute');
jnt4 = rigidBodyJoint('jnt4','revolute');
tform3 = trvec2tform([0.6, -0.1, 0])*eul2tform([-pi/2, 0, 0]); % User defined
tform4 = trvec2tform([1, 0, 0]); % User defined
setFixedTransform(jnt3,tform3);
setFixedTransform(jnt4,tform4);
jnt3.HomePosition = pi/4; % User defined
body3.Joint = jnt3
body4.Joint = jnt4
addBody(robot,body3,'body2'); % Add body3 to body2
addBody(robot,body4,'body2'); % Add body4 to body2

```



- 7** If you have a specific end effector that you care about for control, define it as a rigid body with a fixed joint. For this robot, add an end effector to body4 so that you can get transformations for it.

```

bodyEndEffector = rigidBody('endeffector');
tform5 = trvec2tform([0.5, 0, 0]); % User defined
setFixedTransform(bodyEndEffector.Joint,tform5);
addBody(robot,bodyEndEffector,'body4');

```

- 8** Now that you have created your robot, you can generate robot configurations. With a given configuration, you can also get a transformation between two body frames using `getTransform`. Get a transformation from the end effector to the base.

```

config = randomConfiguration(robot)
tform = getTransform(robot,config,'endeffector','base')

```

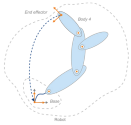
```
config =
```

```
1x2 struct array with fields:
```

```
JointName
JointPosition
```

```
tform =
```

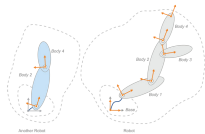
```
-0.5484    0.8362         0         0
-0.8362   -0.5484         0         0
         0         0    1.0000         0
         0         0         0    1.0000
```



Note This transform is specific to the dimensions specified in this example. Values for your robot vary depending on the transformations you define.

- 9 You can create a subtree from your existing robot or other robot models by using `subtree`. Specify the body name to use as the base for the new subtree. You can modify this subtree by adding, changing, or removing bodies.

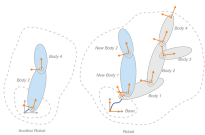
```
newArm = subtree(robot, 'body2');
removeBody(newArm, 'body3');
removeBody(newArm, 'endeffector');
```



- 10 You can also add these subtrees to the robot. Adding a subtree is similar to adding a body. The specified body name acts as a base for attachment, and all transformations on the subtree are relative to that body frame. Before you add the subtree, you must ensure all the names of bodies and joints are unique. Create copies of the bodies and joints, rename them, and replace them on the subtree. Call `addSubtree` to attach the subtree to a specified body.

```
newBody1 = copy(getBody(newArm, 'body2'));
newBody2 = copy(getBody(newArm, 'body4'));
newBody1.Name = 'newBody1';
newBody2.Name = 'newBody2';
newBody1.Joint = rigidBodyJoint('newJnt1', 'revolute');
newBody2.Joint = rigidBodyJoint('newJnt2', 'revolute');
tformTree = trvec2tform([0.2, 0, 0]); % User defined
setFixedTransform(newBody1.Joint, tformTree);
replaceBody(newArm, 'body2', newBody1);
replaceBody(newArm, 'body4', newBody2);
```

```
addSubtree(robot, 'body1', newArm);
```



- 11 Finally, you can use `showdetails` to look at the robot you built. Verify that the joint types are correct.

```
showdetails(robot)
```

Idx	Body Name	Joint Name	Joint Type	Parent Name(Idx)
-----	-----------	------------	------------	------------------


```

-----
1          body1          jnt1          revolte          base
2          body2          jnt2          revolte          body1(
3          body3          jnt3          revolte          body2(
4          body4          jnt4          revolte          body2(
5  endeffector  endeffector_jnt  fixed          body4(
6          newBody1      newJnt1          revolte          body1(
7          newBody2      newJnt2          revolte          newBody1(
-----

```

See Also

[inverseKinematics](#) | [rigidBodyTree](#)

Related Examples

- “Rigid Body Tree Robot Model” on page 2-2

Inverse Kinematics Algorithms

In this section...

“Choose an Algorithm” on page 2-10

“Solver Parameters” on page 2-11

“Solution Information” on page 2-12

“References” on page 2-12

The `inverseKinematics` and `generalizedInverseKinematics` classes give you access to inverse kinematics (IK) algorithms. You can use these algorithms to generate a robot configuration that achieves specified goals and constraints for the robot. This robot configuration is a list of joint positions that are within the position limits of the robot model and do not violate any constraints the robot has.

Choose an Algorithm

MATLAB® supports two algorithms for achieving an IK solution: the BFGS projection algorithm and the Levenberg-Marquardt algorithm. Both algorithms are iterative, gradient-based optimization methods that start from an initial guess at the solution and seek to minimize a specific cost function. If either algorithm converges to a configuration where the cost is close to zero within a specified tolerance, it has found a solution to the inverse kinematics problem. However, for some combinations of initial guesses and desired end effector poses, the algorithm may exit without finding an ideal robot configuration. To handle this, the algorithm utilizes a random restart mechanism. If enabled, the random restart mechanism restarts the iterative search from a random robot configuration whenever that search fails to find a configuration that achieves the desired end effector pose. These random restarts continue until either a qualifying IK solution is found, the maximum time has elapsed, or the iteration limit is reached.

To set your algorithm, specify the `SolverAlgorithm` property as either `'BFGSGradientProjection'` or `'LevenbergMarquardt'`.

BFGS Gradient Projection

The Broyden-Fletcher-Goldfarb-Shanno (BFGS) gradient projection algorithm is a quasi-Newton method that uses the gradients of the cost function from past iterations to generate approximate second-derivative information. The algorithm uses this second-derivative information in determining the step to take in the current iteration. A gradient projection method is used to deal with boundary limits on the cost function that the joint limits of the robot model create. The direction calculated is modified so that the search direction is always valid.

This method is the default algorithm and is more robust at finding solutions than the Levenberg-Marquardt method. It is more effective for configurations near joint limits or when the initial guess is not close to the solution. If your initial guess is close to the solution and a quicker solution is needed, consider the “Levenberg-Marquardt” on page 2-10 method.

Levenberg-Marquardt

The Levenberg-Marquardt (LM) algorithm variant used in the `InverseKinematics` class is an error-damped least-squares method. The error-damped factor helps to prevent the algorithm from escaping a local minimum. The LM algorithm is optimized to converge much faster if the initial guess is close to the solution. However the algorithm does not handle arbitrary initial guesses well. Consider using

this algorithm for finding IK solutions for a series of poses along a desired trajectory of the end effector. Once a robot configuration is found for one pose, that configuration is often a good initial guess at an IK solution for the next pose in the trajectory. In this situation, the LM algorithm may yield faster results. Otherwise, use the “BFGS Gradient Projection” on page 2-10 instead.

Solver Parameters

Each algorithm has specific tunable parameters to improve solutions. These parameters are specified in the `SolverParameters` property of the object.

BFGS Gradient Projection

The solver parameters for the BFGS algorithm have the following fields:

- `MaxIterations` — Maximum number of iterations allowed. The default is 1500.
- `MaxTime` — Maximum number of seconds that the algorithm runs before timing out. The default is 10.
- `GradientTolerance` — Threshold on the gradient of the cost function. The algorithm stops if the magnitude of the gradient falls below this threshold. Must be a positive scalar.
- `SolutionTolerance` — Threshold on the magnitude of the error between the end-effector pose generated from the solution and the desired pose. The weights specified for each component of the pose in the object are included in this calculation. Must be a positive scalar.
- `EnforceJointLimits` — Indicator if joint limits are considered in calculating the solution. `JointLimits` is a property of the robot model in `rigidBodyTree`. By default, joint limits are enforced.
- `AllowRandomRestarts` — Indicator if random restarts are allowed. Random restarts are triggered when the algorithm approaches a solution that does not satisfy the constraints. A randomly generated initial guess is used. `MaxIteration` and `MaxTime` are still obeyed. By default, random restarts are enabled.
- `StepTolerance` — Minimum step size allowed by the solver. Smaller step sizes usually mean that the solution is close to convergence. The default is 10^{-14} .

Levenberg-Marquardt

The solver parameters for the LM algorithm have the following extra fields in addition to what the “BFGS Gradient Projection” on page 2-11 method requires:

- `ErrorChangeTolerance` — Threshold on the change in end-effector pose error between iterations. The algorithm returns if the changes in all elements of the pose error are smaller than this threshold. Must be a positive scalar.
- `DampingBias` — A constant term for damping. The LM algorithm has a damping feature controlled by this constant that works with the cost function to control the rate of convergence. To disable damping, use the `UseErrorDamping` parameter.
- `UseErrorDamping` — 1 (default), Indicator of whether damping is used. Set this parameter to `false` to disable dampening.

Solution Information

While using the inverse kinematics algorithms, each call on the object returns solution information about how the algorithm performed. The solution information is provided as a structure with the following fields:

- `Iterations` — Number of iterations run by the algorithm.
- `NumRandomRestarts` — Number of random restarts because algorithm got stuck in a local minimum.
- `PoseErrorNorm` — The magnitude of the pose error for the solution compared to the desired end effector pose.
- `ExitFlag` — Code that gives more details on the algorithm execution and what caused it to return. For the exit flags of each algorithm type, see “Exit Flags” on page 2-12.
- `Status` — Character vector describing whether the solution is within the tolerance ('success') or the best possible solution the algorithm could find ('best available').

Exit Flags

In the solution information, the exit flags give more details on the execution of the specific algorithm. Look at the `Status` property of the object to find out if the algorithm was successful. Each exit flag code has a defined description.

'BFGSGradientProjection' algorithm exit flags:

- 1 — Local minimum found.
- 2 — Maximum number of iterations reached.
- 3 — Algorithm timed out during operation.
- 4 — Minimum step size. The step size is below the `StepToleranceSize` field of the `SolverParameters` property.
- 5 — No exit flag. Relevant to 'LevenbergMarquardt' algorithm only.
- 6 — Search direction invalid.
- 7 — Hessian is not positive semidefinite.

'LevenbergMarquardt' algorithm exit flags:

- 1 — Local minimum found.
- 2 — Maximum number of iterations reached.
- 3 — Algorithm timed out during operation.
- 4 — Minimum step size. The step size is below the `StepToleranceSize` field of the `SolverParameters` property.
- 5 — The change in end-effector pose error is below the `ErrorChangeTolerance` field of the `SolverParameters` property.

References

- [1] Badreddine, Hassan, Stefan Vandewalle, and Johan Meyers. "Sequential Quadratic Programming (SQP) for Optimal Control in Direct Numerical Simulation of Turbulent Flow." *Journal of Computational Physics*. 256 (2014): 1-16. doi:10.1016/j.jcp.2013.08.044.

- [2] Bertsekas, Dimitri P. *Nonlinear Programming*. Belmont, MA: Athena Scientific, 1999.
- [3] Goldfarb, Donald. "Extension of Davidon's Variable Metric Method to Maximization Under Linear Inequality and Equality Constraints." *SIAM Journal on Applied Mathematics*. Vol. 17, No. 4 (1969): 739-64. doi:10.1137/0117067.
- [4] Nocedal, Jorge, and Stephen Wright. *Numerical Optimization*. New York, NY: Springer, 2006.
- [5] Sugihara, Tomomichi. "Solvability-Unconcerned Inverse Kinematics by the Levenberg-Marquardt Method." *IEEE Transactions on Robotics* Vol. 27, No. 5 (2011): 984-91. doi:10.1109/tro.2011.2148230.
- [6] Zhao, Jianmin, and Norman I. Badler. "Inverse Kinematics Positioning Using Nonlinear Programming for Highly Articulated Figures." *ACM Transactions on Graphics* Vol. 13, No. 4 (1994): 313-36. doi:10.1145/195826.195827.

See Also

`generalizedInverseKinematics` | `inverseKinematics` | `rigidBodyTree`

Related Examples

- "2-D Path Tracing With Inverse Kinematics" on page 2-14
- "Control PR2 Arm Movements Using ROS Actions and Inverse Kinematics" on page 1-121
- "Rigid Body Tree Robot Model" on page 2-2

2-D Path Tracing With Inverse Kinematics

Introduction

This example shows how to calculate inverse kinematics for a simple 2D manipulator using the `inverseKinematics` class. The manipulator robot is a simple 2-degree-of-freedom planar manipulator with revolute joints which is created by assembling rigid bodies into a `rigidBodyTree` object. A circular trajectory is created in a 2-D plane and given as points to the inverse kinematics solver. The solver calculates the required joint positions to achieve this trajectory. Finally, the robot is animated to show the robot configurations that achieve the circular trajectory.

Construct The Robot

Create a `rigidBodyTree` object and rigid bodies with their associated joints. Specify the geometric properties of each rigid body and add it to the robot.

Start with a blank rigid body tree model.

```
robot = rigidBodyTree('DataFormat','column','MaxNumBodies',3);
```

Specify arm lengths for the robot arm.

```
L1 = 0.3;
L2 = 0.3;
```

Add 'link1' body with 'joint1' joint.

```
body = rigidBody('link1');
joint = rigidBodyJoint('joint1','revolute');
setFixedTransform(joint, trvec2tform([0 0 0]));
joint.JointAxis = [0 0 1];
body.Joint = joint;
addBody(robot, body, 'base');
```

Add 'link2' body with 'joint2' joint.

```
body = rigidBody('link2');
joint = rigidBodyJoint('joint2','revolute');
setFixedTransform(joint, trvec2tform([L1,0,0]));
joint.JointAxis = [0 0 1];
body.Joint = joint;
addBody(robot, body, 'link1');
```

Add 'tool' end effector with 'fix1' fixed joint.

```
body = rigidBody('tool');
joint = rigidBodyJoint('fix1','fixed');
setFixedTransform(joint, trvec2tform([L2, 0, 0]));
body.Joint = joint;
addBody(robot, body, 'link2');
```

Show details of the robot to validate the input properties. The robot should have two non-fixed joints for the rigid bodies and a fixed body for the end-effector.

```
showdetails(robot)
```

```
-----
Robot: (3 bodies)
```

Idx	Body Name	Joint Name	Joint Type	Parent Name(Idx)	Children Name(s)
1	link1	joint1	revolute	base(0)	link2(2)
2	link2	joint2	revolute	link1(1)	tool(3)
3	tool	fix1	fixed	link2(2)	

Define The Trajectory

Define a circle to be traced over the course of 10 seconds. This circle is in the xy plane with a radius of 0.15.

```
t = (0:0.2:10)'; % Time
count = length(t);
center = [0.3 0.1 0];
radius = 0.15;
theta = t*(2*pi/t(end));
points = center + radius*[cos(theta) sin(theta) zeros(size(theta))];
```

Inverse Kinematics Solution

Use an `inverseKinematics` object to find a solution of robotic configurations that achieve the given end-effector positions along the trajectory.

Pre-allocate configuration solutions as a matrix `qs`.

```
q0 = homeConfiguration(robot);
ndof = length(q0);
qs = zeros(count, ndof);
```

Create the inverse kinematics solver. Because the xy Cartesian points are the only important factors of the end-effector pose for this workflow, specify a non-zero weight for the fourth and fifth elements of the weight vector. All other elements are set to zero.

```
ik = inverseKinematics('RigidBodyTree', robot);
weights = [0, 0, 0, 1, 1, 0];
endEffector = 'tool';
```

Loop through the trajectory of points to trace the circle. Call the `ik` object for each point to generate the joint configuration that achieves the end-effector position. Store the configurations to use later.

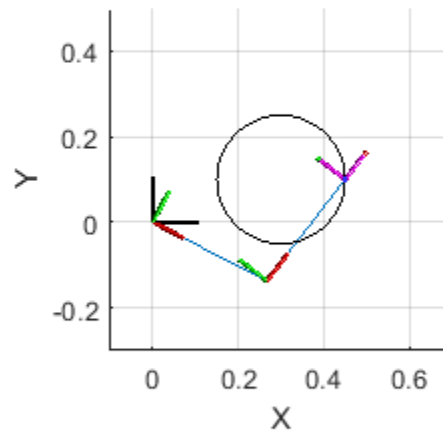
```
qInitial = q0; % Use home configuration as the initial guess
for i = 1:count
    % Solve for the configuration satisfying the desired end effector
    % position
    point = points(i,:);
    qSol = ik(endEffector, trvec2tform(point), weights, qInitial);
    % Store the configuration
    qs(i,:) = qSol;
    % Start from prior solution
    qInitial = qSol;
end
```

Animate The Solution

Plot the robot for each frame of the solution using that specific robot configuration. Also, plot the desired trajectory.

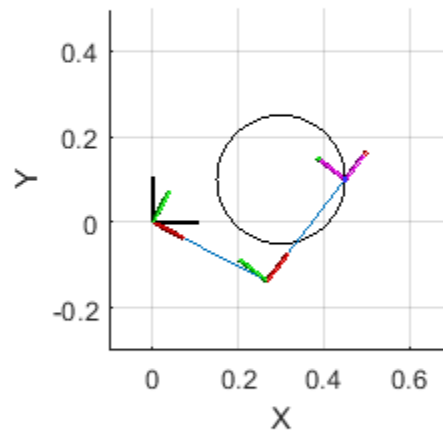
Show the robot in the first configuration of the trajectory. Adjust the plot to show the 2-D plane that circle is drawn on. Plot the desired trajectory.

```
figure
show(robot,qs(1,:));
view(2)
ax = gca;
ax.Projection = 'orthographic';
hold on
plot(points(:,1),points(:,2),'k')
axis([-0.1 0.7 -0.3 0.5])
```



Set up a `rateControl` object to display the robot trajectory at a fixed rate of 15 frames per second. Show the robot in each configuration from the inverse kinematic solver. Watch as the arm traces the circular trajectory shown.

```
framesPerSecond = 15;
r = rateControl(framesPerSecond);
for i = 1:count
    show(robot,qs(i,:),'PreservePlot',false);
    drawnow
    waitfor(r);
end
```

See Also

[inverseKinematics](#) | [rigidBody](#) | [rigidBodyJoint](#) | [rigidBodyTree](#)

Related Examples

- “Control PR2 Arm Movements Using ROS Actions and Inverse Kinematics” on page 1-121
- “Inverse Kinematics Algorithms” on page 2-10

Solve Inverse Kinematics for a Four-Bar Linkage

This example shows how to solve inverse kinematics for a four-bar linkage, a simple planar closed-chain linkage. Robotics System Toolbox™ doesn't directly support closed-loop mechanisms. However, the loop-closing joints can be approximated using kinematic constraints. This example shows how to setup a rigid body tree for a four-bar linkage, specify the kinematic constraints, and solve for a desired end-effector position.

Initialize the four-bar linkage rigid body tree model.

```
robot = rigidBodyTree('Dataformat','column','MaxNumBodies',7);
```

Define body names, parent names, joint names, joint types, and fixed transforms in cell arrays. The fixed transforms define the geometry of the four-bar linkage. The linkage rotates in the xz -plane. An offset of -0.1 is used in the y -axis on the 'b4' body to isolate the motion of the overlapping joints for 'b3' and 'b4'.

```
bodyNames = {'b1','b2','b3','b4','b5','b6'};
parentNames = {'base','b1','b2','base','b4','b5'};
jointNames = {'j1','j2','j3','j4','j5','j6'};
jointTypes = {'revolute','revolute','fixed','revolute','revolute','fixed'};
fixedTforms = {eye(4), ...
               trvec2tform([0 0 0.5]), ...
               trvec2tform([0.8 0 0]), ...
               trvec2tform([0.0 -0.1 0]), ...
               trvec2tform([0.8 0 0]), ...
               trvec2tform([0 0 0.5])};
```

Use a for loop to assemble the four-bar linkage:

- Create a rigid body and specify the joint type.
- Specify the `JointAxis` property for any non-fixed joints.
- Specify the fixed transformation.
- Add the body to the rigid body tree.

```
for k = 1:6
    b = rigidBody(bodyNames{k});
    b.Joint = rigidBodyJoint(jointNames{k},jointTypes{k});

    if ~strcmp(jointTypes{k},'fixed')
        b.Joint.JointAxis = [0 1 0];
    end

    b.Joint.setFixedTransform(fixedTforms{k});

    addBody(robot,b,parentNames{k});
end
```

Add a final body to function as the end-effector (handle) for the four-bar linkage.

```
bn = 'handle';
b = rigidBody(bn);
setFixedTransform(b.Joint,trvec2tform([0 -0.15 0]));
addBody(robot,b,'b6');
```

Specify kinematic constraints for the `GeneralizedInverseKinematics` object:

- **Position constraint 1** : The origins of 'b3' body frame and 'b6' body frame should always overlap. This keeps the handle in line with the approximated closed-loop mechanism. Use the -0.1 offset for the y-coordinate.
- **Position constraint 2** : End-effector should target the desired position.
- **Joint limit bounds** : Satisfy the joint limits in the rigid body tree model.

```
gik = generalizedInverseKinematics('RigidBodyTree',robot);
gik.ConstraintInputs = {'position',... % Position constraint for closed-loop mechanism
                       'position',... % Position constraint for end-effector
                       'joint'};      % Joint limits
gik.SolverParameters.AllowRandomRestart = false;

% Position constraint 1
positionTarget1 = constraintPositionTarget('b6','ReferenceBody','b3');
positionTarget1.TargetPosition = [0 -0.1 0];
positionTarget1.Weights = 50;
positionTarget1.PositionTolerance = 1e-6;

% Joint limit bounds
jointLimBounds = constraintJointBounds(gik.RigidBodyTree);
jointLimBounds.Weights = ones(1,size(gik.RigidBodyTree.homeConfiguration,1))*10;

% Position constraint 2
desiredEEPosition = [0.9 -0.1 0.9]'; % Position is relative to base.
positionTarget2 = constraintPositionTarget('handle');
positionTarget2.TargetPosition = desiredEEPosition;
positionTarget2.PositionTolerance = 1e-6;
positionTarget2.Weights = 1;
```

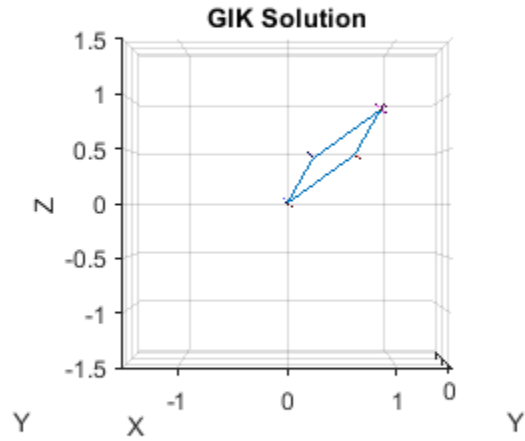
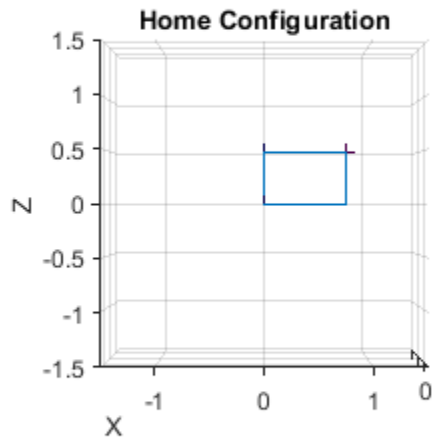
Compute the kinematic solution using the `gik` object. Specify the initial guess and the different kinematic constraints in the proper order.

```
iniGuess = homeConfiguration(robot);
[q, solutionInfo] = gik(iniGuess,positionTarget1,positionTarget2,jointLimBounds);
```

Examine the results in `solutionInfo`. Show the kinematic solution compared to the home configuration. Plots are shown in the `xz`-plane.

```
loopClosingViolation = solutionInfo.ConstraintViolations(1).Violation;
jointBndViolation = solutionInfo.ConstraintViolations(2).Violation;
eePositionViolation = solutionInfo.ConstraintViolations(3).Violation;

subplot(1,2,1)
show(robot,homeConfiguration(robot));
title('Home Configuration')
view([0 -1 0]);
subplot(1,2,2)
show(robot,q);
title('GIK Solution')
view([0 -1 0]);
```



See Also

Classes

`constraintJointBounds` | `constraintPoseTarget` | `generalizedInverseKinematics` | `inverseKinematics` | `rigidBodyTree`

Related Examples

- “Rigid Body Tree Robot Model” on page 2-2
- “Plan a Reaching Trajectory With Multiple Kinematic Constraints” on page 1-132

Robot Dynamics

In this section...

“Dynamics Properties” on page 2-21

“Dynamics Functions” on page 2-22

Robot dynamics is the relationship between the forces acting on a robot and the resulting motion of the robot. In Robotics System Toolbox, manipulator dynamics information is contained within a `rigidBodyTree` object. This object describes a rigid body tree model that has multiple `rigidBody` objects connected through `rigidBodyJoint` objects. The `rigidBodyJoint`, `rigidBody`, and `rigidBodyTree` objects all contain information related to the robot kinematics and dynamics.

Note To use dynamics functions, you must set the `DataFormat` property to 'row' or 'column'. This setting takes inputs and gives outputs as row or column vectors for relevant robotics calculations, such as robot configurations or joint torques.

Dynamics Properties

When working with robot dynamics, specify the information for individual bodies of your manipulator robot using properties on the `rigidBody` objects:

- **Mass** — Mass of the rigid body in kilograms.
- **CenterOfMass** — Center of mass position of the rigid body, specified as an [x y z] vector. The vector describes the location of the center of mass relative to the body frame in meters.
- **Inertia** — Inertia of rigid body, specified as an [Ixx Iyy Izz Iyz Ixz Ixy] vector relative to the body frame in kilogram square meters. The first three elements of the vector are the diagonal elements of the inertia tensor (moment of inertia). The last three elements are the off-diagonal elements of the inertia tensor (product of inertia). The inertia tensor is a positive definite matrix:

$$\begin{pmatrix} I_{xx} & I_{xy} & I_{xz} \\ I_{xy} & I_{yy} & I_{yz} \\ I_{xz} & I_{yz} & I_{zz} \end{pmatrix}$$

For information related to your whole manipulator robot model, specify these `rigidBodyTree` object properties:

- **Gravity** — Gravitational acceleration experienced by the robot, specified as an [x y z] vector in meters per second squared. By default, there is no gravitational acceleration.
- **DataFormat** — The input and output data format for the kinematics and dynamics functions. Set this property to 'row' or 'column' to use dynamics functions. This setting takes inputs and gives outputs as row or column vectors for relevant robotics calculations, such as robot configurations or joint torques.

Dynamics Functions

The following dynamics functions are available for robot manipulators. You can use these functions after specifying all the relevant dynamics properties on your `rigidBodyTree` robot model.

- `forwardDynamics` — Compute joint accelerations given joint torques and states
- `inverseDynamics` — Compute required joint torques given desired motion
- `externalForce` — Compose external force matrix relative to base
- `gravityTorque` — Compute joint torques that compensate gravity
- `centerOfMass` — Compute center of mass position and Jacobian
- `massMatrix` — Compute joint-space mass matrix
- `velocityProduct` — Compute joint torques that cancel velocity-induced forces

See Also

`generalizedInverseKinematics` | `inverseKinematics` | `rigidBodyTree`

Related Examples

- “Control PR2 Arm Movements Using ROS Actions and Inverse Kinematics” on page 1-121

Occupancy Grids

In this section...

“Overview” on page 2-23

“World, Grid, and Local Coordinates” on page 2-23

“Inflation of Coordinates” on page 2-24

Overview

Occupancy grids are used to represent a robot workspace as a discrete grid. Information about the environment can be collected from sensors in real time or be loaded from prior knowledge. Laser range finders, bump sensors, cameras, and depth sensors are commonly used to find obstacles in your robot’s environment.

Occupancy grids are used in robotics algorithms such as path planning (see `mobileRobotPRM` or `plannerRRT`). They are used in mapping applications for integrating sensor information in a discrete map, in path planning for finding collision-free paths, and for localizing robots in a known environment (see `monteCarloLocalization` or `matchScans`). You can create maps with different sizes and resolutions to fit your specific application.

For 3-D occupancy maps, see `occupancyMap3D`.

For 2-D occupancy grids, there are two representations:

- Binary occupancy grid (see `binaryOccupancyMap`)
- Probability occupancy grid (see `occupancyMap`)

A binary occupancy grid uses `true` values to represent the occupied workspace (obstacles) and `false` values to represent the free workspace. This grid shows where obstacles are and whether a robot can move through that space. Use a binary occupancy grid if memory size is a factor in your application.

A probability occupancy grid uses probability values to create a more detailed map representation. This representation is the preferred method for using occupancy grids. This grid is commonly referred to as simply an occupancy grid. Each cell in the occupancy grid has a value representing the probability of the occupancy of that cell. Values close to 1 represent a high certainty that the cell contains an obstacle. Values close to 0 represent certainty that the cell is not occupied and obstacle free. The probabilistic values can give better fidelity of objects and improve performance of certain algorithm applications.

Binary and probability occupancy grids share several properties and algorithm details. Grid and world coordinates apply to both types of occupancy grids. The inflation function also applies to both grids, but each grid implements it differently. The effects of the log-odds representation and probability saturation apply to probability occupancy grids only.

World, Grid, and Local Coordinates

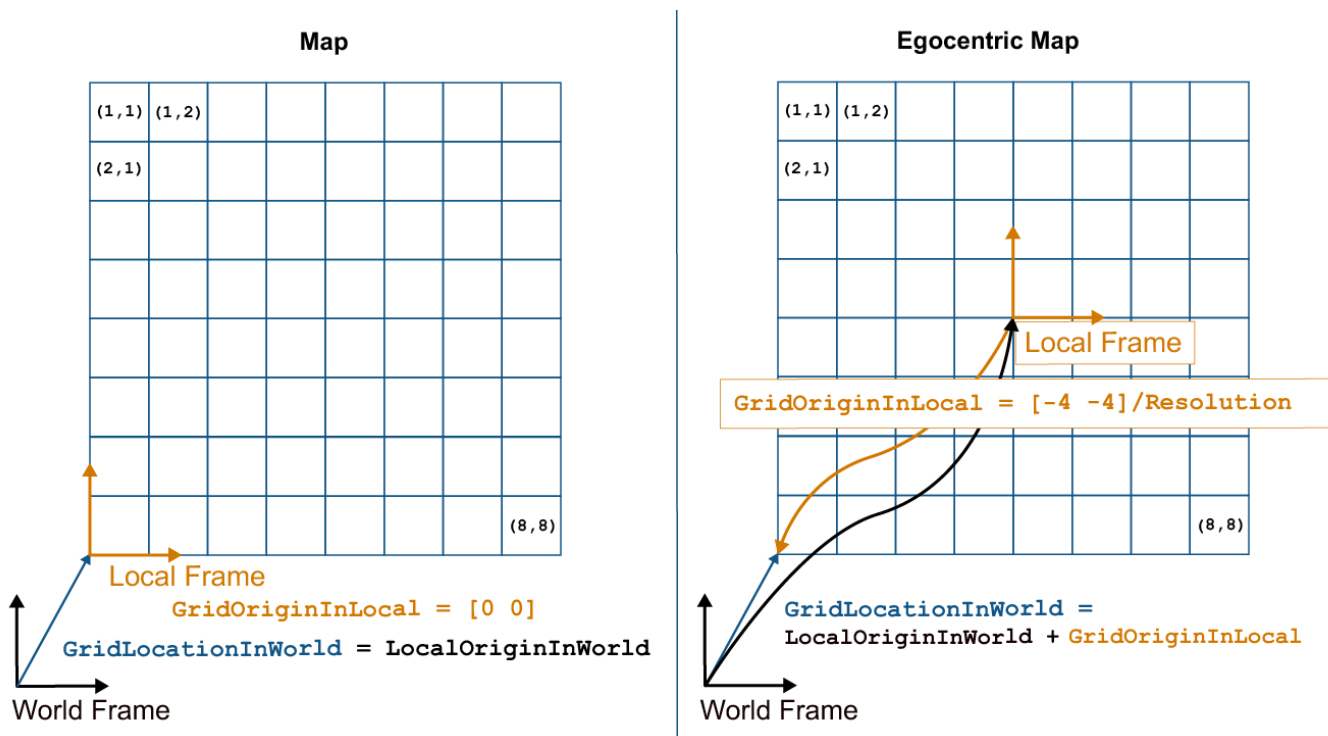
When working with occupancy grids in MATLAB, you can use either world, local, or grid coordinates.

The absolute reference frame in which the robot operates is referred to as the world frame in the occupancy grid. Most operations are performed in the world frame, and it is the default selection

when using MATLAB functions in this toolbox. World coordinates are used as an absolute coordinate frame with a fixed origin, and points can be specified with any resolution. However, all locations are converted to grid locations because of data storage and resolution limits on the map itself.

The local frame refers to the egocentric frame for a vehicle navigating the map. The `GridOriginInLocal` and `LocalOriginInWorld` properties define the origin of the grid in local coordinates and the relative location of the local frame in the world coordinates. You can adjust this local frame using the `move` function. For an example using the local frame as an egocentric map to emulate a vehicle moving around and sending local obstacles, see “Create Egocentric Occupancy Maps Using Range Sensors” (Navigation Toolbox).

Grid coordinates define the actual resolution of the occupancy grid and the finite locations of obstacles. The origin of grid coordinates is in the top-left corner of the grid, with the first location having an index of (1, 1). However, the `GridLocationInWorld` property of the occupancy grid in MATLAB defines the bottom-left corner of the grid in world coordinates. When creating an occupancy grid object, properties such as `XWorldLimits` and `YWorldLimits` are defined by the input width, height, and resolution. This figure shows a visual representation of these properties and the relation between world and grid coordinates.



Inflation of Coordinates

Both the binary and normal occupancy grids have an option for inflating obstacles. This inflation is used to add a factor of safety on obstacles and create buffer zones between the robot and obstacle in the environment. The `inflate` function of an occupancy grid object converts the specified radius to the number of cells rounded up from the `resolution*radius` value. Each algorithm uses this cell value separately to modify values around obstacles.

Binary Occupancy Grid

The `inflate` function takes each occupied cell and directly inflates it by adding occupied space around each point. This basic inflation example illustrates how the radius value is used.

Inflate Obstacles in a Binary Occupancy Grid

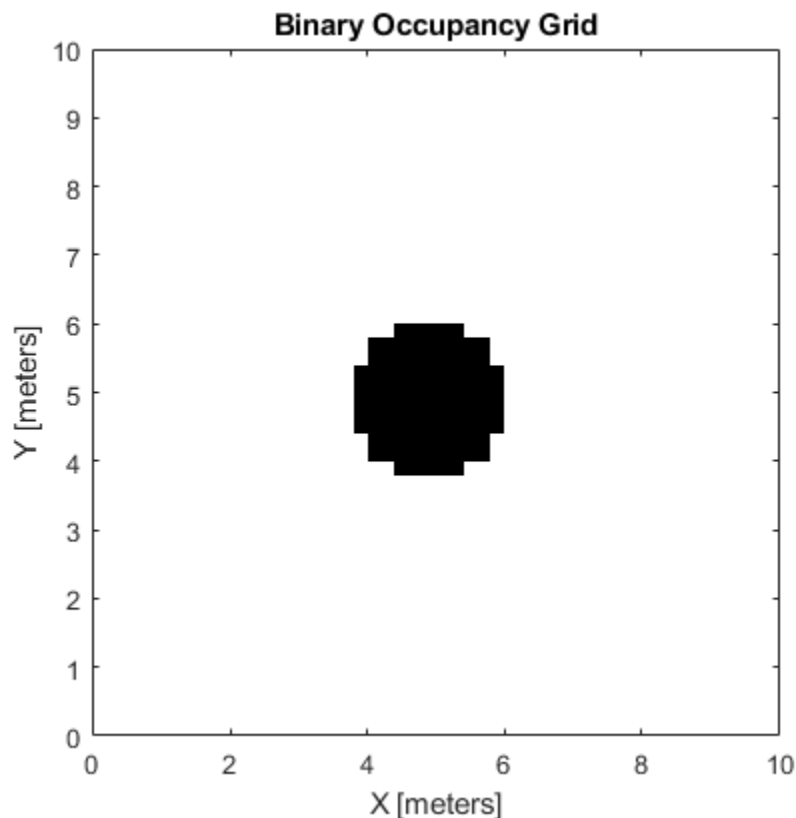
This example shows how to create the map, set the obstacle locations and inflate it by a radius of 1m. Extra plots on the figure help illustrate the inflation and shifting due to conversion to grid locations.

Create binary occupancy grid. Set occupancy of position [5,5].

```
map = binaryOccupancyMap(10,10,5);
setOccupancy(map,[5 5], 1);
```

Inflate occupied spaces on map by 1m.

```
inflate(map,1);
show(map)
```



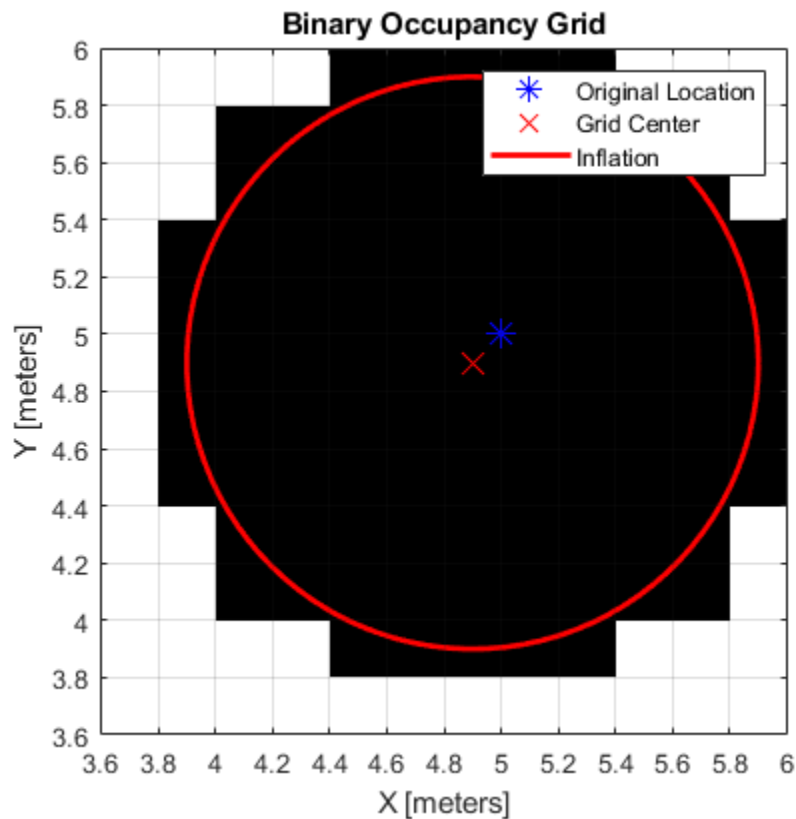
Plot original location, converted grid position and draw the original circle. You can see from this plot, that the grid center is [4.9 4.9], which is shifted from the [5 5] location. A 1m circle is drawn from there and notice that any cells that touch this circle are marked as occupied. The figure is zoomed in to the relevant area.

```
hold on
theta = linspace(0,2*pi);
```

```

x = 4.9+cos(theta); % x circle coordinates
y = 4.9+sin(theta); % y circle coordinates
plot(5,5,'*b','MarkerSize',10) % Original location
plot(4.9,4.9,'xr','MarkerSize',10) % Grid location center
plot(x,y,'-r','LineWidth',2); % Circle of radius 1m.
axis([3.6 6 3.6 6])
ax = gca;
ax.XTick = [3.6:0.2:6];
ax.YTick = [3.6:0.2:6];
grid on
legend('Original Location','Grid Center','Inflation')

```



As you can see from the above figure, even cells that barely overlap with the inflation radius are labeled as occupied.

See Also

[binaryOccupancyMap](#) | [occupancyMap](#) | [occupancyMap3D](#)

Related Examples

- “Create Egocentric Occupancy Maps Using Range Sensors” (Navigation Toolbox)
- “Build Occupancy Map from Lidar Scans and Poses” (Navigation Toolbox)

Probabilistic Roadmaps (PRM)

In this section...

“Tune the Number of Nodes” on page 2-27

“Tune the Connection Distance” on page 2-31

“Create or Update PRM” on page 2-33

A probabilistic roadmap (PRM) is a network graph of possible paths in a given map based on free and occupied spaces. The `mobileRobotPRM` object randomly generates nodes and creates connections between these nodes based on the PRM algorithm parameters. Nodes are connected based on the obstacle locations specified in `Map`, and on the specified `ConnectionDistance`. You can customize the number of nodes, `NumNodes`, to fit the complexity of the map and the desire to find the most efficient path. The PRM algorithm uses the network of connected nodes to find an obstacle-free path from a start to an end location. To plan a path through an environment effectively, tune the `NumNodes` and `ConnectionDistance` properties.

When creating or updating the `mobileRobotPRM` class, the node locations are randomly generated, which can affect your final path between multiple iterations. This selection of nodes occurs when you specify `Map` initially, change the parameters, or `update` is called. To get consistent results with the same node placement, use `rng` to save the state of the random number generation. See “Tune the Connection Distance” on page 2-31 for an example using `rng`.

Tune the Number of Nodes

Use the `NumNodes` property on the `mobileRobotPRM` object to tune the algorithm. `NumNodes` specifies the number of points, or nodes, placed on the map, which the algorithm uses to generate a roadmap. Using the `ConnectionDistance` property as a threshold for distance, the algorithm connects all points that do not have obstacles blocking the direct path between them.

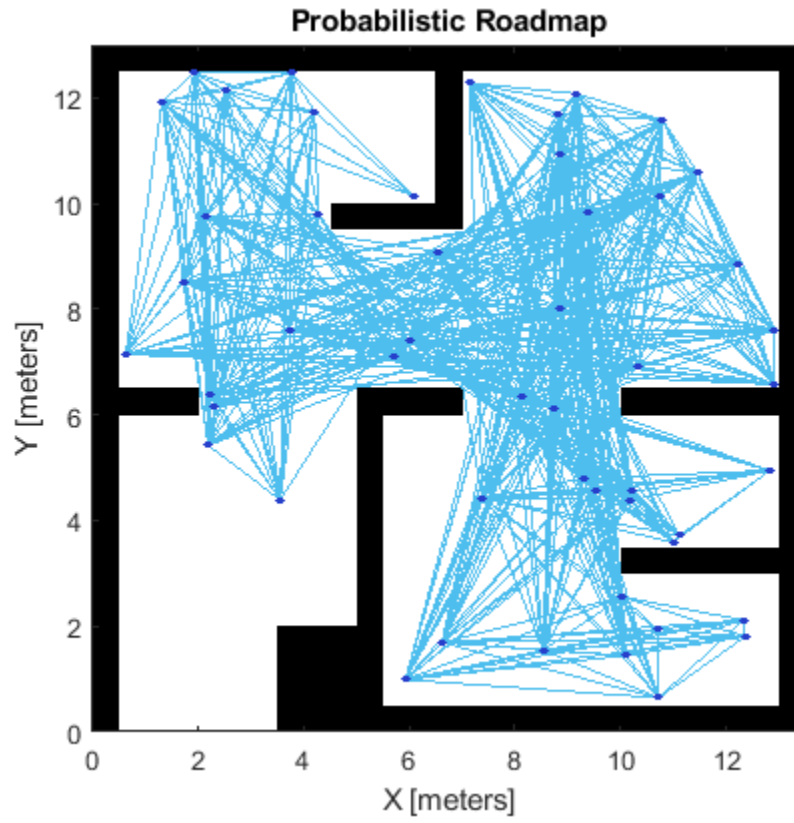
Increasing the number of nodes can increase the efficiency of the path by giving more feasible paths. However, the increased complexity increases computation time. To get good coverage of the map, you might need a large number of nodes. Due to the random placement of nodes, some areas of the map may not have enough nodes to connect to the rest of the map. In this example, you create a large and small number of nodes in a roadmap.

Load a map file as a logical matrix, `simpleMaps`, and create an occupancy grid.

```
load exampleMaps.mat
map = binaryOccupancyMap(simpleMap,2);
```

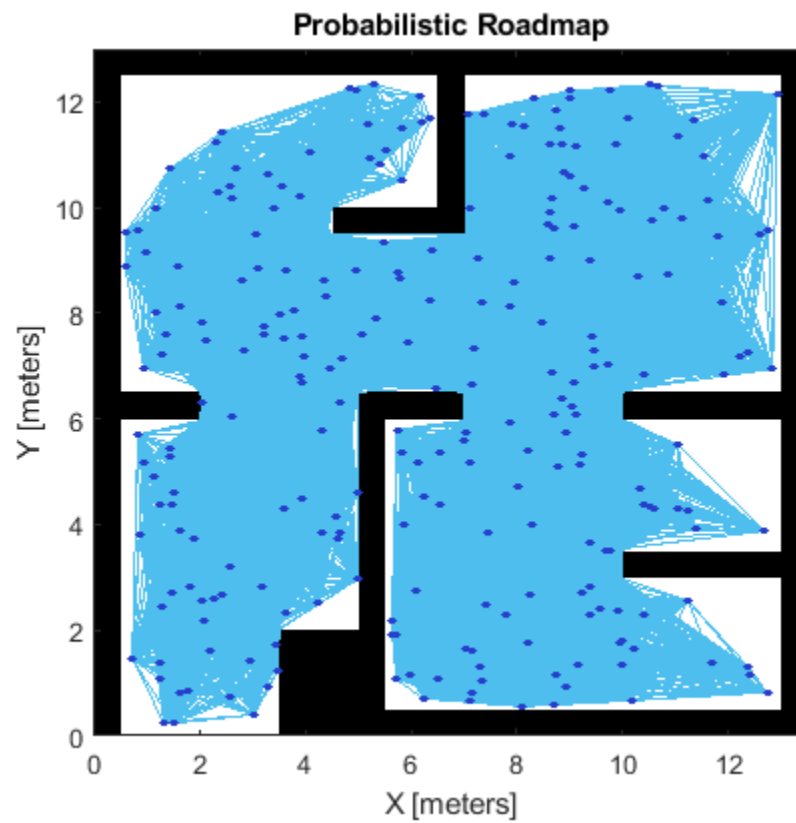
Create a simple roadmap with 50 nodes.

```
prmSimple = mobileRobotPRM(map,50);
show(prmSimple)
```



Create a dense roadmap with 250 nodes.

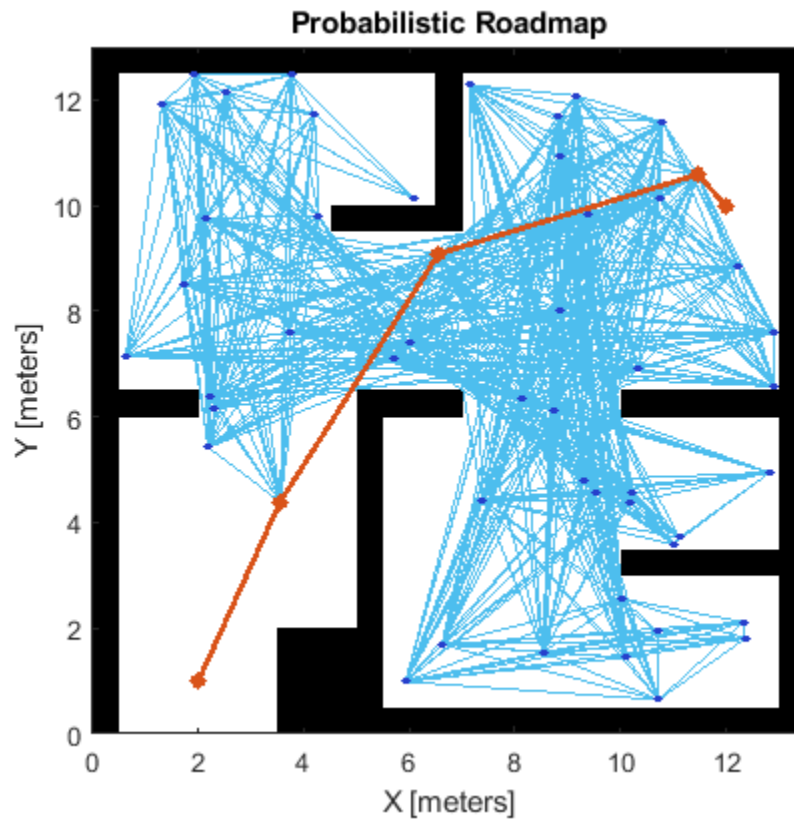
```
prmComplex = mobileRobotPRM(map,250);  
show(prmComplex)
```



The additional nodes increase the complexity but yield more options to improve the path. Given these two maps, you can calculate a path using the PRM algorithm and see the effects.

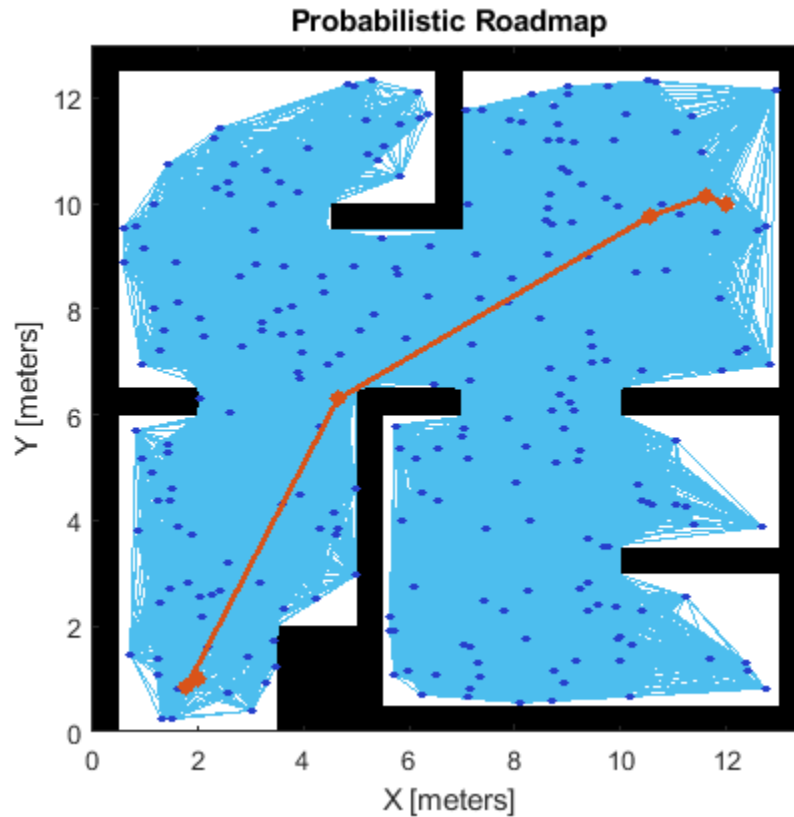
Calculate a simple path.

```
startLocation = [2 1];  
endLocation = [12 10];  
path = findpath(prmSimple,startLocation,endLocation);  
show(prmSimple)
```



Calculate a complex path.

```
path = findpath(prmComplex, startLocation, endLocation);  
show(prmComplex)
```



Increasing the nodes allows for a more direct path, but adds more computation time to finding a feasible path. Because of the random placement of points, the path is not always more direct or efficient. Using a small number of nodes can make paths worse than depicted and even restrict the ability to find a complete path.

Tune the Connection Distance

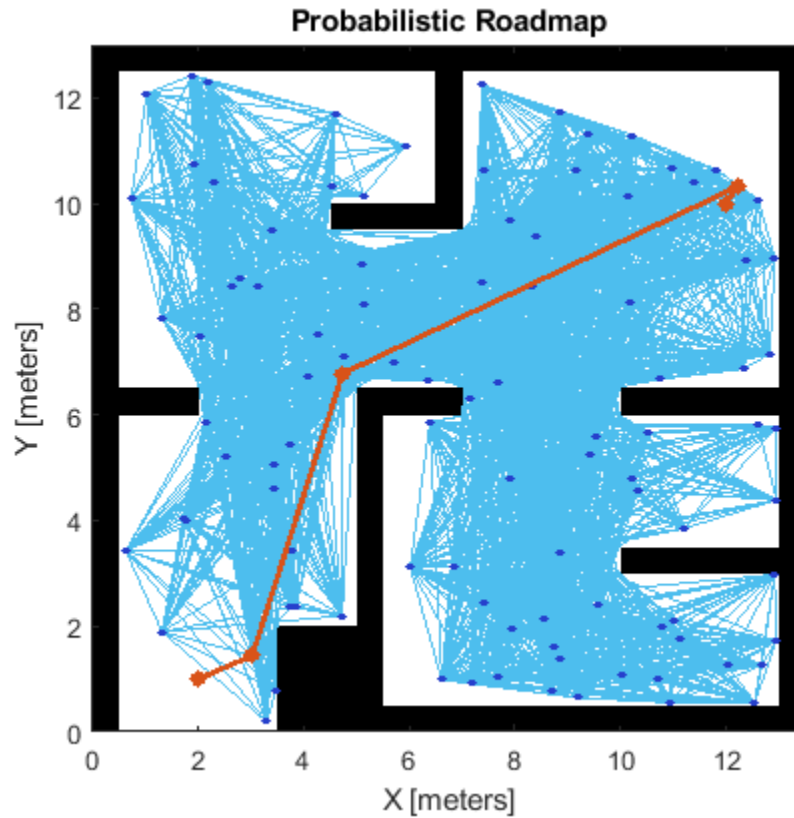
Use the `ConnectionDistance` property on the PRM object to tune the algorithm. `ConnectionDistance` is an upper threshold for points that are connected in the roadmap. Each node is connected to all nodes within this connection distance that do not have obstacles between them. By lowering the connection distance, you can limit the number of connections to reduce the computation time and simplify the map. However, a lowered distance limits the number of available paths from which to find a complete obstacle-free path. When working with simple maps, you can use a higher connection distance with a small number of nodes to increase efficiency. For complex maps with lots of obstacles, a higher number of nodes with a lowered connection distance increases the chance of finding a solution.

Load a map as a logical matrix, `simpleMap`, and create an occupancy grid.

```
load exampleMaps.mat
map = binaryOccupancyMap(simpleMap,2);
```

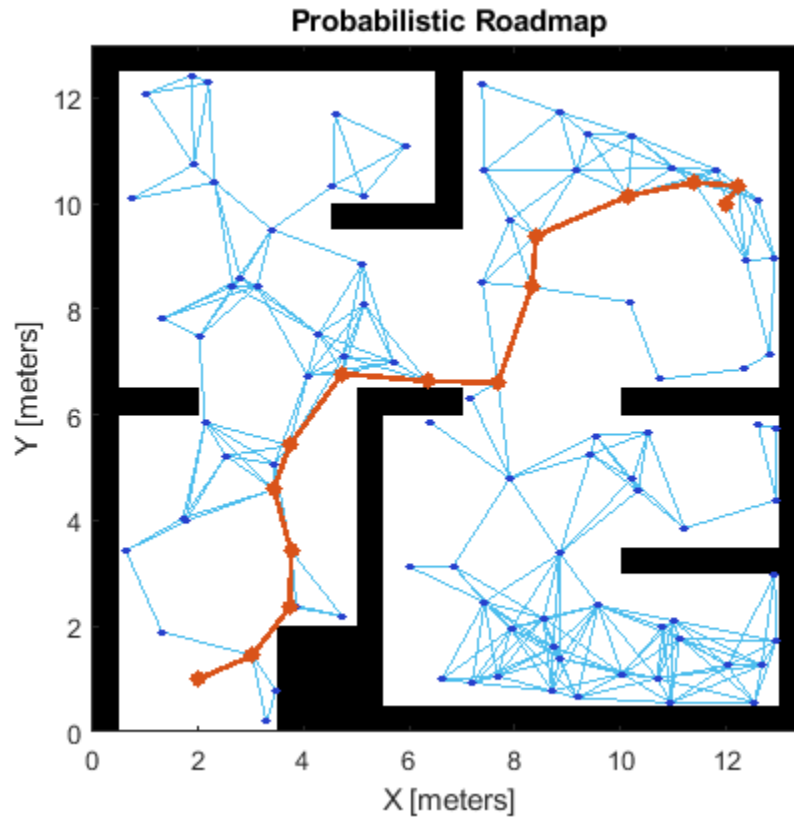
Create a roadmap with 100 nodes and calculate the path. The default `ConnectionDistance` is set to `inf`. Save the random number generation settings using the `rng` function. The saved settings enable you to reproduce the same points and see the effect of changing `ConnectionDistance`.

```
rngState = rng;  
prm = mobileRobotPRM(map,100);  
startLocation = [2 1];  
endLocation = [12 10];  
path = findpath(prm,startLocation,endLocation);  
show(prm)
```



Reload the random number generation settings to have PRM use the same nodes. Lower ConnectionDistance to 2 m. Show the calculated path.

```
rng(rngState);  
prm.ConnectionDistance = 2;  
path = findpath(prm,startLocation,endLocation);  
show(prm)
```

Create or Update PRM

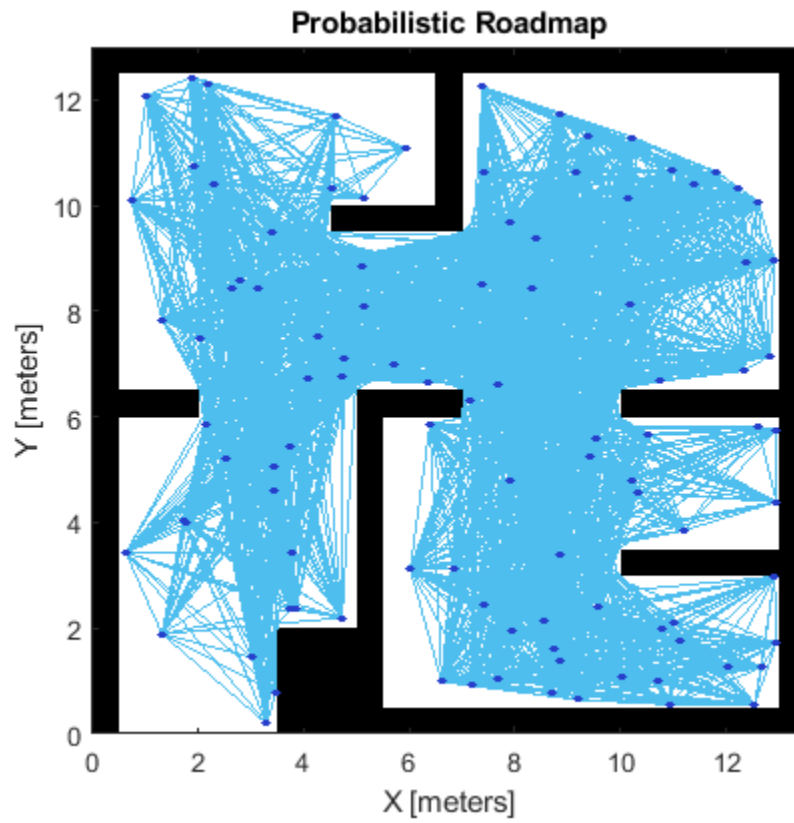
When using the `mobileRobotPRM` object and modifying properties, with each new function call, the object triggers the roadmap points and connections to be recalculated. Because recalculating the map can be computationally intensive, you can reuse the same roadmap by calling `findpath` with different starting and ending locations.

Load the map, `simpleMap`, from a `.mat` file as a logical matrix and create an occupancy grid.

```
load('exampleMaps.mat')
map = binaryOccupancyMap(simpleMap,2);
```

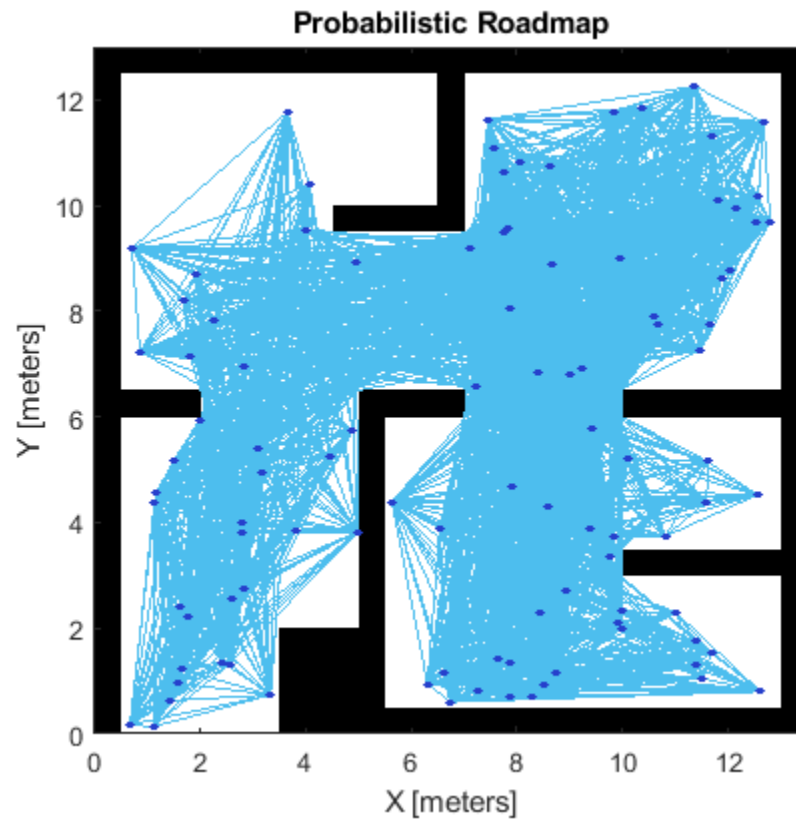
Create a roadmap. Your nodes and connections might look different due to the random placement of nodes.

```
prm = mobileRobotPRM(map,100);
show(prm)
```



Call `update` or change a parameter to update the nodes and connections.

```
update(prm)  
show(prm)
```



The PRM algorithm recalculates the node placement and generates a new network of nodes.

References

- [1] Kavraki, L.E., P. Svestka, J.-C. Latombe, and M.H. Overmars. "Probabilistic roadmaps for path planning in high-dimensional configuration spaces," *IEEE Transactions on Robotics and Automation*. Vol. 12, No. 4, Aug 1996 pp. 566–580.

See Also

`findpath` | `mobileRobotPRM`

Pure Pursuit Controller

In this section...

“Reference Coordinate System” on page 2-36

“Look Ahead Distance” on page 2-36

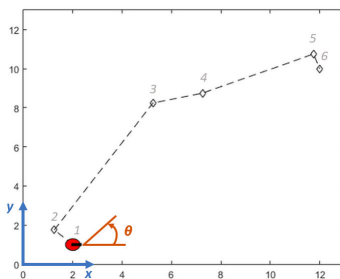
“Limitations” on page 2-37

Pure pursuit is a path tracking algorithm. It computes the angular velocity command that moves the robot from its current position to reach some look-ahead point in front of the robot. The linear velocity is assumed constant, hence you can change the linear velocity of the robot at any point. The algorithm then moves the look-ahead point on the path based on the current position of the robot until the last point of the path. You can think of this as the robot constantly chasing a point in front of it. The property `LookAheadDistance` decides how far the look-ahead point is placed.

The controller `PurePursuit` object is not a traditional controller, but acts as a tracking algorithm for path following purposes. Your controller is unique to a specified a list of waypoints. The desired linear and maximum angular velocities can be specified. These properties are determined based on the vehicle specifications. Given the pose (position and orientation) of the vehicle as an input, the object can be used to calculate the linear and angular velocities commands for the robot. How the robot uses these commands is dependent on the system you are using, so consider how robots can execute a motion given these commands. The final important property is the `LookAheadDistance`, which tells the robot how far along on the path to track towards. This property is explained in more detail in a section below.

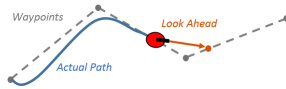
Reference Coordinate System

It is important to understand the reference coordinate frame used by the pure pursuit algorithm for its inputs and outputs. The figure below shows the reference coordinate system. The input waypoints are $[x \ y]$ coordinates, which are used to compute the robot velocity commands. The robot's pose is input as a pose and orientation (θ) list of points as $[x \ y \ \theta]$. The positive x and y directions are in the right and up directions respectively (blue in figure). The θ value is the angular orientation of the robot measured counterclockwise in radians from the x -axis (robot currently at θ radians).

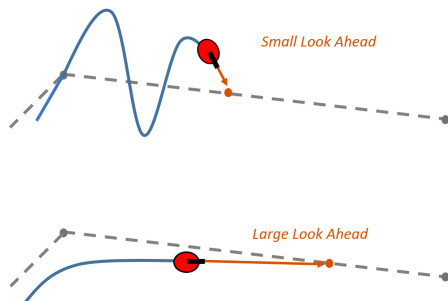


Look Ahead Distance

The `LookAheadDistance` property is the main tuning property for the controller. The look ahead distance is how far along the path the robot should look from the current location to compute the angular velocity commands. The figure below shows the robot and the look-ahead point. As displayed in this image, note that the actual path does not match the direct line between waypoints.



The effect of changing this parameter can change how your robot tracks the path and there are two major goals: regaining the path and maintaining the path. In order to quickly regain the path between waypoints, a small `LookAheadDistance` will cause your robot to move quickly towards the path. However, as can be seen in the figure below, the robot overshoots the path and oscillates along the desired path. In order to reduce the oscillations along the path, a larger look ahead distance can be chosen, however, it might result in larger curvatures near the corners.



The `LookAheadDistance` property should be tuned for your application and robot system. Different linear and angular velocities will affect this response as well and should be considered for the path following controller.

Limitations

There are a few limitations to note about this pure pursuit algorithm:

- As shown above, the controller cannot exactly follow direct paths between waypoints. Parameters must be tuned to optimize the performance and to converge to the path over time.
- This pure pursuit algorithm does not stabilize the robot at a point. In your application, a distance threshold for a goal location should be applied to stop the robot near the desired goal.

References

- [1] Coulter, R. *Implementation of the Pure Pursuit Path Tracking Algorithm*. Carnegie Mellon University, Pittsburgh, Pennsylvania, Jan 1990.

See Also

`controllerVFH` | `stateEstimatorPF`

Particle Filter Parameters

In this section...

“Number of Particles” on page 2-38

“Initial Particle Location” on page 2-39

“State Transition Function” on page 2-40

“Measurement Likelihood Function” on page 2-41

“Resampling Policy” on page 2-41

“State Estimation Method” on page 2-42

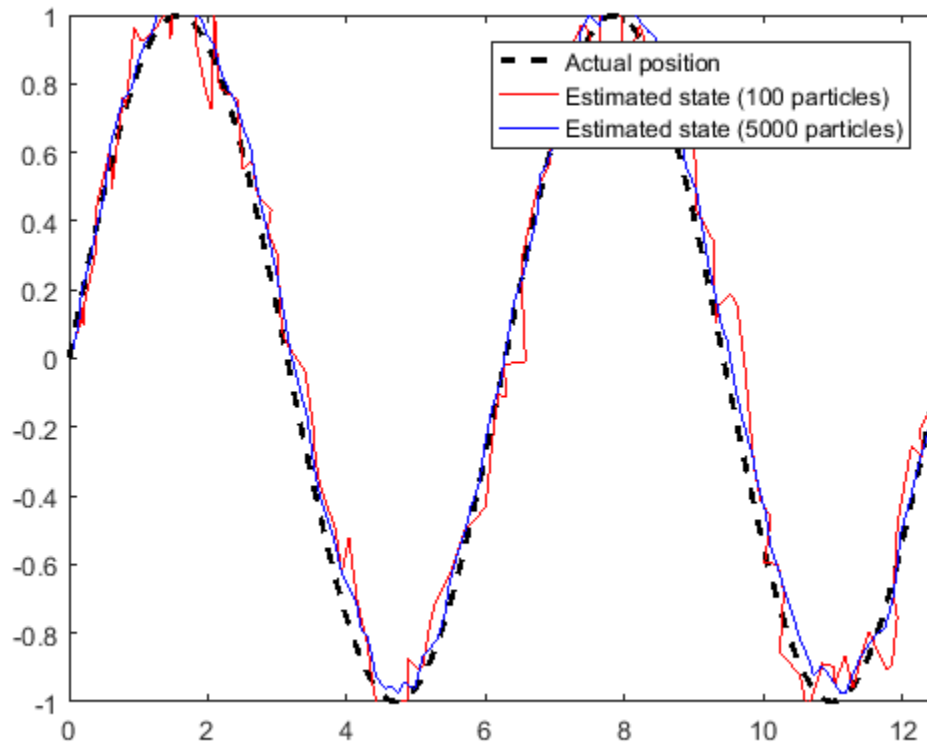
To use the `stateEstimatorPF` particle filter, you must specify parameters such as the number of particles, the initial particle location, and the state estimation method. Also, if you have a specific motion and sensor model, you specify these parameters in the state transition function and measurement likelihood function, respectively. The details of these parameters are detailed on this page. For more information on the particle filter workflow, see “Particle Filter Workflow” on page 2-43.

Number of Particles

To specify the number of particles, use the `initialize` method. Each particle is a hypothesis of the current state. The particles are distributed across your state space based on either a specified mean and covariance, or on the specified state bounds. Depending on the `StateEstimationMethod` property, either the particle with the highest weight or the mean of all particles is taken to determine the best state estimate.

The default number of particles is 1000. Unless performance is an issue, do not use fewer than 1000 particles. A higher number of particles can improve the estimate but sacrifices performance speed, because the algorithm has to process more particles. Tuning the number of particles is the best way to affect your particle filters performance.

These results, which are based on the `stateEstimatorPF` example, show the difference in tracking accuracy when using 100 particles and 5000 particles.



Initial Particle Location

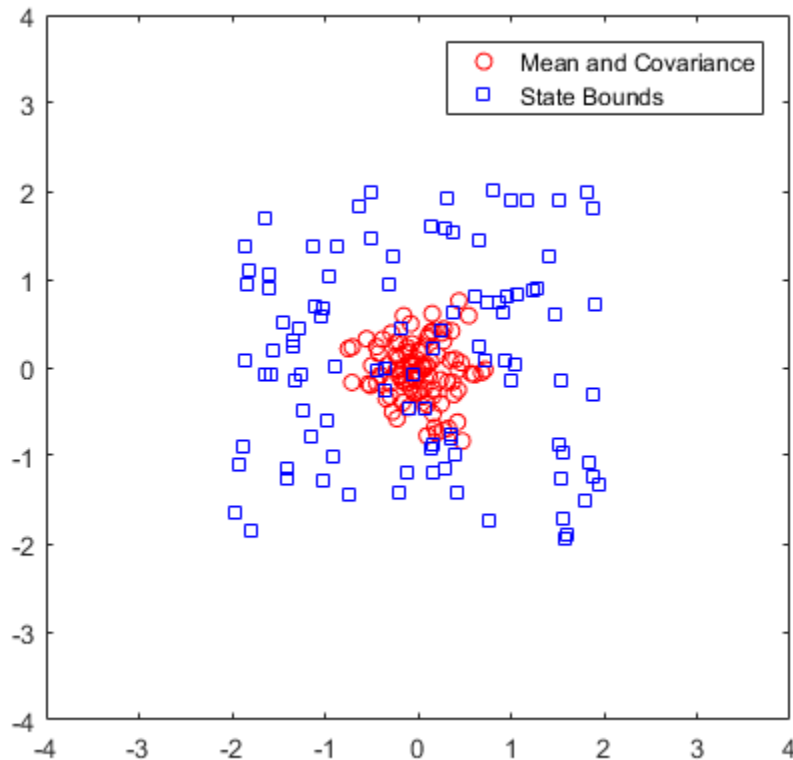
When you initialize your particle filter, you can specify the initial location of the particles using:

- Mean and covariance
- State bounds

Your initial state is defined as a mean with a covariance relative to your system. This mean and covariance correlate to the initial location and uncertainty of your system. The `stateEstimatorPF` object distributes particles based on your covariance around the given mean. The algorithm uses this distribution of particles to get the best estimation of state, so an accurate initialization of particles helps to converge to the best state estimation quickly.

If an initial state is unknown, you can evenly distribute your particles across a given state bounds. The state bounds are the limits of your state. For example, when estimating the position of a robot, the state bounds are limited to the environment that the robot can actually inhabit. In general, an even distribution of particles is a less efficient way to initialize particles to improve the speed of convergence.

The plot shows how the mean and covariance specification can cluster particles much more effectively in a space rather than specifying the full state bounds.



State Transition Function

The state transition function, `StateTransitionFcn`, of a particle filter helps to evolve the particles to the next state. It is used during the prediction step of the “Particle Filter Workflow” on page 2-43. In the `stateEstimatorPF` object, the state transition function is specified as a callback function that takes the previous particles, and any other necessary parameters, and outputs the predicted location. The function header syntax is:

```
function predictParticles = stateTransitionFcn(pf,prevParticles,varargin)
```

By default, the state transition function assumes a Gaussian motion model with constant velocities. The function uses a Gaussian distribution to determine the position of the particles in the next time step.

For your application, it is important to have a state transition function that accurately describes how you expect the system to behave. To accurately evolve all the particles, you must develop and implement a motion model for your system. If particles are not distributed around the next state, the `stateEstimatorPF` object does not find an accurate estimate. Therefore, it is important to understand how your system can behave so that you can track it accurately.

You also must specify system noise in `StateTransitionFcn`. Without random noise applied to the predicted system, the particle filter does not function as intended.

Although you can predict many systems based on their previous state, sometimes the system can include extra information. The use of `varargin` in the function enables you to input any extra

parameters that are relevant for predicting the next state. When you call `predict`, you can include these parameters using:

```
predict(pf,param1,param2)
```

Because these parameters match the state transition function you defined, calling `predict` essentially calls the function as:

```
predictParticles = stateTransitionFcn(pf,prevParticles,param1,param2)
```

The output particles, `predictParticles`, are then either used by the “Measurement Likelihood Function” on page 2-41 to correct the particles, or used in the next prediction step if correction is not required.

Measurement Likelihood Function

After predicting the next state, you can use measurements from sensors to correct your predicted state. By specifying a `MeasurementLikelihoodFcn` in the `stateEstimatorPF` object, you can correct your predicted particles using the `correct` function. This measurement likelihood function, by definition, gives a weight for the state hypotheses (your particles) based on a given measurement. Essentially, it gives you the likelihood that the observed measurement actually matches what each particle observes. This likelihood is used as a weight on the predicted particles to help with correcting them and getting the best estimation. Although the prediction step can prove accurate for a small number of intermediate steps, to get accurate tracking, use sensor observations to correct the particles frequently.

The specification of the `MeasurementLikelihoodFcn` is similar to the `StateTransitionFcn`. It is specified as a function handle in the properties of the `stateEstimatorPF` object. The function header syntax is:

```
function likelihood = measurementLikelihoodFcn(pf,predictParticles,measurement,varargin)
```

The output is the likelihood of each predicted particle based on the measurement given. However, you can also specify more parameters in `varargin`. The use of `varargin` in the function enables you to input any extra parameters that are relevant for correcting the predicted state. When you call `correct`, you can include these parameters using:

```
correct(pf,measurement,param1,param2)
```

These parameters match the measurement likelihood function you defined:

```
likelihood = measurementLikelihoodFcn(pf,predictParticles,measurement,param1,param2)
```

The `correct` function uses the `likelihood` output for particle resampling and giving the final state estimate.

Resampling Policy

The resampling of particles is a vital step for continuous tracking of objects. It enables you to select particles based on the current state, instead of using the particle distribution given at initialization. By continuously resampling the particles around the current estimate, you can get more accurate tracking and improve long-term performance.

When you call `correct`, the particles used for state estimation can be resampled depending on the `ResamplingPolicy` property specified in the `stateEstimatorPF` object. This property is specified

as a `resamplingPolicyPF` object. The `TriggerMethod` property on that object tells the particle filter which method to use for resampling.

You can trigger resampling at either a fixed interval or when a minimum effective particle ratio is reached. The fixed interval method resamples at a set number of iterations, which is specified in the `SamplingInterval` property. The minimum effective particle ratio is a measure of how well the current set of particles approximates the posterior distribution. The number of effective particles is calculated by:

$$N_{eff} = \frac{1}{\sum_{i=1}^N (w^i)^2}$$

In this equation, N is the number of particles, and w is the normalized weight of each particle. The effective particle ratio is then $N_{eff} / \text{NumParticles}$. Therefore, the effective particle ratio is a function of the weights of all the particles. After the weights of the particles reach a low enough value, they are not contributing to the state estimation. This low value triggers resampling, so the particles are closer to the current state estimation and have higher weights.

State Estimation Method

The final step of the particle filter workflow is the selection of a single state estimate. The particles and their weights sampled across the distribution are used to give the best estimation of the actual state. However, you can use the particles information to get a single state estimate in multiple ways. With the `stateEstimatorPF` object, you can either choose the best estimate based on the particle with the highest weight or take a mean of all the particles. Specify the estimation method in the `StateEstimationMethod` property as either `'mean'` (default) or `'maxweight'`.

Because you can estimate the state from all of the particles in many ways, you can also extract each particle and its weight from the `stateEstimatorPF` using the `Particles` property.

See Also

`resamplingPolicyPF` | `stateEstimatorPF`

Related Examples

- “Estimate Robot Position in a Loop Using Particle Filter”

More About

- “Particle Filter Workflow” on page 2-43

Particle Filter Workflow

A particle filter is a recursive, Bayesian state estimator that uses discrete particles to approximate the posterior distribution of the estimated state.

The particle filter algorithm computes the state estimate recursively and involves two steps:

- Prediction - The algorithm uses the previous state to predict the current state based on a given system model.
- Correction - The algorithm uses the current sensor measurement to correct the state estimate.

The algorithm also periodically redistributes, or resamples, the particles in the state space to match the posterior distribution of the estimated state.

The estimated state consists of all the state variables. Each particle represents a discrete state hypothesis. The set of all particles is used to help determine the final state estimate.

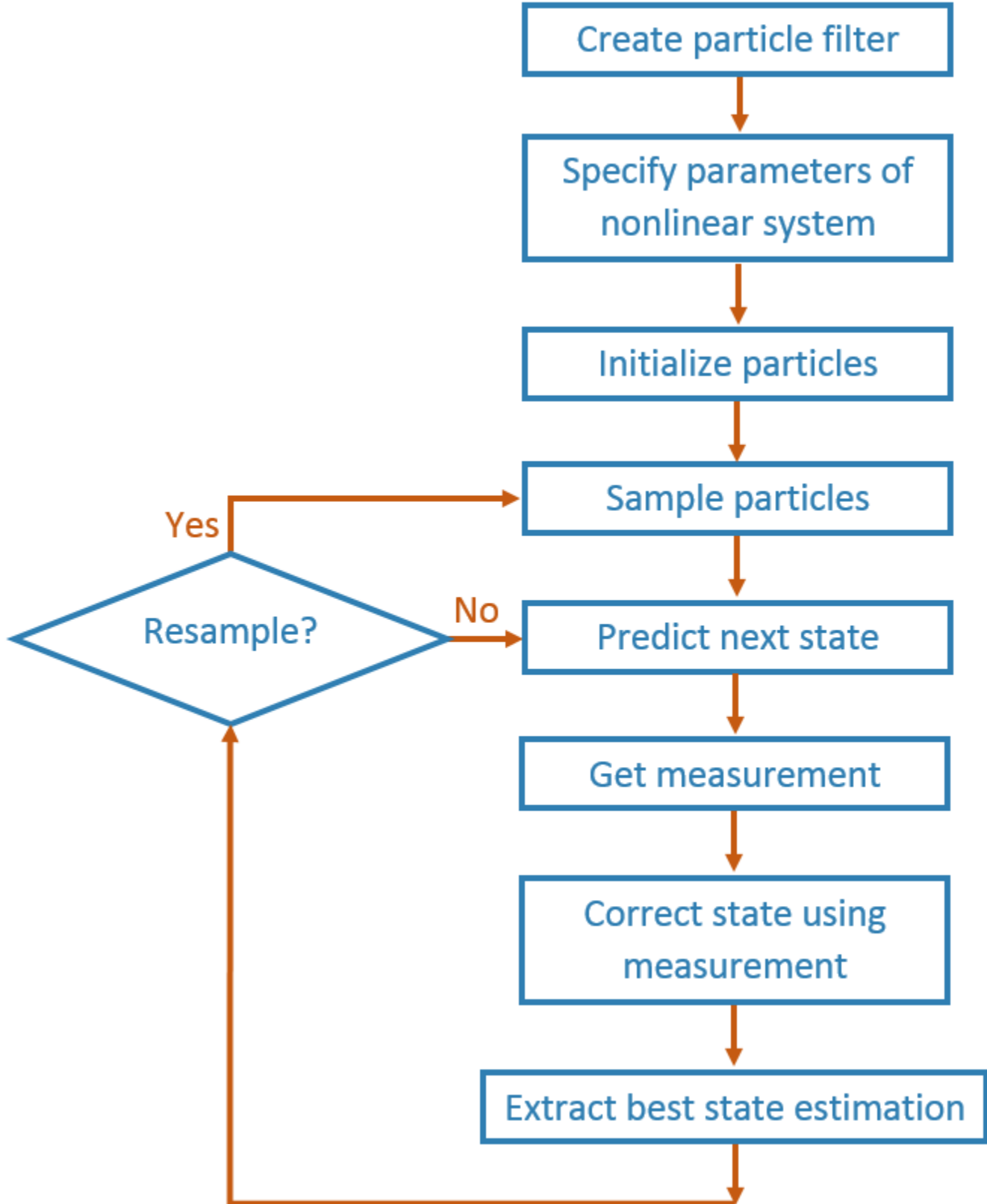
You can apply the particle filter to arbitrary nonlinear system models. Process and measurement noise can follow arbitrary non-Gaussian distributions.

To use the particle filter properly, you must specify parameters such as the number of particles, the initial particle location, and the state estimation method. Also, if you have a specific motion and sensor model, you specify these parameters in the state transition function and measurement likelihood function, respectively. For more information, see “Particle Filter Parameters” on page 2-38.

Follow this basic workflow to create and use a particle filter. This page details the estimation workflow and shows an example of how to run a particle filter in a loop to continuously estimate state.

Estimation Workflow

When using a particle filter, there is a required set of steps to create the particle filter and estimate state. The prediction and correction steps are the main iteration steps for continuously estimating state.



Create Particle Filter

Create a `stateEstimatorPF` object.

Set Parameters of Nonlinear System

Modify these `stateEstimatorPF` parameters to fit for your specific system or application:

- `StateTransitionFcn`
- `MeasurementLikelihoodFcn`
- `ResamplingPolicy`
- `ResamplingMethod`
- `StateEstimationMethod`

Default values for these parameters are given for basic operation.

The `StateTransitionFcn` and `MeasurementLikelihoodFcn` functions define the system behavior and measurement integration. They are vital for the particle filter to track accurately. For more information, see “Particle Filter Parameters” on page 2-38.

Initialize Particles

Use the `initialize` function to set the number of particles and the initial state.

Sample Particles from a Distribution

You can sample the initial particle locations in two ways:

- Initial pose and covariance — If you have an idea of your initial state, it is recommended you specify the initial pose and covariance. This specification helps to cluster particles closer to your estimate so tracking is more effective from the start.
- State bounds — If you do not know your initial state, you can specify the possible limits of each state variable. Particles are uniformly distributed across the state bounds for each variable. Widely distributed particles are not as effective at tracking, because fewer particles are near the actual state. Using state bounds usually requires more particles, computation time, and iterations to converge to the actual state estimate.

Predict

Based on a specified state transition function, particles evolve to estimate the next state. Use `predict` to execute the state transition function specified in the `StateTransitionFcn` property.

Get Measurement

The measurements collected from sensors are used in the next step to correct the current predicted state.

Correct

Measurements are then used to adjust the predicted state and correct the estimate. Specify your measurements using the `correct` function. `correct` uses the `MeasurementLikelihoodFcn` to calculate the likelihood of sensor measurements for each particle. Resampling of particles is required to update your estimation as the state changes in subsequent iterations. This step triggers resampling based on the `ResamplingMethod` and `ResamplingPolicy` properties.

Extract Best State Estimation

After calling `correct`, the best state estimate is automatically extracted based on the `Weights` of each particle and the `StateEstimationMethod` property specified in the object. The best estimated state and covariance is output by the `correct` function.

Resample Particles

This step is not separately called, but is executed when you call `correct`. Once your state has changed enough, resample your particles based on the newest estimate. The `correct` method checks the `ResamplingPolicy` for the triggering of particle resampling according to the current distribution of particles and their weights. If resampling is not triggered, the same particles are used for the next estimation. If your state does not vary by much or if your time step is low, you can call the `predict` and `correct` methods without resampling.

Continuously Predict and Correct

Repeat the previous prediction and correction steps as needed for estimating state. The correction step determines if resampling of the particles is required. Multiple calls for `predict` or `correct` might be required when:

- No measurement is available but control inputs and time updates are occur at a high frequency. Use the `predict` method to evolve the particles to get the updated predicted state more often.
- Multiple measurement reading are available. Use `correct` to integrate multiple readings from the same or multiple sensors. The function corrects the state based on each set of information collected.

See Also

`correct` | `getStateEstimate` | `initialize` | `predict` | `stateEstimatorPF`

Related Examples

- “Track a Car-Like Robot Using Particle Filter” on page 1-61
- “Estimate Robot Position in a Loop Using Particle Filter”

More About

- “Particle Filter Parameters” on page 2-38

Standard Units for Robotics System Toolbox

Robotics System Toolbox uses a fixed set of standards for units to ensure consistency across algorithms and applications. Unless specified otherwise, functions and classes in this toolbox represent all values in units based on the International System of Units (SI). The table below summarizes the relevant quantities and their SI derived units.

Quantity	Unit (abbrev.)
Length	meter (m)
Time	second (s)
Angle	radian (rad)
Velocity	meter/second (m/s)
Angular Velocity	radian/second (rad/s)
Acceleration	meter/second ² (m/s ²)
Angular Acceleration	radian/second ² (rad/s ²)
Mass	kilogram (kg)
Force	Newton (N)
Torque	Newton-meter (N-m)
Moment of Inertia	kilogram-meter ² (kg-m ²)

See Also

More About

- “Coordinate Transformations in Robotics” on page 2-48

Coordinate Transformations in Robotics

In this section...

“Axis-Angle” on page 2-48

“Euler Angles” on page 2-48

“Homogeneous Transformation Matrix” on page 2-49

“Quaternion” on page 2-49

“Rotation Matrix” on page 2-49

“Translation Vector” on page 2-50

“Conversion Functions and Transformations” on page 2-50

In robotics applications, many different coordinate systems can be used to define where robots, sensors, and other objects are located. In general, the location of an object in 3-D space can be specified by position and orientation values. There are multiple possible representations for these values, some of which are specific to certain applications. Translation and rotation are alternative terms for position and orientation. Robotics System Toolbox supports representations that are commonly used in robotics and allows you to convert between them. You can transform between coordinate systems when you apply these representations to 3-D points. These supported representations are detailed below with brief explanations of their usage and numeric equivalent in MATLAB. Each representation has an abbreviation for its name. This is used in the naming of arguments and conversion functions that are supported in this toolbox.

At the end of this section, you can find out about the conversion functions that we offer to convert between these representations.

Robotics System Toolbox assumes that positions and orientations are defined in a right-handed Cartesian coordinate system.

Axis-Angle

Abbreviation: `axang`

A rotation in 3-D space described by a scalar rotation around a fixed axis defined by a vector.

Numeric Representation: 1-by-3 unit vector and a scalar angle combined as a 1-by-4 vector

For example, a rotation of $\pi/2$ radians around the y-axis would be:

```
axang = [0 1 0 pi/2]
```

Euler Angles

Abbreviation: `eul`

Euler angles are three angles that describe the orientation of a rigid body. Each angle is a scalar rotation around a given coordinate frame axis. The Robotics System Toolbox supports two rotation orders. The 'ZYX' axis order is commonly used for robotics applications. We also support the 'ZYZ' axis order which is also denoted as “Roll Pitch Yaw (rpy).” Knowing which axis order you use is important for apply the rotation to points and in converting to other representations.

Numeric Representation: 1-by-3 vector of scalar angles

For example, a rotation around the y -axis of π would be expressed as:

```
eul = [0 pi 0]
```

Note: The axis order is not stored in the transformation, so you must be aware of what rotation order is to be applied.

Homogeneous Transformation Matrix

Abbreviation: `tform`

A homogeneous transformation matrix combines a translation and rotation into one matrix.

Numeric Representation: 4-by-4 matrix

For example, a rotation of angle α around the y -axis and a translation of 4 units along the y -axis would be expressed as:

```
tform =
  cos  $\alpha$   0      sin  $\alpha$   0
  0          1      0          4
 -sin  $\alpha$   0      cos  $\alpha$   0
  0          0      0          1
```

You should **pre-multiply** your transformation matrix with your homogeneous coordinates, which are represented as a matrix of row vectors (n -by-4 matrix of points). Utilize the transpose (') to rotate your points for matrix multiplication. For example:

```
points = rand(100,4);
tformPoints = (tform*points)';
```

Quaternion

Abbreviation: `quat`

A quaternion is a four-element vector with a scalar rotation and 3-element vector. Quaternions are advantageous because they avoid singularity issues that are inherent in other representations. The first element, w , is a scalar to normalize the vector with the three other values, $[x y z]$ defining the axis of rotation.

Numeric Representation: 1-by-4 vector

For example, a rotation of $\pi/2$ around the y -axis would be expressed as:

```
quat = [0.7071 0 0.7071 0]
```

Rotation Matrix

Abbreviation: `rotm`

A rotation matrix describes a rotation in 3-D space. It is a square, orthonormal matrix with a determinant of 1.

Numeric Representation: 3-by-3 matrix

For example, a rotation of α degrees around the x-axis would be:

```
rotm =
    1     0     0
    0   cos  $\alpha$   -sin  $\alpha$ 
    0   sin  $\alpha$    cos  $\alpha$ 
```

You should **pre-multiply** your rotation matrix with your coordinates, which are represented as a matrix of row vectors (n -by-3 matrix of points). Utilize the transpose (') to rotate your points for matrix multiplication. For example:

```
points = rand(100,3);
rotPoints = (rotm*points)';
```

Translation Vector

Abbreviation: trvec

A translation vector is represented in 3-D Euclidean space as Cartesian coordinates. It only involves coordinate translation applied equally to all points. There is no rotation involved.

Numeric Representation: 1-by-3 vector

For example, a translation by 3 units along the x -axis and 2.5 units along the z -axis would be expressed as:

```
trvec = [3 0 2.5]
```

Conversion Functions and Transformations

Robotics System Toolbox provides conversion functions for the previously mentioned transformation representations. Not all conversions are supported by a dedicated function. Below is a table showing which conversions are supported (in blue). The abbreviations for the rotation and translation representations are shown as well.

Converting To \ Converting From	Axis-Angle (axang)	Euler Angles (eul)	Quaternion (quat)	Rotation Matrix (rotm)	Homogeneous Transformation (tform)	Translation Vector (trvec)
Axis-Angle (axang)	Black		Blue	Blue	Blue	
Euler Angles (eul)		Black	Blue	Blue	Blue	
Quaternion (quat)	Blue	Blue	Black	Blue	Blue	
Rotation Matrix (rotm)	Blue	Blue	Blue	Black	Blue	
Homogeneous Transformation (tform)	Blue	Blue	Blue	Blue	Black	Blue
Translation Vector (trvec)					Blue	Black

The names of all the conversion functions follow a standard format. They follow the form $\alpha\beta$ where α is the abbreviation for what you are converting from and β is what

you are converting to as an abbreviation. For example, converting from Euler angles to quaternion would be `eu12quat`.

All the functions expect valid inputs. If you specify invalid inputs, the outputs will be undefined.

There are other conversion functions for converting between radians and degrees, Cartesian and homogeneous coordinates, and for calculating wrapped angle differences. For a full list of conversions, see “Coordinate Transformations and Trajectories” .

See Also

More About

- “Standard Units for Robotics System Toolbox” on page 2-47

Execute Code at a Fixed-Rate

In this section...

“Introduction” on page 2-52

“Run Loop at Fixed Rate” on page 2-52

“Overrun Actions for Fixed Rate Execution” on page 2-52

Introduction

By executing code at constant intervals, you can accurately time and schedule tasks. Using a `rateControl` object allows you to control the rate of your code execution. These examples show different applications for the `rateControl` object including its uses with ROS and sending commands for robot control.

Run Loop at Fixed Rate

Create a rate object that runs at 1 Hz.

```
r = rateControl(1);
```

Start a loop using the `rateControl` object inside to control the loop execution. Reset the object prior to the loop execution to reset timer. Print the iteration and time elapsed.

```
reset(r)
for i = 1:10
    time = r.TotalElapsedTime;
    fprintf('Iteration: %d - Time Elapsed: %f\n',i,time)
    waitfor(r);
end
```

```
Iteration: 1 - Time Elapsed: 0.009784
Iteration: 2 - Time Elapsed: 1.000772
Iteration: 3 - Time Elapsed: 2.000627
Iteration: 4 - Time Elapsed: 3.000987
Iteration: 5 - Time Elapsed: 4.044617
Iteration: 6 - Time Elapsed: 5.000857
Iteration: 7 - Time Elapsed: 6.007045
Iteration: 8 - Time Elapsed: 7.000570
Iteration: 9 - Time Elapsed: 8.012785
Iteration: 10 - Time Elapsed: 9.002134
```

Each iteration executes at a 1-second interval.

Overrun Actions for Fixed Rate Execution

The `rateControl` object uses the `OverrunAction` property to decide how to handle code that takes longer than the desired period to operate. The options are `'slip'` (default) or `'drop'`. This example shows how the `OverrunAction` affects code execution.

Setup desired rate and loop time. `slowFrames` is an array of times when the loop should be stalled longer than the desired rate.

```
desiredRate = 1;
loopTime = 20;
slowFrames = [3 7 12 18];
```

Create the Rate object and specify the `OverrunAction` property. 'slip' indicates that the `waitfor` function will return immediately if the time for `LastPeriod` is greater than the `DesiredRate` property.

```
rate = rateControl(desiredRate);
rate.OverrunAction = 'slip';
```

Reset Rate object and begin loop. This loop will execute at the desired rate until the loop time is reached. When the `TotalElapsedTime` reaches a slow frame time, it will stall for longer than the desired period.

```
reset(rate);

while rate.TotalElapsedTime < loopTime
    if ~isempty(find(slowFrames == floor(rate.TotalElapsedTime)))
        pause(desiredRate + 0.1)
    end
    waitfor(rate);
end
```

View statistics on the Rate object. Notice the number of periods.

```
stats = statistics(rate)

stats = struct with fields:
    Periods: [1x20 double]
    NumPeriods: 20
    AveragePeriod: 1.0241
    StandardDeviation: 0.0430
    NumOverruns: 4
```

Change the `OverrunAction` to 'drop'. 'drop' indicates that the `waitfor` function will return at the next time step, even if the `LastPeriod` is greater than the `DesiredRate` property. This effectively drops the iteration that was missed by the slower code execution.

```
rate.OverrunAction = 'drop';
```

Reset Rate object and begin loop.

```
reset(rate);

while rate.TotalElapsedTime < loopTime
    if ~isempty(find(slowFrames == floor(rate.TotalElapsedTime)))
        pause(1.1)
    end
    waitfor(rate);
end
stats2 = statistics(rate)

stats2 = struct with fields:
    Periods: [1x16 double]
    NumPeriods: 16
    AveragePeriod: 1.2501
```

```
StandardDeviation: 0.4408  
NumOverruns: 4
```

Using the 'drop' over run action resulted in 16 periods when the 'slip' resulted in 20 periods. This difference is because the 'slip' did not wait until the next interval based on the desired rate. Essentially, using 'slip' tries to keep the `AveragePeriod` property as close to the desired rate. Using 'drop' ensures the code will execute at an even interval relative to `DesiredRate` with some iterations being skipped.

See Also

`rateControl` | `rosrate` | `waitfor`

Accelerate Robotics Algorithms with Code Generation

In this section...

“Create Separate Function for Algorithm” on page 2-55
 “Perform Code Generation for Algorithm” on page 2-56
 “Check Performance of Generated Code” on page 2-56
 “Replace Algorithm Function with MEX Function” on page 2-56

You can generate code for select Robotics System Toolbox algorithms to speed up their execution. Set up the algorithm that supports code generation as a separate function that you can insert into your workflow. To use code generation, you must have a MATLAB Coder™ license. For a list of code generation support in Robotics System Toolbox, see Functions Supporting Code Generation.

For this example, use a `inverseKinematics` object with a `rigidBodyTree` robot model to solve for robot configurations that achieve a desired end-effector position.

Create Separate Function for Algorithm

Create a separate function, `ikCodegen`, that runs the inverse kinematics algorithm. Create `inverseKinematics` object and build the `rigidBodyTree` model inside the function. Specify `%#codegen` inside the function to identify it as a function for code generation.

```
function qConfig = ikCodegen(endEffectorName,tform,weights,initialGuess)
    %#codegen

    robot = rigidBodyTree('MaxNumBodies',3,'DataFormat','row');
    body1 = rigidBody('body1');
    body1.Joint = rigidBodyJoint('jnt1','revolute');

    body2 = rigidBody('body2');
    jnt2 = rigidBodyJoint('jnt2','revolute');
    setFixedTransform(jnt2,trvec2tform([1 0 0]))
    body2.Joint = jnt2;

    body3 = rigidBody('tool');
    jnt3 = rigidBodyJoint('jnt3','revolute');
    setFixedTransform(jnt3,trvec2tform([1 0 0]))
    body3.Joint = jnt3;

    addBody(robot,body1,'base')
    addBody(robot,body2,'body1')
    addBody(robot,body3,'body2')

    ik = inverseKinematics('RigidBodyTree',robot);

    [qConfig,~] = ik(endEffectorName,tform,weights,initialGuess);
end
```

Save the function in your current folder.

Perform Code Generation for Algorithm

You can use either the `codegen` function or the **MATLAB Coder** app to generate code. In this example, generate a MEX file by calling `codegen` on the MATLAB command line. Specify sample input arguments for each input to the function using the `-args` input argument

Specify sample values for the input arguments.

```
endEffectorName = 'tool';
tform = trvec2tform([0.7 -0.7 0]);
weights = [0.25 0.25 0.25 1 1 1];
initialGuess = [0 0 0];
```

Call the `codegen` function and specify the input arguments in a cell array. This function creates a separate `ikCodegen_mex` function to use. You can also produce C code by using the `options` input argument.

```
codegen ikCodegen -args {endEffectorName,tform,weights,initialGuess}
```

If your input can come from variable-size lengths, specify the canonical type of the inputs by using `coder.typeof` with the `codegen` function.

Check Performance of Generated Code

Compare the timing of the generated MEX function to the timing of your original function by using `timeit`.

```
time = timeit(@() ikCodegen(endEffectorName,tform,weights,initialGuess))
mexTime = timeit(@() ikCodegen_mex(endEffectorName,tform,weights,initialGuess))
```

```
time =
    0.0425
```

```
mexTime =
    0.0011
```

The MEX function runs over 30 times faster in this example. Results might vary in your system.

Replace Algorithm Function with MEX Function

Open the main function for running your robotics workflow. Replace the `ik` object call with the MEX function that you created using code generation. For this example, use the simple 2-D path tracing example.

Open the “2-D Path Tracing With Inverse Kinematics” on page 2-14 example.

```
openExample('robotics/TwoDInverseKinematicsExampleExample')
```

Modify the example code to use the new `ikCodegen_mex` function. The code that follows is a copy of the example with modifications to use of the new MEX function. Defining the robot model is done inside the function, so skip the **Construct the Robot** section.

Define The Trajectory

```
t = (0:0.2:10)'; % Time
count = length(t);
center = [0.3 0.1 0];
radius = 0.15;
theta = t*(2*pi/t(end));
points = center + radius*[cos(theta) sin(theta) zeros(size(theta))];
```

Inverse Kinematics Solution

Pre-allocate configuration solutions as a matrix, `qs`. Specify the weights for the end-effector transformation and the end-effector name.

```
q0 = [0 0 0];
ndof = length(q0);
qs = zeros(count, ndof);
weights = [0, 0, 0, 1, 1, 0];
endEffector = 'tool';
```

Loop through the trajectory of points to trace the circle. Replace the `ik` object call with the `ikCodegen_mex` function. Calculate the solution for each point to generate the joint configuration that achieves the end-effector position. Store the configurations to use later.

```
qInitial = q0; % Use home configuration as the initial guess
for i = 1:count
    % Solve for the configuration satisfying the desired end effector
    % position
    point = points(i,:);
    qSol = ikCodegen_mex(endEffector, trvec2tform(point), weights, qInitial);
    % Store the configuration
    qs(i,:) = qSol;
    % Start from prior solution
    qInitial = qSol;
end
```

Animate Solution

Now that all the solutions have been generated. Animate the results. You must recreate the robot because it was originally defined inside the function. Iterate through all the solutions.

```
robot = rigidBodyTree('MaxNumBodies',15,'DataFormat','row');
body1 = rigidBody('body1');
body1.Joint = rigidBodyJoint('jnt1','revolute');

body2 = rigidBody('body2');
jnt2 = rigidBodyJoint('jnt2','revolute');
setFixedTransform(jnt2, trvec2tform([0.3 0 0]))
body2.Joint = jnt2;

body3 = rigidBody('tool');
jnt3 = rigidBodyJoint('jnt3','revolute');
setFixedTransform(jnt3, trvec2tform([0.3 0 0]))
body3.Joint = jnt3;

addBody(robot, body1, 'base')
addBody(robot, body2, 'body1')
addBody(robot, body3, 'body2')
```

```
% Show first solution and set view.
figure
show(robot,qs(1,:));
view(2)
ax = gca;
ax.Projection = 'orthographic';
hold on
plot(points(:,1),points(:,2),'k')
axis([-0.1 0.7 -0.3 0.5])

% Iterate through the solutions
framesPerSecond = 15;
r = rateControl(framesPerSecond);
for i = 1:count
    show(robot,qs(i,:), 'PreservePlot', false);
    drawnow
    waitfor(r);
end
```

This example showed you how can you generate code for specific algorithms or functions to improve their speed and simply replace them with the generated MEX function in your workflow.

See Also

[codegen](#) | [inverseKinematics](#) | [timeit](#)

Related Examples

- “2-D Path Tracing With Inverse Kinematics” on page 2-14
- Functions Supporting Code Generation
- “Generate C Code at the Command Line” (MATLAB Coder)
- “Generate C Code by Using the MATLAB Coder App” (MATLAB Coder)

Install Robotics System Toolbox Add-ons

To expand the capabilities of the Robotics System Toolbox and gain additional functionality for specific tasks and applications, use add-ons. You can find and install add-ons using the Add-On Explorer.

- 1 To install add-ons relevant to the Robotics System Toolbox, type in the MATLAB command window:

```
roboticsAddons
```

- 2 Select the add-on that you want. For example:
 - **Robotics System Toolbox UAV Library**
- 3 Click **Install**, and select either:
 - **Install**
 - **Download Only...** — Downloads an install file to use offline.
- 4 Continue to follow the setup instructions on the **Add-Ons Explorer** to install your add-ons.

To update or manage your add-ons, call `roboticsAddons` and select **Manage Add-Ons**.

See Also

Related Examples

- "Add-Ons"

Code Generation from MATLAB Code

Several Robotics System Toolbox functions are enabled to generate C/C++ code. Code generation from MATLAB code requires the MATLAB Coder product. To generate code from robotics functions, follow these steps:

- Write your function or application that uses Robotics System Toolbox functions that are enabled for code generation. For code generation, some of these functions have requirements that you must follow. See “Code Generation Support” on page 2-61.
- Add the `%#codegen` directive to your MATLAB code.
- Follow the workflow for code generation from MATLAB code using either the MATLAB Coder app or the command-line interface.

Using the app, the basic workflow is:

- 1 Set up a project. Specify your top-level functions and define input types.

The app screens your code for code generation readiness. It reports issues such as a function that is not supported for code generation.

- 2 Check for run-time issues.

The app generates and runs a MEX version of your function. This step detects issues that can be hard to detect in the generated C/C++ code.

- 3 Configure the code generation settings for your application.

- 4 Generate C/C++ code.

- 5 Verify the generated C/C++ code. If you have an Embedded Coder® license, you can use software-in-the-loop execution (SIL) or processor-in-the-loop (PIL) execution.

For a tutorial, see “Generate C Code by Using the MATLAB Coder App” (MATLAB Coder).

Using the command-line interface, the basic workflow is:

- To detect issues and verify the behavior of the generated code, generate a MEX version of your function.
- Use `coder.config` to create a code configuration object for a library or executable.
- Modify the code configuration object properties as required for your application.
- Generate code using the `codegen` command.
- Verify the generated code. If you have an Embedded Coder license, you can use software-in-the-loop execution (SIL) or processor-in-the-loop (PIL) execution.

For a tutorial, see “Generate C Code at the Command Line” (MATLAB Coder).

To view a full list of code generation support, see Functions Supporting Code Generation. You can also view the **Extended Capabilities** section on any reference page.

See Also

More About

- Functions Supporting Code Generation

Code Generation Support

To generate code from MATLAB code that contains Robotics System Toolbox functions, classes, or System objects, you must have the MATLAB Coder software.

To view a full list of code generation support, see [Functions Supporting Code Generation](#). You can also view the **Extended Capabilities** section on any reference page.

See Also

More About

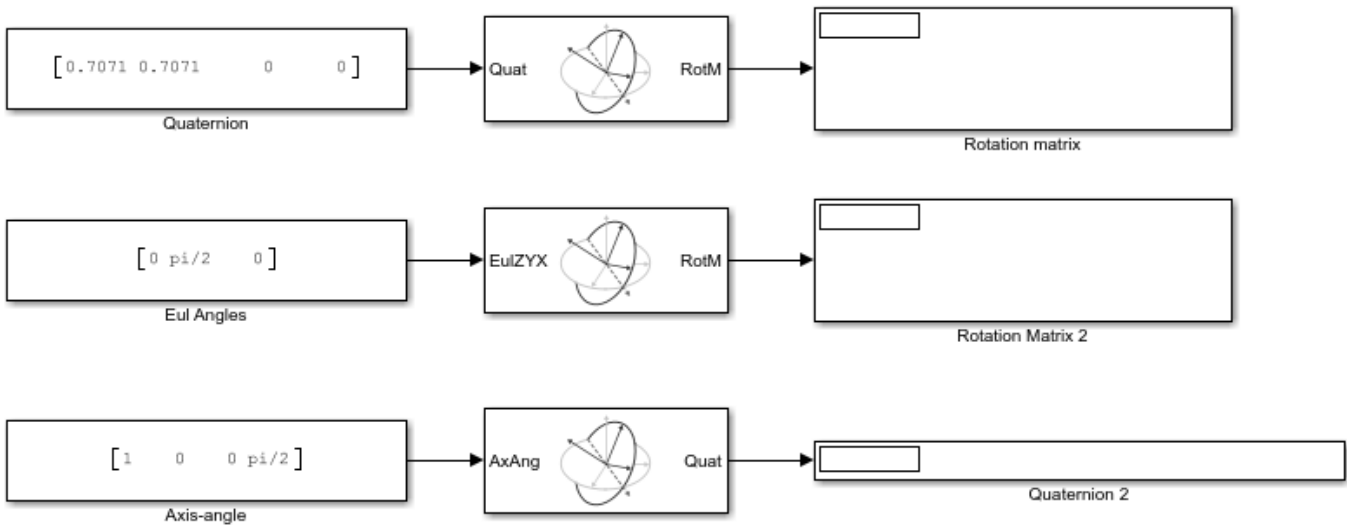
- “Code Generation from MATLAB Code” on page 2-60

Examples for Simulink Blocks

Convert Coordinate System Transformations

This model shows how to convert some basic coordinate system transformations into other coordinate systems. Input vectors are expected to be vertical vectors.

```
open_system('coord_trans_block_example_model.slx')
```



Compute Geometric Jacobian for Manipulators in Simulink

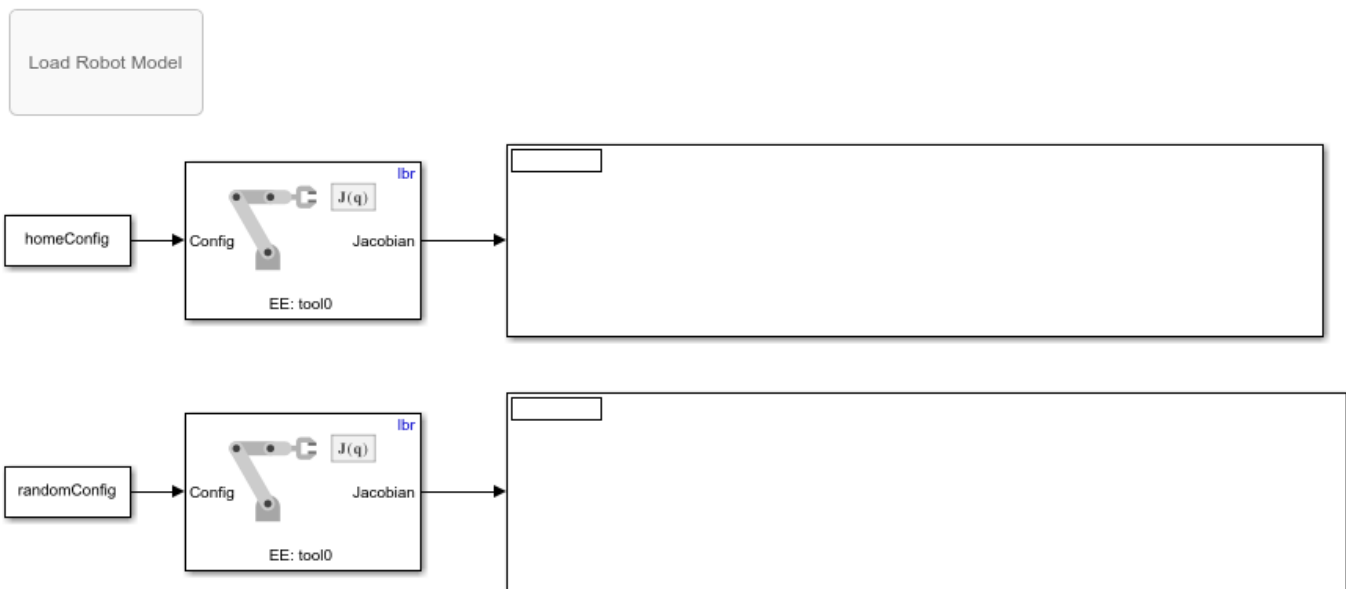
This example shows how to calculate the geometric Jacobian for a robot manipulator by using a `rigidBodyTree` model. The Jacobian maps the joint-space velocity to the end-effector velocity relative to the base coordinate frame. In this example, you define a robot model and robot configurations in MATLAB® and pass them to Simulink® to be used with the manipulator algorithm blocks.

Load a `RigidBodyTree` object that models a KUKA LBR robot. Use the `homeConfiguration` function to get the home configuration or home joint positions of the robot. Use the `randomConfiguration` function to generate a random configuration within the specified joint limits.

```
load('exampleRobots.mat','lbr')
lbr.DataFormat = 'column';
homeConfig = homeConfiguration(lbr);
randomConfig = randomConfiguration(lbr);
```

Open the model. If necessary, use the **Load Robot Model** callback button to reload the robot model and the configuration vectors. The 'tool0' body is selected as the end-effector in both blocks.

```
open_system('get_jacobian_example.slx')
```



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Run the model to display the Jacobian for each configuration.

See Also

Blocks

Forward Dynamics | Get Jacobian | Gravity Torque | Inverse Dynamics | Joint Space Mass Matrix

Classes

`rigidBodyTree`

Functions

externalForce | homeConfiguration | importrobot | randomConfiguration

Related Examples

- “Perform Safe Trajectory Tracking Control Using Robotics Manipulator Blocks” on page 1-194

Get Transformations for Manipulator Bodies in Simulink

This example shows how to get the transformation between bodies in a `rigidBodyTree` robot model. In this example, you define a robot model and robot configuration in MATLAB® and pass them to Simulink® to be used with the manipulator algorithm block.

Load the robot model of the KUKA LBR robot as a `RigidBodyTree` object. Use the `homeConfiguration` function to get the home configuration as joint positions of the robot.

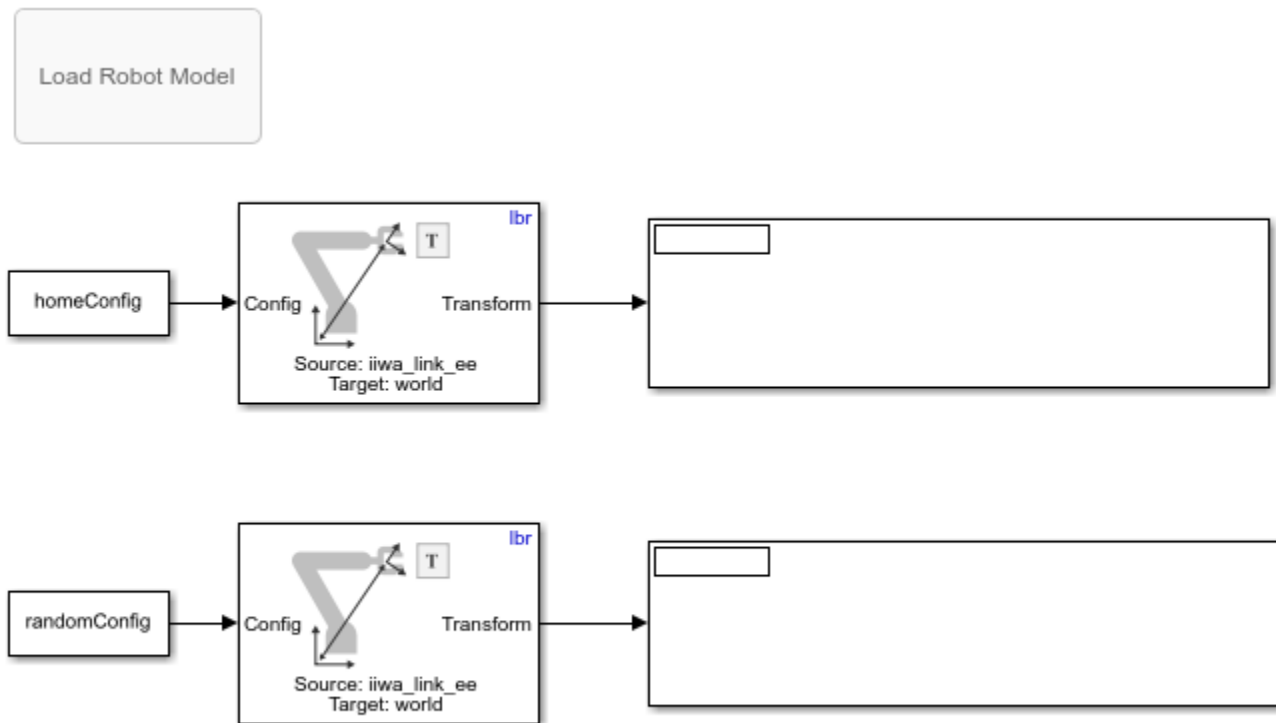
```
load('exampleLBR.mat','lbr')
lbr.DataFormat = 'column';

homeConfig = homeConfiguration(lbr);
randomConfig = randomConfiguration(lbr);
```

Open the model. If necessary, use the **Load Robot Model** callback button to reload the robot model and configuration vectors.

The Get Transform block calculates the transformation from the source body to the target body. This transformation converts coordinates from the source body frame to the given target body frame. This example gives you transformations to convert coordinates from the 'iiwa_link_ee' end effector into the 'world' base coordinates.

```
open_system('get_transform_example.slx')
```



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Run the model to get the transformations.

See Also

Blocks

Forward Dynamics | Get Jacobian | Get Transform | Gravity Torque | Inverse Dynamics | Joint Space Mass Matrix

Classes

rigidBodyTree

Functions

homeConfiguration | importrobot | randomConfiguration

Related Examples

- “Perform Safe Trajectory Tracking Control Using Robotics Manipulator Blocks” on page 1-194

Calculate Manipulator Gravity Dynamics in Simulink

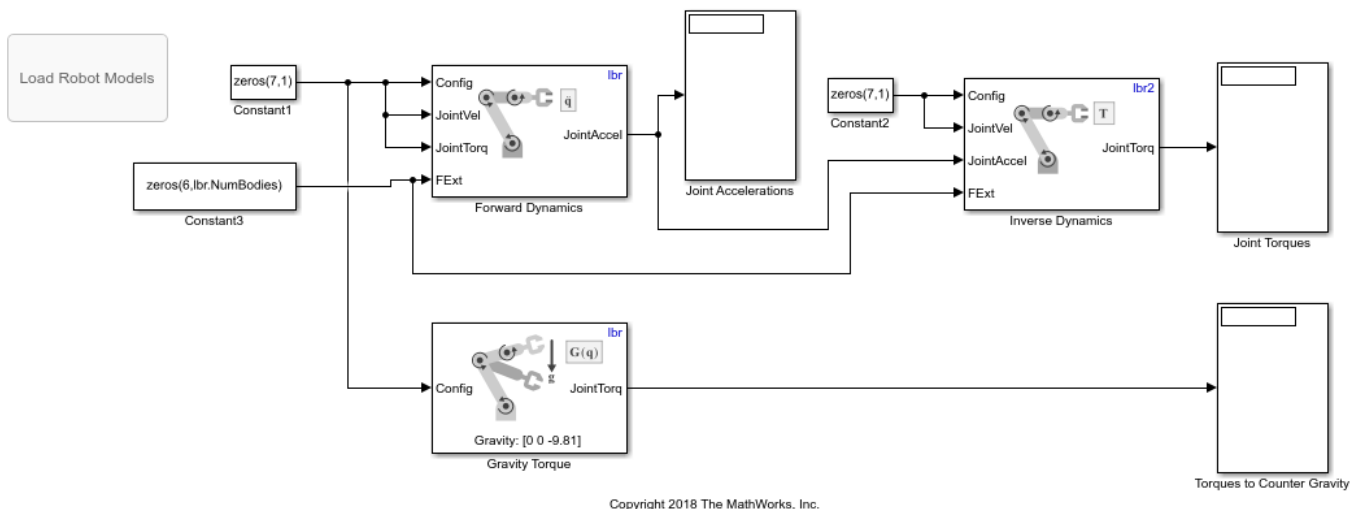
This example shows how to use the manipulator algorithm blocks to compute and compare dynamics due to gravity for a manipulator robot.

Specify two similar robot models with different gravity accelerations. Load the KUKA LBR robot model into the MATLAB® workspace and create a copy of it. For the first robot model, `lbr`, specify a normal gravity vector, $[0 \ 0 \ -9.81]$. For the copy, `lbr2`, use the default gravity vector, $[0 \ 0 \ 0]$. These robot models are also specified in the **Rigid body tree** parameters of the blocks in the model.

```
load('exampleLBR.mat','lbr')
lbr.DataFormat = 'column';
lbr2 = copy(lbr);
lbr.Gravity = [0 0 -9.81];
```

Open the gravity dynamics model. If needed, reload the robot models specified by the MATLAB code using the **Load Robot Models** callback button.

```
open_system('gravity_dynamics_model.slx')
```



The Forward Dynamics block calculates the joint accelerations due to gravity for a given `lbr` robot configuration with no initial velocity, torque, or external force. The Inverse Dynamics block then computes the torques needed for the joint to create those same accelerations with no gravity by using the `lbr2` robot. Finally, the Gravity Torque block calculates the torque required to counteract gravity for the `lbr` robot.

Run the model. Besides some small numerical differences, the gravity torque and the torque required for accelerations due to gravity are the same value with opposite directions.

See Also

Blocks

Forward Dynamics | Get Jacobian | Gravity Torque | Inverse Dynamics | Joint Space Mass Matrix | Velocity Product Torque

Classes

rigidBodyTree

Functions

externalForce | homeConfiguration | importrobot | randomConfiguration

Related Examples

- “Perform Safe Trajectory Tracking Control Using Robotics Manipulator Blocks” on page 1-194

Trace An End-Effector Trajectory with Inverse Kinematics in Simulink

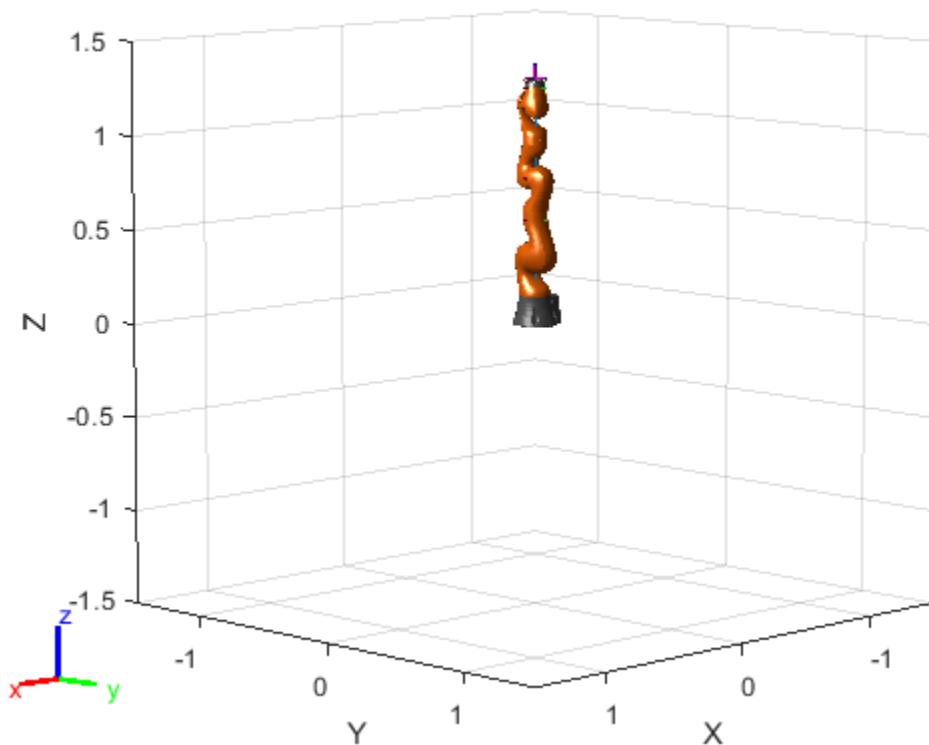
Use a rigid body robot model to compute inverse kinematics using Simulink®. Define a trajectory for the robot end effector and loop through the points to solve robot configurations that trace this trajectory.

Import a robot model from a URDF (unified robot description format) file as a RigidBodyTree object.

```
robot = importrobot('iiwa14.urdf');
robot.DataFormat = 'column';
```

View the robot.

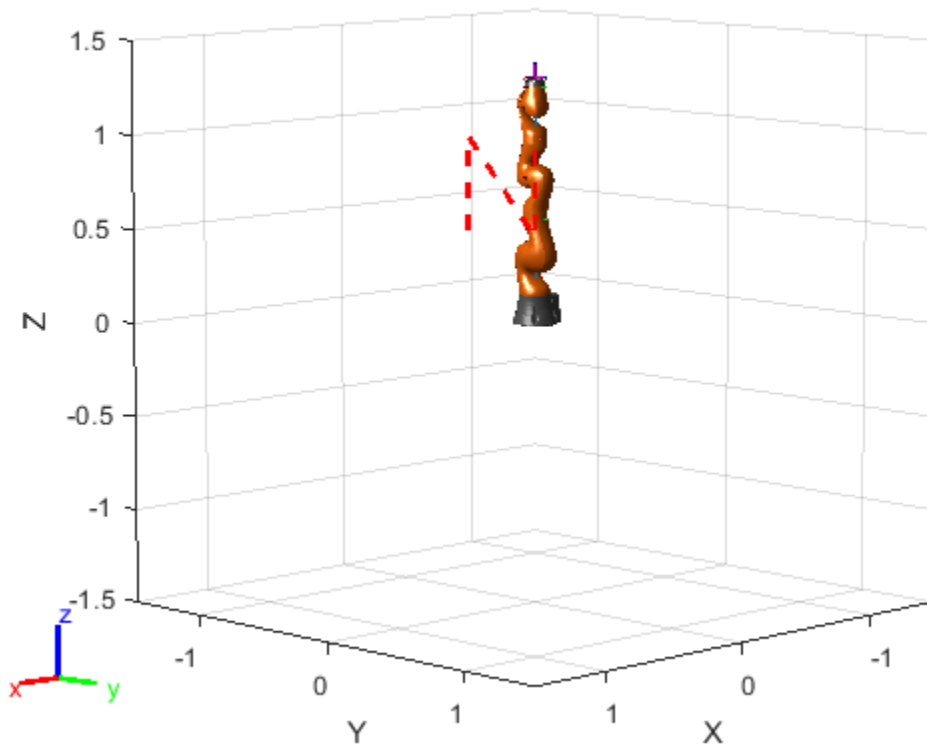
```
ax = show(robot);
```



Specify a robot trajectory. These xyz-coordinates draw an N-shape in front of the robot.

```
x = 0.5*zeros(1,4)+0.25;
y = 0.25*[-1 -1 1 1];
z = 0.25*[-1 1 -1 1] + 0.75;

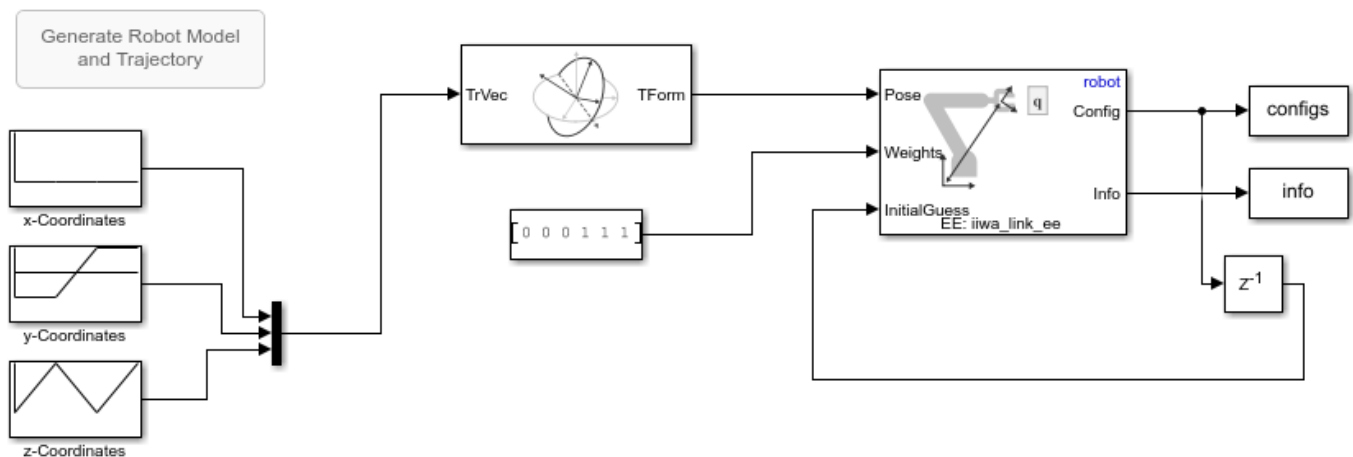
hold on
plot3(x,y,z, '--r', 'LineWidth',2, 'Parent', ax)
hold off
```



Open a model that performs inverse kinematics. The xyz -coordinates defined in MATLAB® are converted to homogeneous transformations and input as the desired Pose. The output inverse-kinematic solution is fed back as the initial guess for the next solution. This initial guess helps track the end-effector pose and generate smooth configurations.

You can press the callback button to regenerate the robot model and trajectory you just defined.

```
close
open_system('sm_ik_trajectory_model.slx')
```



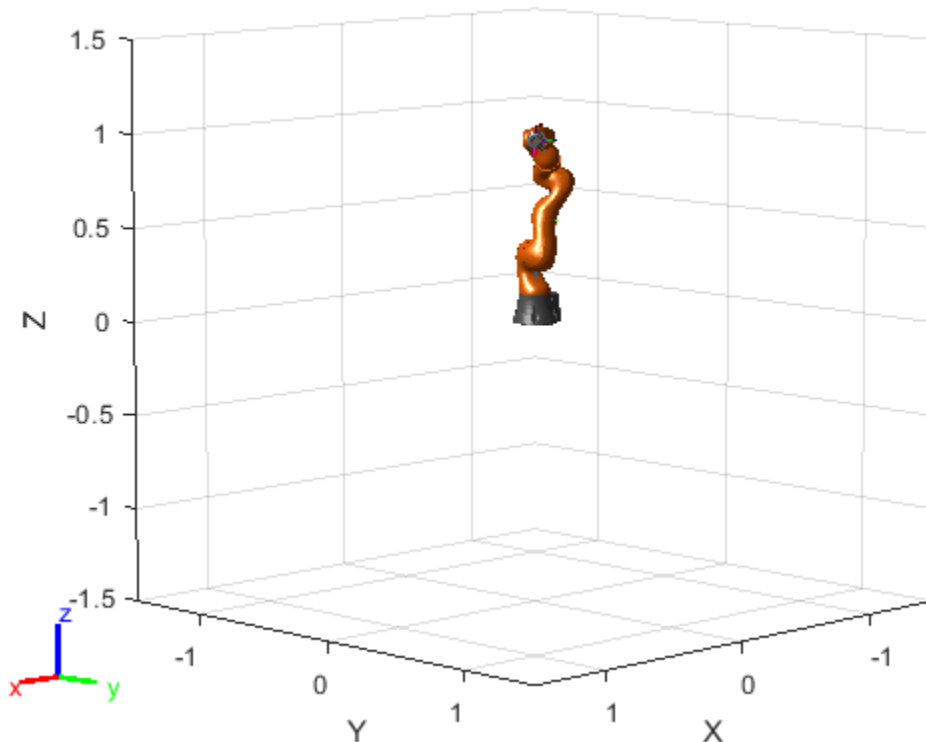
% Run the simulation. The model should generate the robot configurations (configs) that follow the specified trajectory for the end effector.

```
sim('sm_ik_trajectory_model.slx')
```

Loop through the robot configurations and display the robot for each time step. Store the end-effector positions in xyz.

```
figure('Visible','on');
tformIndex = 1;
for i = 1:10:numel(configs.Data)/7
    currConfig = configs.Data(:,1,i);
    show(robot,currConfig);
    drawnow

    xyz(tformIndex,:) = tform2trvec(getTransform(robot,currConfig,'iiwa_link_ee'));
    tformIndex = tformIndex + 1;
end
```

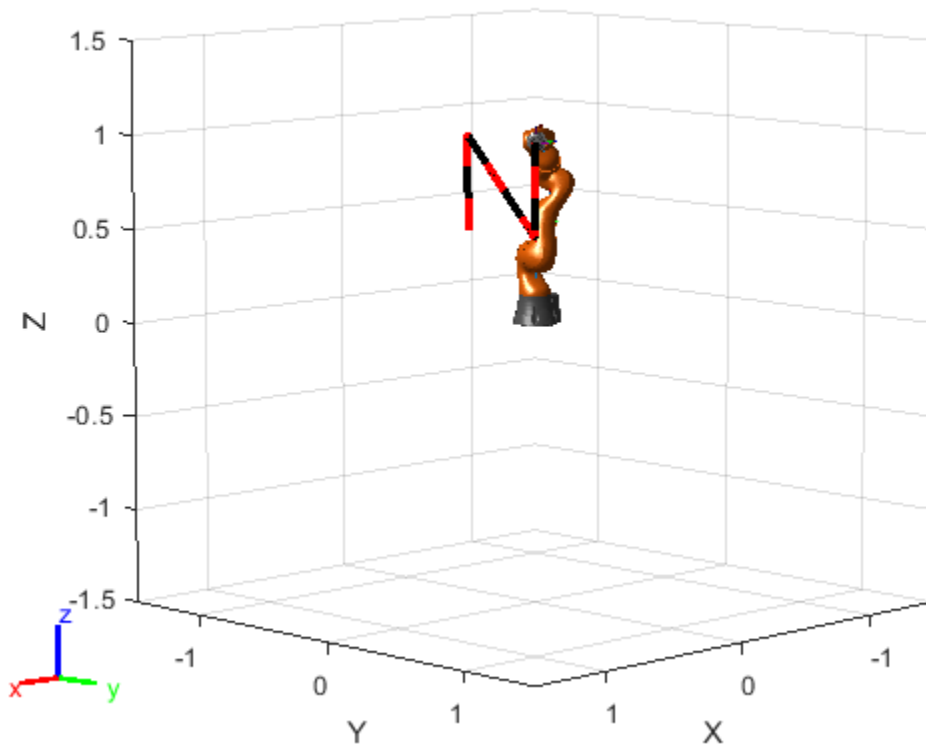


Draw the final trajectory of the end effector as a black line. The figure shows the end effector tracing the N-shape originally defined (red dotted line).

```
figure('Visible','on')
show(robot,configs.Data(:,1,end));

hold on
plot3(xyz(:,1),xyz(:,2),xyz(:,3),'-k','LineWidth',3);
```

```
plot3(x,y,z,'--r','LineWidth',3)  
hold off
```



See Also

Objects

[generalizedInverseKinematics](#) | [inverseKinematics](#) | [rigidBodyTree](#)

Blocks

[Get Transform](#) | [Inverse Dynamics](#) | [Inverse Kinematics](#)

Related Examples

- “Control PR2 Arm Movements Using ROS Actions and Inverse Kinematics” on page 1-121
- “Inverse Kinematics Algorithms” on page 2-10

Get Mass Matrix for Manipulators in Simulink

This example shows how to calculate the mass matrix for a robot manipulator using a `rigidBodyTree` model. In this example, you define a robot model and robot configurations in MATLAB® and pass them to Simulink® to be used with the manipulator algorithm blocks.

Load a `RigidBodyTree` object that models a KUKA LBR robot. Use the `homeConfiguration` functions to get the home configuration or home joint positions of the robot. Use the `randomConfiguration` function to generate a random configuration within the robot joint limits.

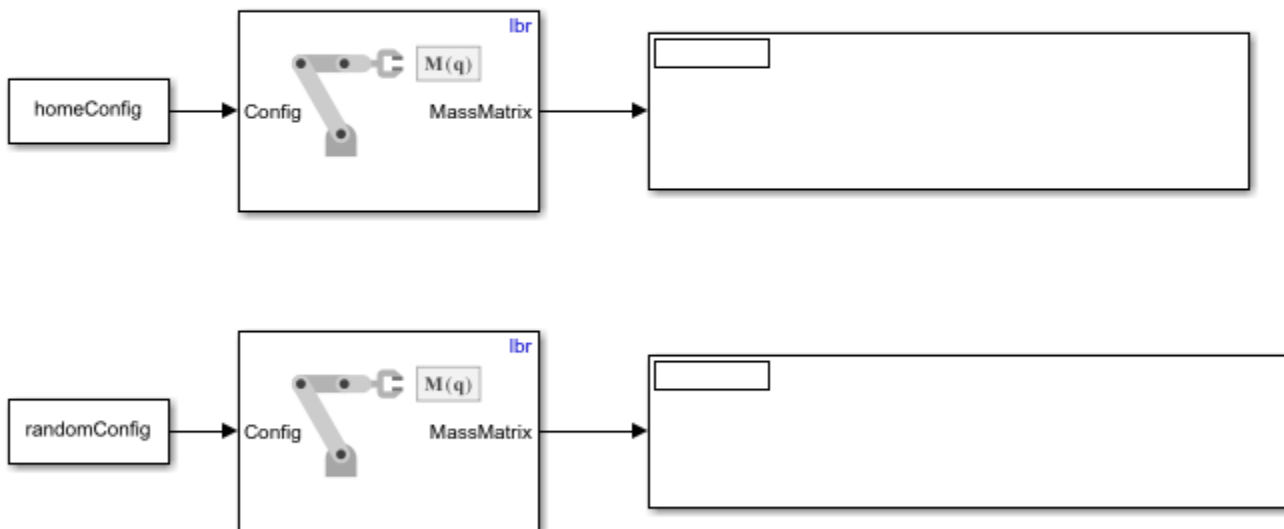
```
load('exampleRobots.mat','lbr')
lbr.DataFormat = 'column';
```

```
homeConfig = homeConfiguration(lbr);
randomConfig = randomConfiguration(lbr);
```

Open the model. If necessary, use the **Load Robot Model** callback button to reload the robot model and configuration vectors.

The Joint Space Mass Matrix block calculates the mass matrix for the given configuration.

```
open_system('mass_matrix_example.slx')
```



Run the model to display the mass matrices for each configuration.

See Also

Blocks

Forward Dynamics | Get Jacobian | Get Transform | Gravity Torque | Inverse Dynamics

Classes

rigidBodyTree

Functions

homeConfiguration | importrobot | randomConfiguration

Related Examples

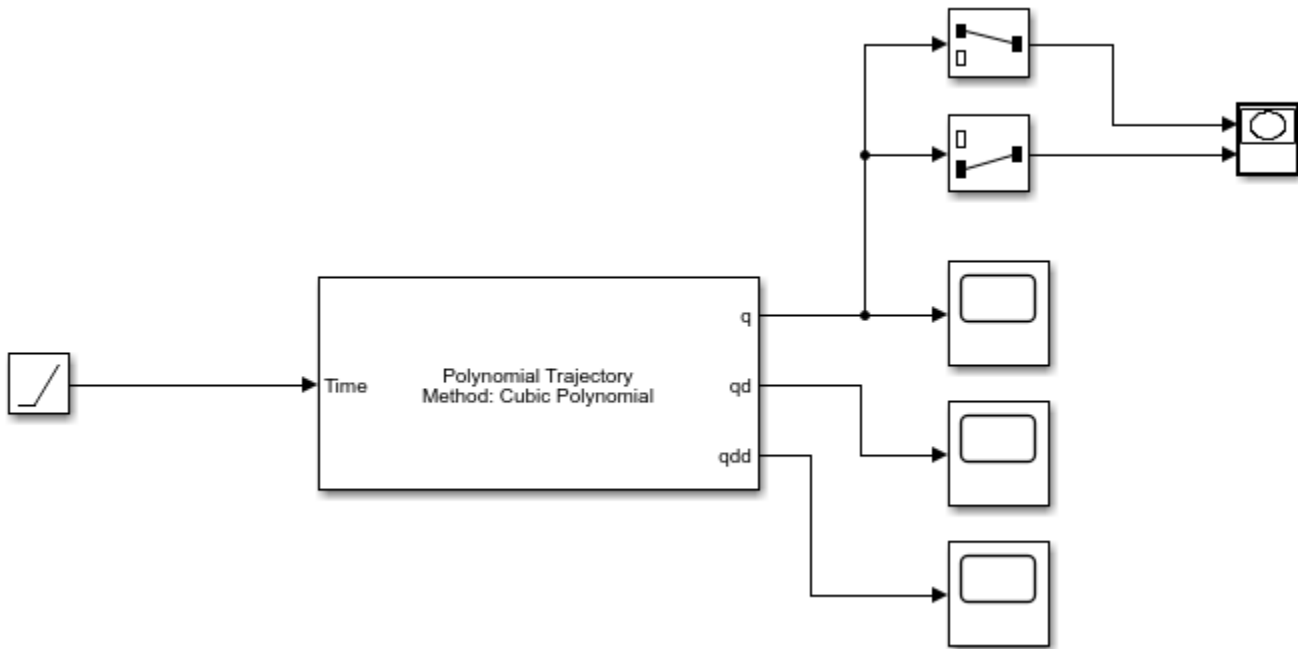
- “Perform Safe Trajectory Tracking Control Using Robotics Manipulator Blocks” on page 1-194

Generate Cubic Polynomial Trajectory

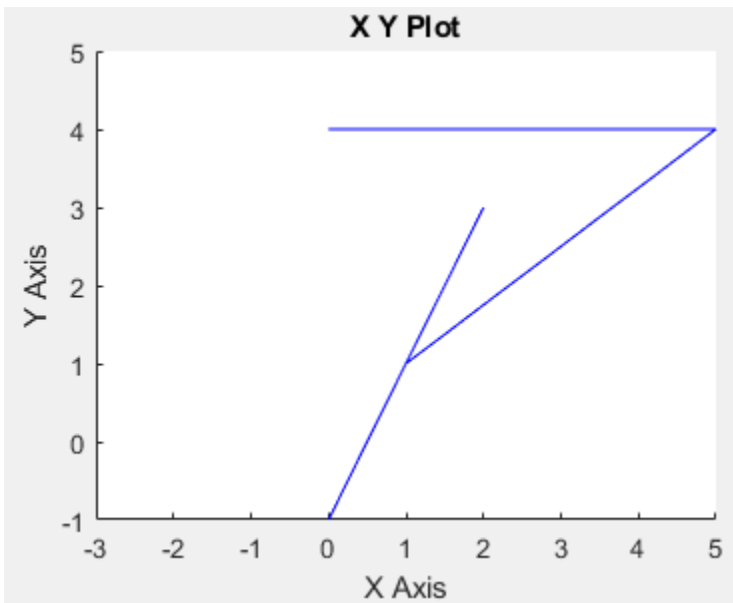
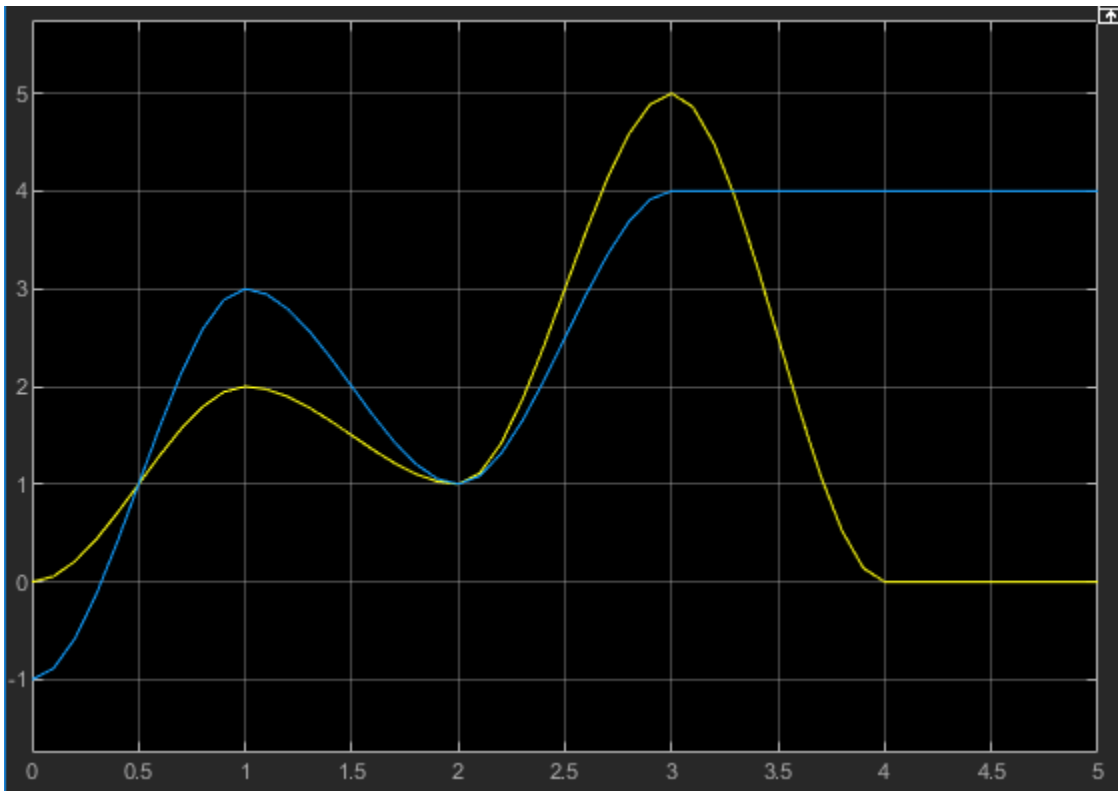
This example shows how to generate a cubic polynomial trajectory using the **Polynomial Trajectory** block.

Open the model. The block has a set of 2-D waypoints defined in the block mask. The **Time** input is just a ramp signal to simulate time progressing.

```
open_system('cubic_polytraj_ex1.slx')
```



Run the simulation. The first figure shows the output of the q vector for the positions of the trajectory. Notice the cubic polynomial shape to the trajectory between waypoints. The **XY Plot** shows the actual 2-D trajectory, which hits the waypoints specified in the block mask.

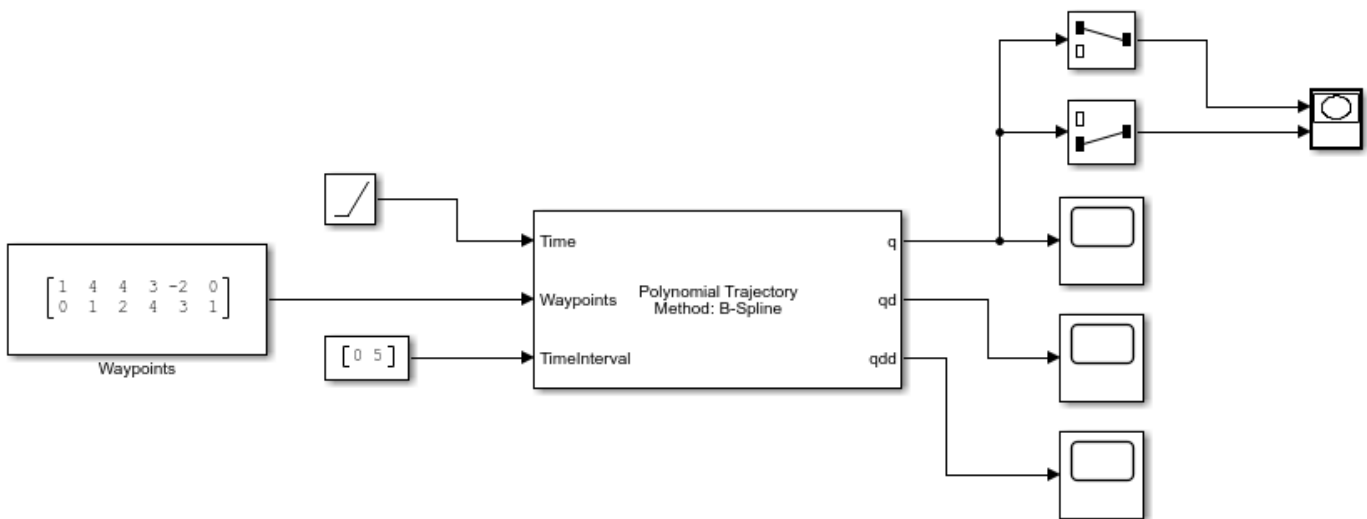


Generate B-Spline Trajectory

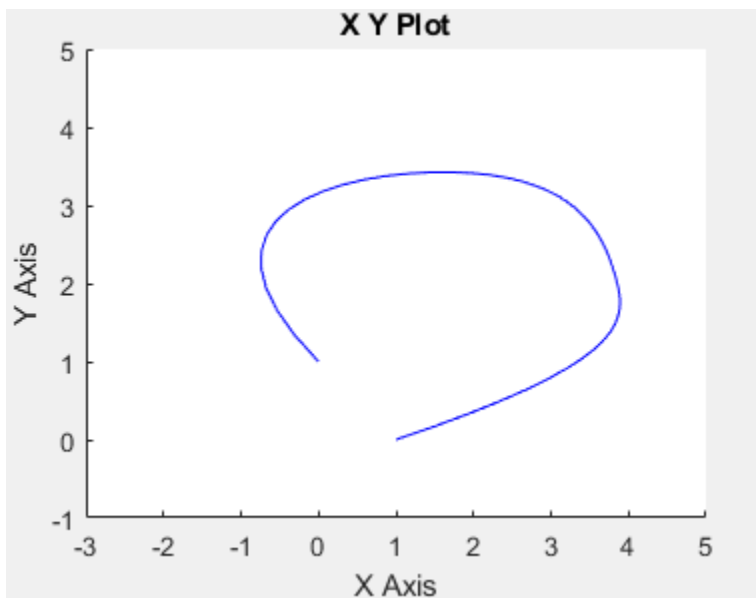
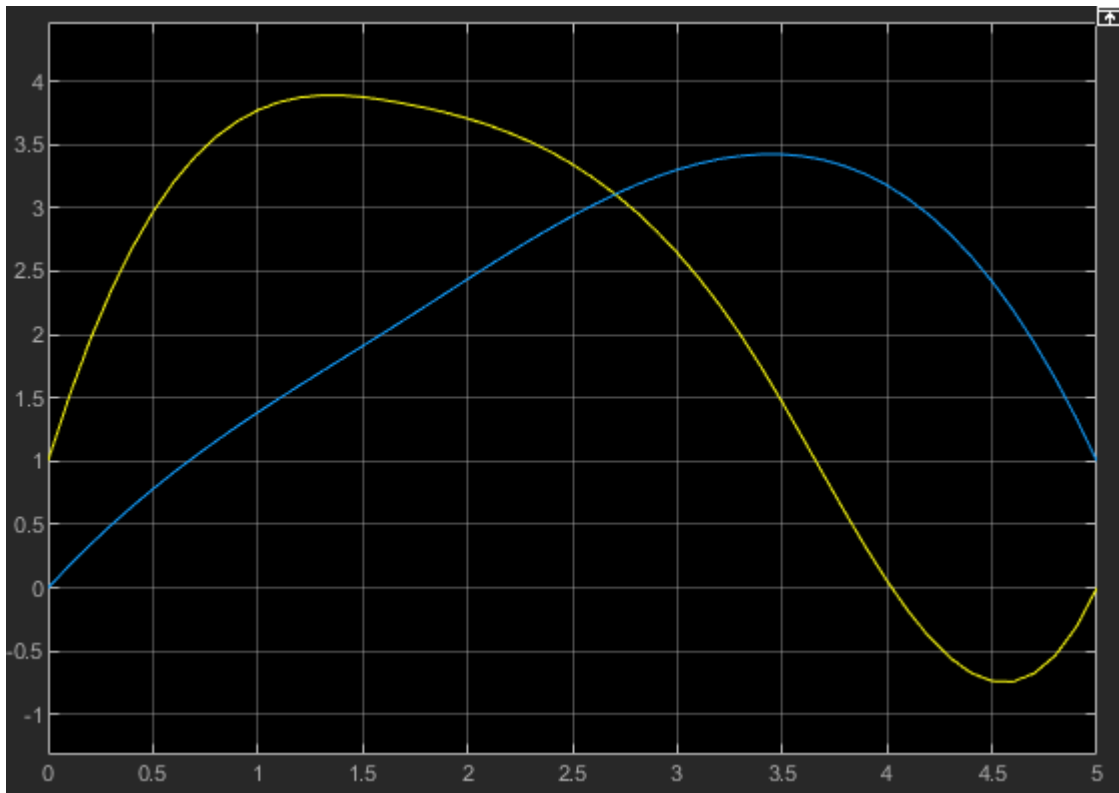
This example shows how to generate a B-spline trajectory using the **Polynomial Trajectory** block.

Open the model. The **Waypoints** and **TimeInterval** inputs are toggled in the block mask by setting **Waypoint source** to External. For B-splines, the waypoints are actually control points for the convex polygon, but the first and last waypoints are met. The **Time** input is just a ramp signal to simulate time progressing.

```
open_system('bspline_polytraj_ex1.slx')
```



Run the simulation. The first figure shows the output of the q vector for the positions of the trajectory. The **X Y Plot** shows the actual 2-D trajectory, which stays inside the defined control points and hits the first and last waypoints.

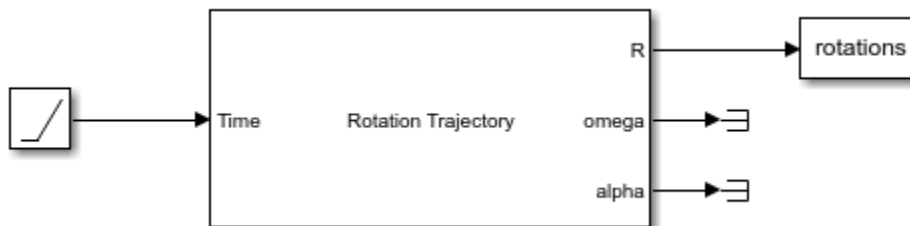


Generate Rotation Trajectory

This example shows how to generate a trajectory that interpolates between rotations using the **Rotation Trajectory** block.

Open and simulate the model. The **Rotation Trajectory** block outputs the trajectory between two rotations and saves the intermediate rotations to the `rotations` variable. This example generates a simple rotation trajectory from the x-axis to the z-axis.

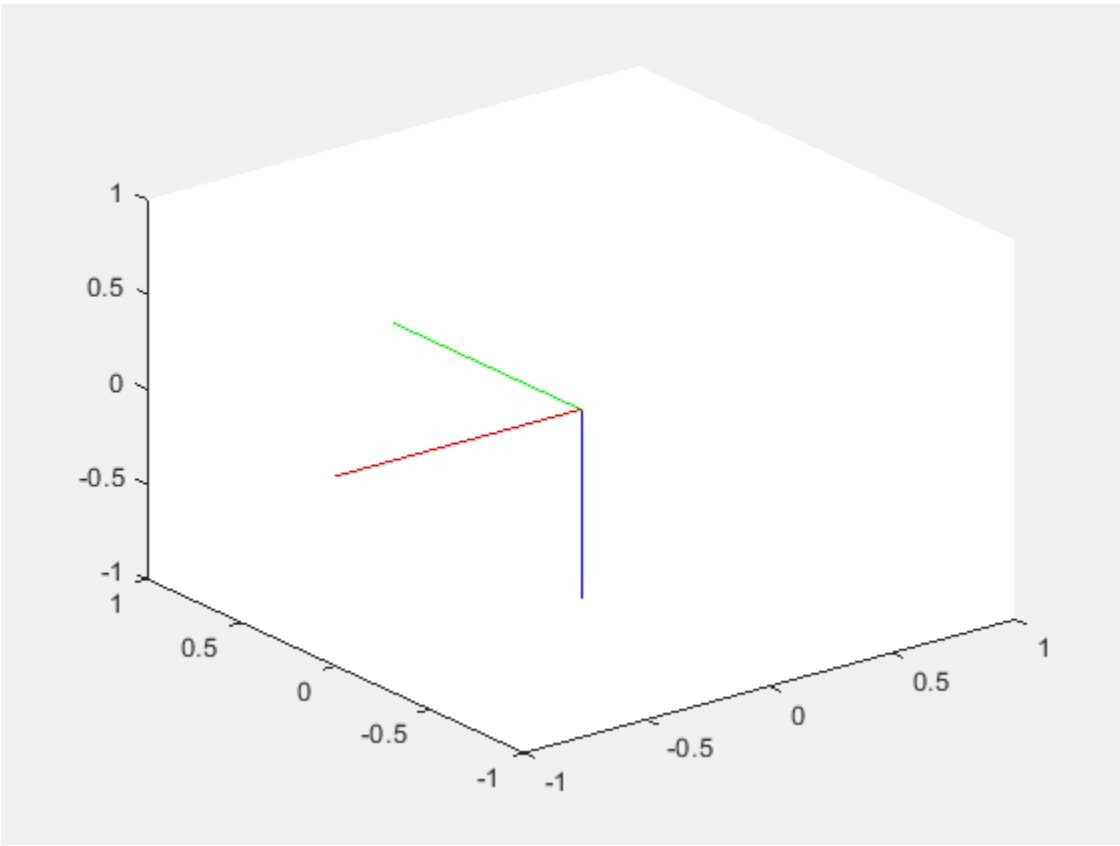
```
open_system('rot_traj_ex1.slx')
simOut = sim('rot_traj_ex1.slx');
```



Use `plotTransforms` to plot the rotation trajectory.

```
numRotations = size(simOut.rotations,3);
translations = zeros(3,numRotations);
figure("Visible","on")

for i = 1:numRotations
    plotTransforms(translations(:,i)',simOut.rotations(:,i)')
    xlim([-1 1])
    ylim([-1 1])
    zlim([-1 1])
    drawnow
    pause(0.1)
end
```



Use Custom Time Scaling for a Rotation Trajectory

This example shows how to specify custom time-scaling in the **Rotation Trajectory** block to execute an interpolated trajectory. Two rotations are specified in the block to generate a trajectory between them. The goal is to move between rotations using a nonlinear time scaling with more time samples closer to the final rotation.

Specify the Time Scaling

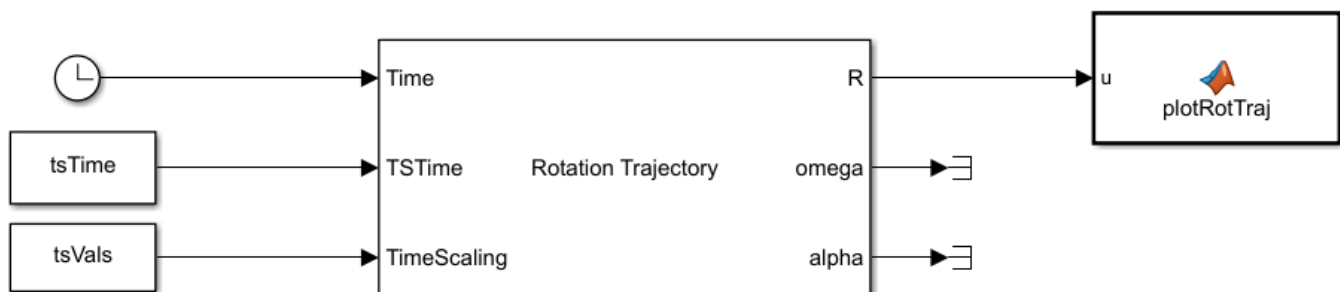
Create vectors for the time scaling time vector and time scaling values. The time scaling time is linear vector from 0 to 5 seconds at 0.1 second intervals. The time scaling values follow a cubic trajectory with the appropriate derivatives specified for velocity and acceleration. These values are used in the model.

```
tsTime = 0:0.1:5;
tsVals(1,:) = (tsTime/5).^3;           % Position
tsVals(2,:) = ((3/125).*tsTime).^2;   % Velocity
tsVals(3,:) = (18/125^2).*tsTime;     % Acceleration
```

Open the Model

The **Clock** block outputs simulation time and is used for querying the rotation trajectory at those specify time points. The full set of time scaling time and values are input to the **Rotation Trajectory** block, but the **Time** input defined when to sample from this trajectory. The MATLAB® function block uses `plotTransforms` to plot a coordinate frame that moves along the generated rotation trajectory.

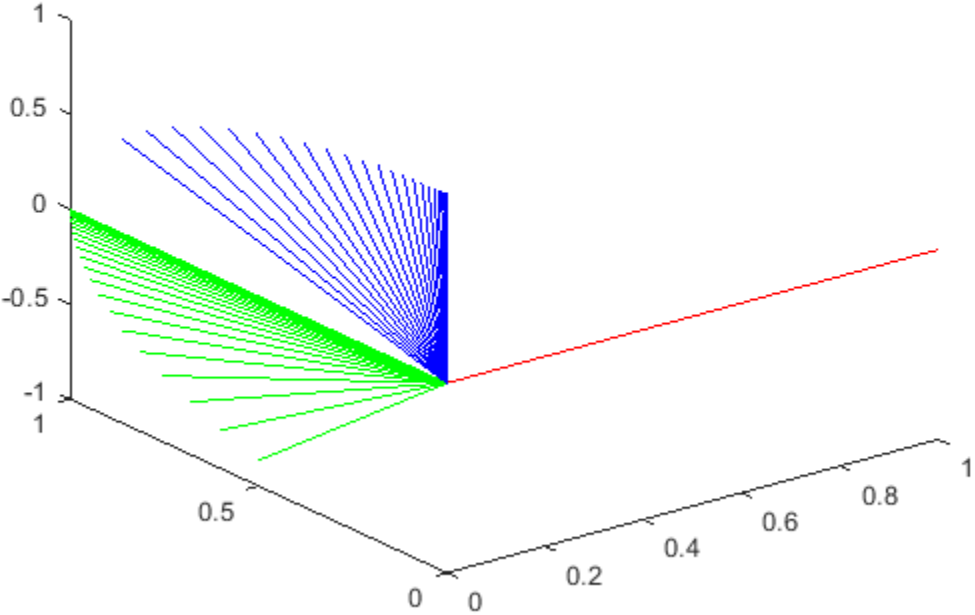
```
open_system("custom_time_scaling_rotation")
```



Simulate the Model

Simulate the model. The plot shows how the rotation follows a nonlinear interpolated trajectory parameterized in time. The model runs with a fixed-step solver at an interval of 0.1 seconds, so each frame is 0.1 seconds apart. Notice that the transformations are sampled more closely near the final rotation.

```
sim("custom_time_scaling_rotation")
hold off
```



Execute Transformation Trajectory Using Manipulator and Inverse Kinematics

This example shows how to generate a transformation trajectory using the **Transform Trajectory** block and execute it for a manipulator robot using inverse kinematics.

Generate two homogenous transformations for the start and end points of the trajectory.

```
tform1 = trvec2tform([0.25 -0.25 1])
```

```
tform1 = 4x4
```

```
1.0000    0    0    0.2500
    0    1.0000    0   -0.2500
    0    0    1.0000    1.0000
    0    0    0    1.0000
```

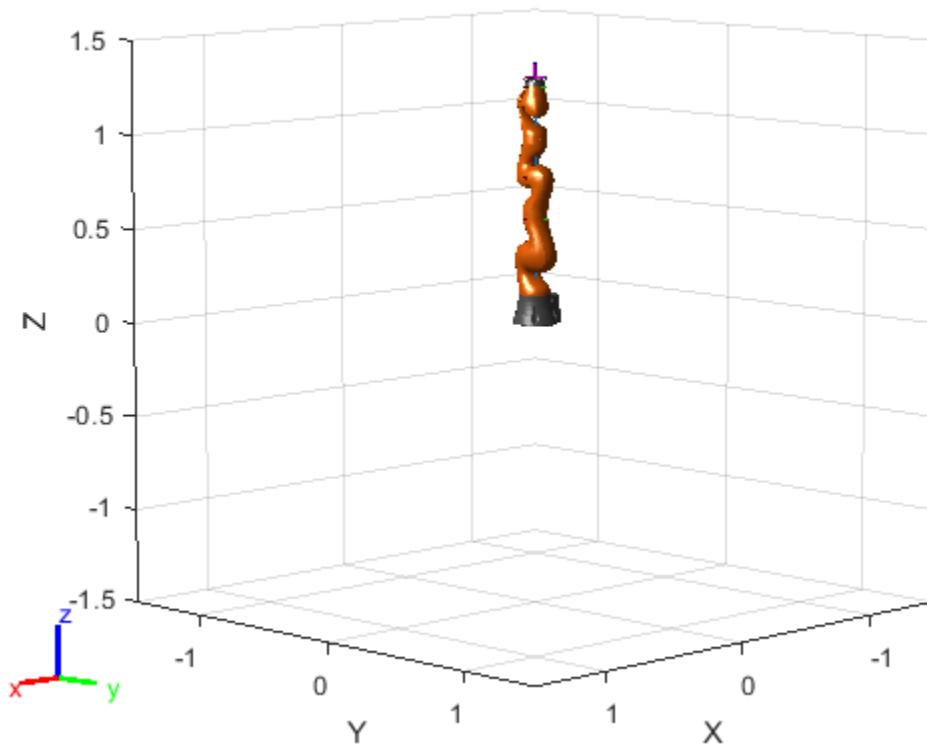
```
tform2 = trvec2tform([0.25 0.25 0.5])
```

```
tform2 = 4x4
```

```
1.0000    0    0    0.2500
    0    1.0000    0    0.2500
    0    0    1.0000    0.5000
    0    0    0    1.0000
```

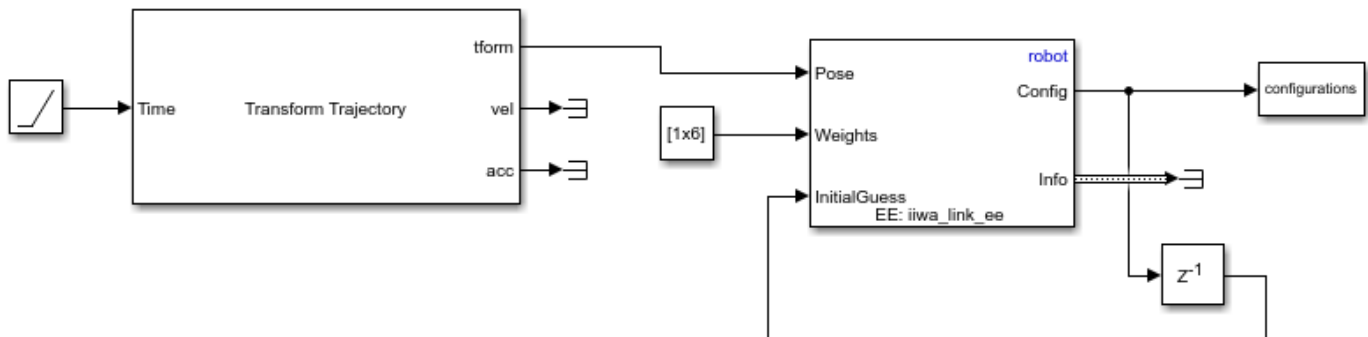
Import the robot model and specify the data format for Simulink®.

```
robot = importrobot('iiwa14.urdf');
robot.DataFormat = 'column';
show(robot);
```



Open the model. The **Transform Trajectory** block interpolates between the initial and final transformation specified in the block mask. These transformations are fed to the **Inverse Kinematics** block to solve for the robot configuration that makes the end effector reach the desired transformation. The configurations are output to the workspace as configurations.

```
open_system('transform_traj_ex1.slx')
```



Run the simulation and get the robot configurations.

```
simOut = sim('transform_traj_ex1.slx')
```

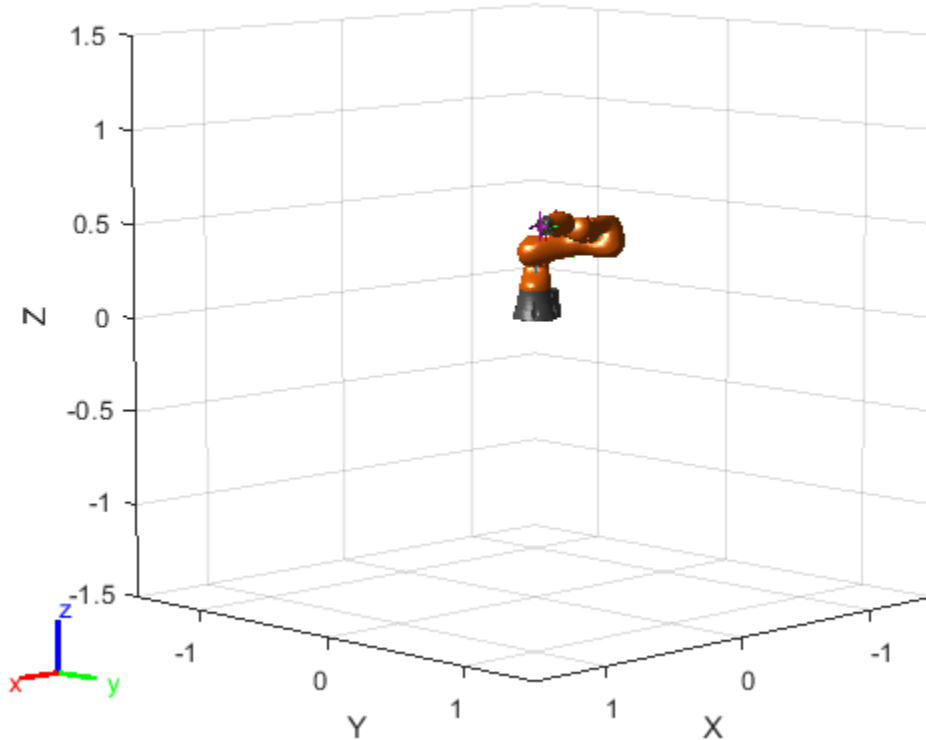
```
simOut =  
    Simulink.SimulationOutput:
```

```
configurations: [7x1x52 double]
               tout: [52x1 double]

SimulationMetadata: [1x1 Simulink.SimulationMetadata]
ErrorMessage: [0x0 char]
```

Show the robot configurations to animate the robot going through the trajectory.

```
for i = 1:numel(simOut.configurations)/7
    currConfig = simOut.configurations(:,:,i);
    show(robot,currConfig);
    drawnow
end
```



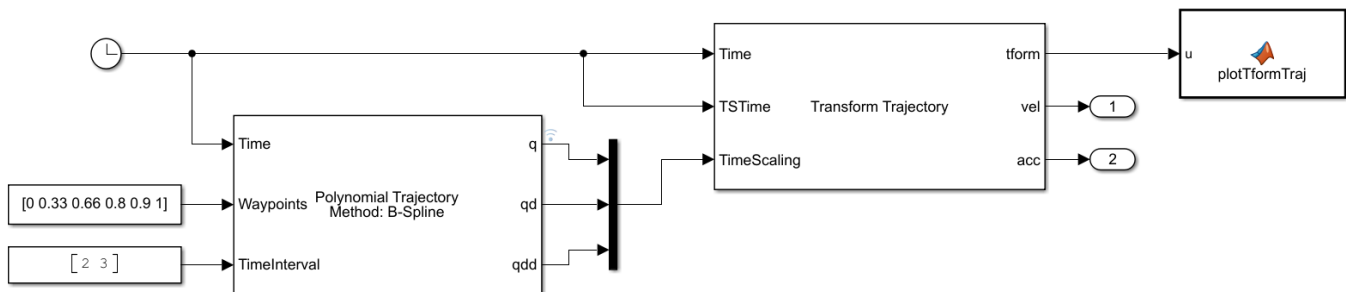
Use Custom Time Scaling for a Transform Trajectory

This example shows how to specify custom time-scaling in the **Transform Trajectory** block to execute an interpolated trajectory. Two transformations are specified in the block to generate a trajectory between the two. The goal is to move between transforms using a nonlinear time scaling where the trajectory moves quickly at the start and slowly at the end.

Open the Model

A custom time scaling trajectory is generated using the **Polynomial Trajectory** block, which gives the position, velocity, and acceleration defined by the custom time scaling at the instant in time, as given by the **Clock** block. The **Clock** block outputs simulation time and is used for querying the transformation trajectory at those specify time points. The input **Waypoints** define the waypoints of the nonlinear time scaling to use and includes a shorter time interval between points near the final time. The 3×1 time scaling, output from the **Polynomial Trajectory** block as **q**, **qd**, and **qdd**, is input to the **Transform Trajectory** block with the current clock time as the **TSTime**, which indicates this is the time scaling at that instance. The MATLAB® function block uses `plotTransforms` to plot a coordinate frame that moves along the generated transformation trajectory.

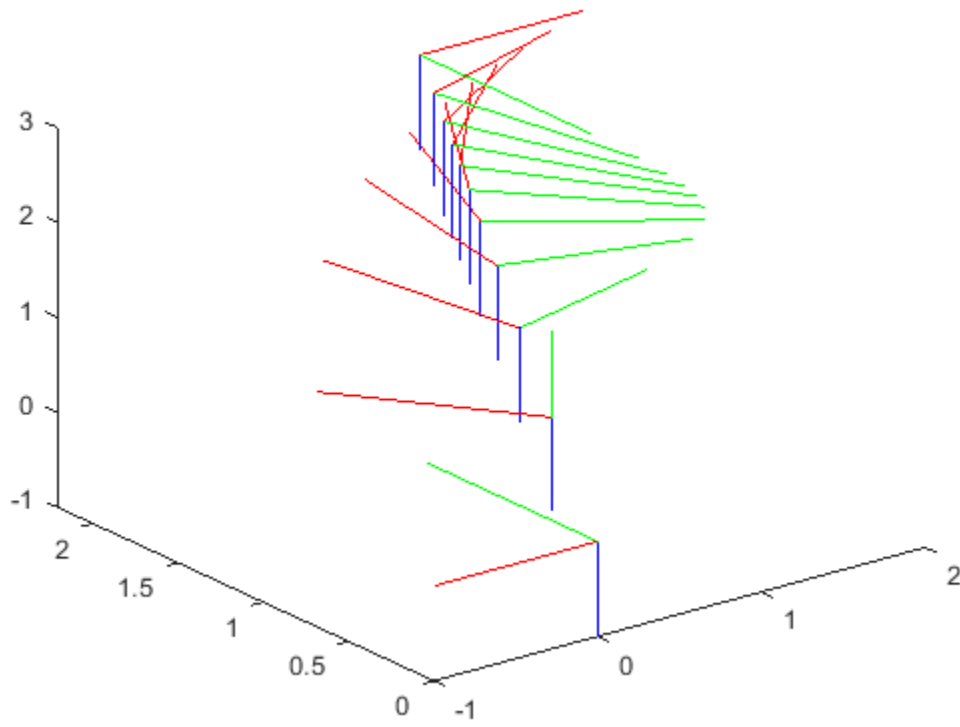
```
open_system("custom_time_scaling_transform")
```



Simulate the Model

Simulate the model. The plot shows how the transformation follows a nonlinear interpolated trajectory parameterized in time. The model runs with a fixed-step solver at an interval of 0.1 seconds, so each frame is 0.1 seconds apart. Notice that the transformations are sampled more closely near the final transformation.

```
sim("custom_time_scaling_transform")
hold off
```

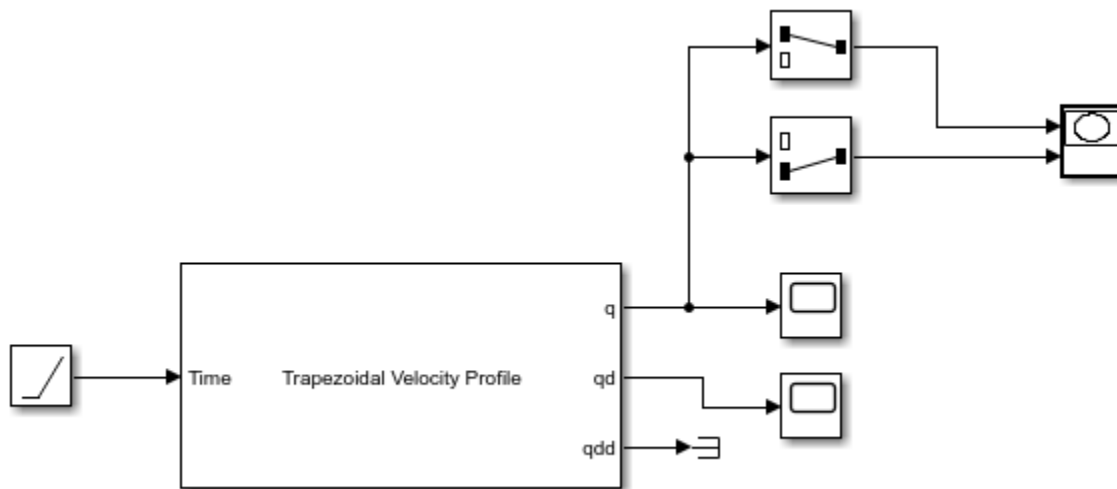



Generate Trapezoidal Velocity Trajectory

This example shows how to generate a trapezoidal velocity trajectory using the **Trapezoidal Velocity** block.

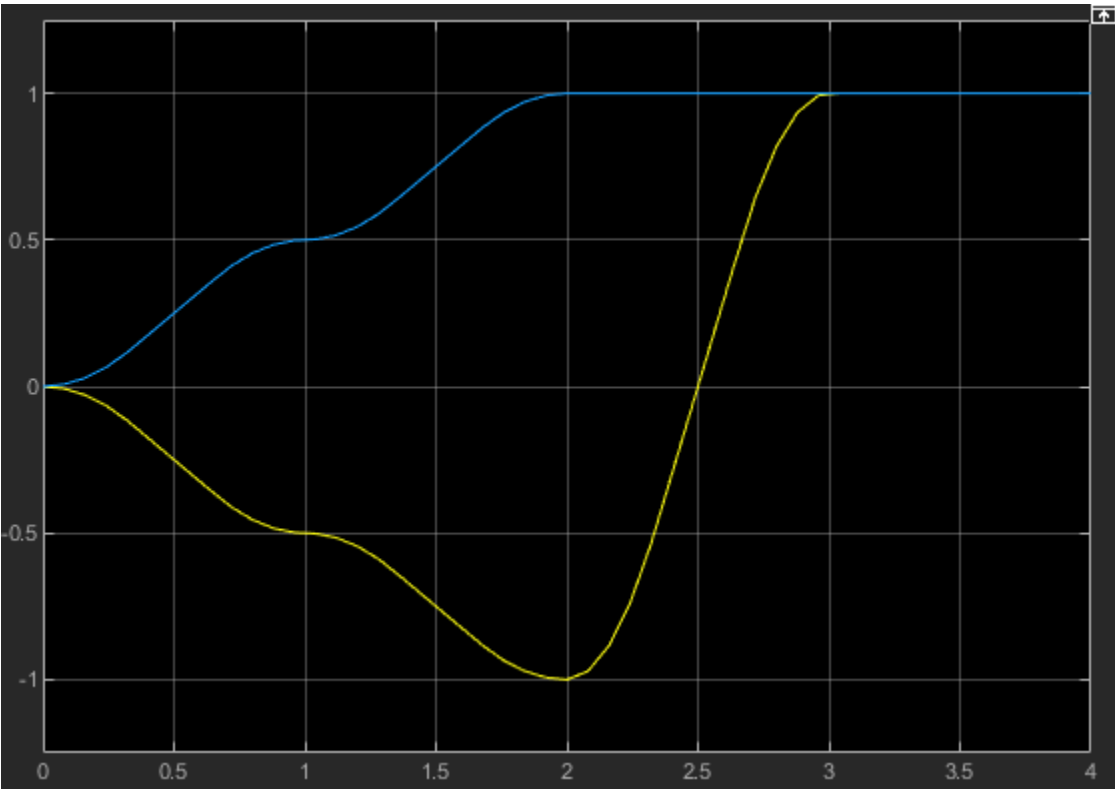
Open the model. The waypoints are specified in the block mask. The position and velocity outputs are connected to scopes and the position is plotted to an **XY Plot**. The **Time** input is just a ramp signal to simulate time progressing.

```
open_system('trapvel_traj_ex1.slx')
```

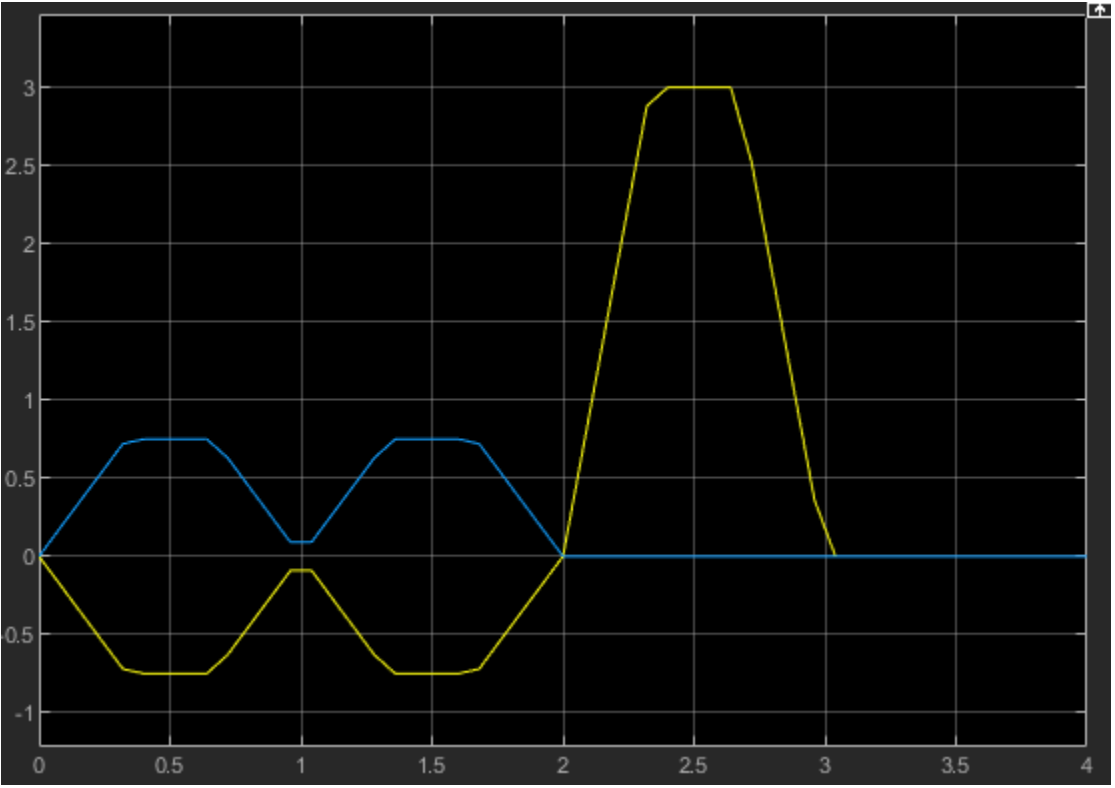


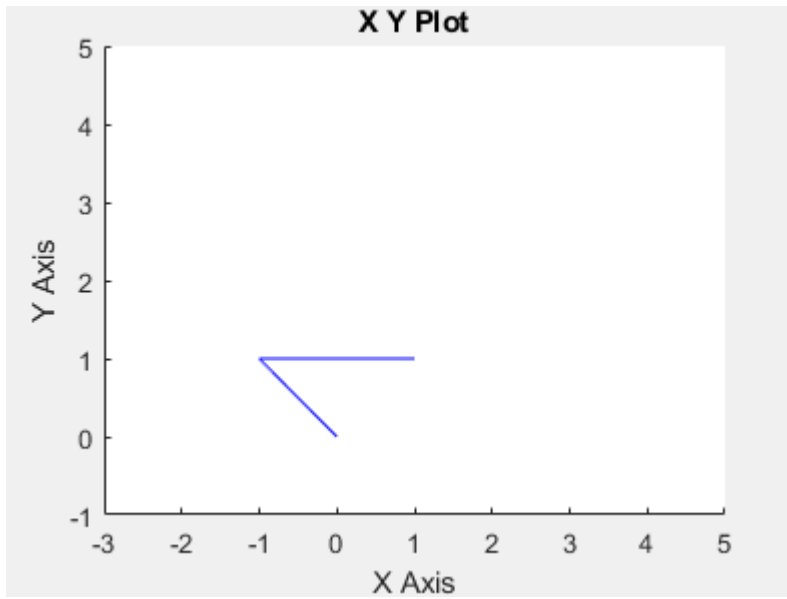
Run the Simulation. The first figure shows the output of the q vector for the positions of the trajectory. The second figure shows the qdd vector for the velocity. Notice the trapezoidal profile for each waypoint transition. The **XY Plot** shows the actual 2-D trajectory, which hits the specified waypoints.

Positions



Velocities





Compute Velocity Product for Manipulators in Simulink

This example shows how to calculate the velocity-induced torques for a robot manipulator by using a `rigidBodyTree` model. In this example, you define a robot model and robot configuration in MATLAB® and pass them to Simulink® to be used with the manipulator algorithm blocks.

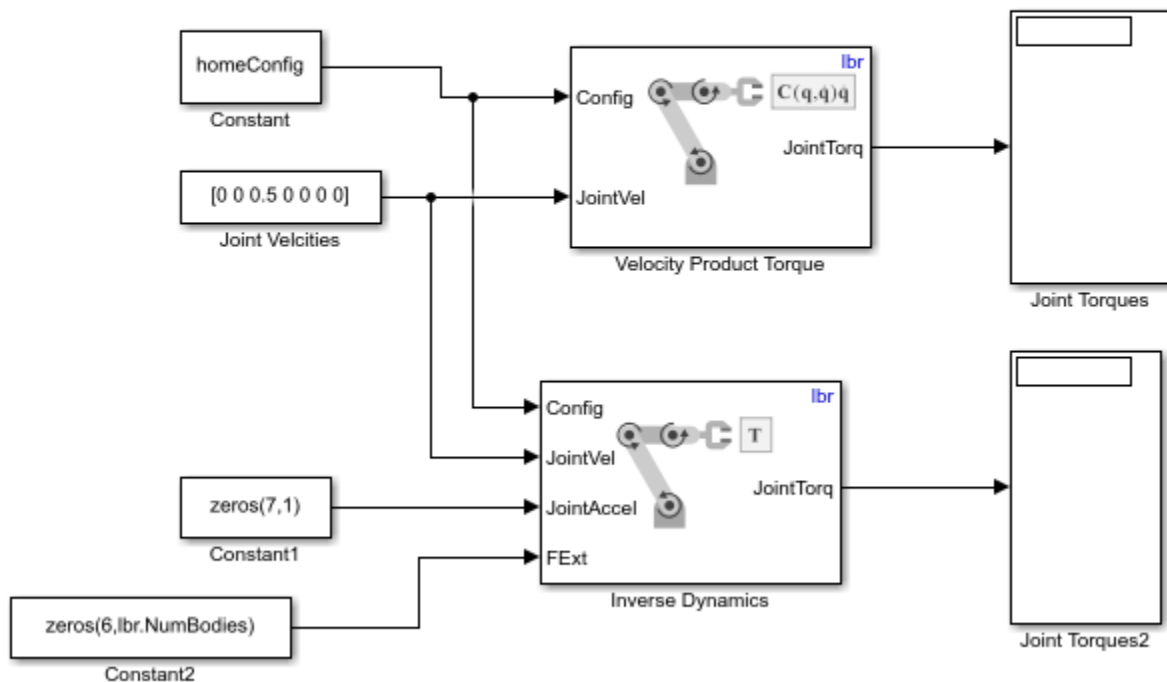
Load a `RigidBodyTree` object that models a KUKA LBR robot. Use the `homeConfiguration` function to get the home configuration or home joint positions of the robot.

```
load('exampleLBR.mat','lbr')
lbr.DataFormat = 'column';
```

```
homeConfig = homeConfiguration(lbr);
```

Open the model. If necessary, use the **Load Robot Model** callback button to reload the robot model and configuration vector.

```
open_system('velocity_product_example.slx')
```



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Run the model. The Velocity Product block calculates the torques induced by the given velocities. Verify these values by passing the same velocities to the Inverse Dynamics block with no acceleration or external forces.

See Also

Blocks

Forward Dynamics | Get Jacobian | Gravity Torque | Inverse Dynamics | Joint Space Mass Matrix

Classes

rigidBodyTree

Functions

externalForce | homeConfiguration | importrobot | randomConfiguration

Related Examples

- “Perform Safe Trajectory Tracking Control Using Robotics Manipulator Blocks” on page 1-194

Plan Path for a Unicycle Robot in Simulink

This example demonstrates how to execute an obstacle-free path between two locations on a given map in Simulink®. The path is generated using a probabilistic road map (PRM) planning algorithm (`mobileRobotPRM`). Control commands for navigating this path are generated using the **Pure Pursuit** controller block. A unicycle kinematic motion model simulates the robot motion based on those commands.

Load the Map and Simulink Model

Load the occupancy map, which defines the map limits and obstacles within the map. `exampleMaps.mat` contain multiple maps including `simpleMap`, which this example uses.

```
load exampleMaps.mat
```

Specify a start and end location within the map.

```
startLoc = [5 5];  
goalLoc = [12 3];
```

Model Overview

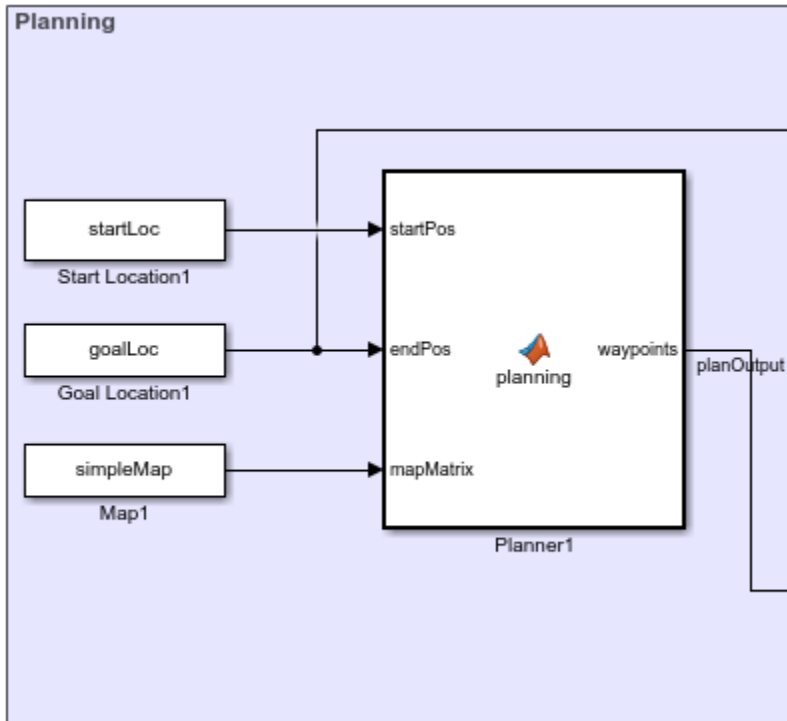
Open the Simulink Model

```
open_system('pathPlanningUnicycleSimulinkModel.slx')
```

The model is composed of three primary parts:

- **Planning**
- **Control**
- **Plant Model**

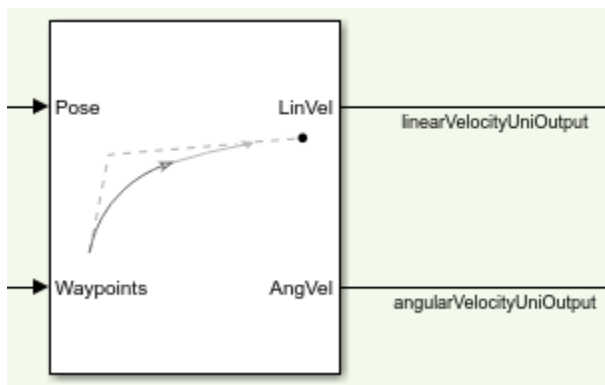
Planning



The **Planner** MATLAB® function block uses the `mobileRobotPRM` path planner and takes a start location, goal location, and map as inputs. The block outputs an array of waypoints that the robot follows. The planned waypoints are used downstream by the **Pure Pursuit** controller block.

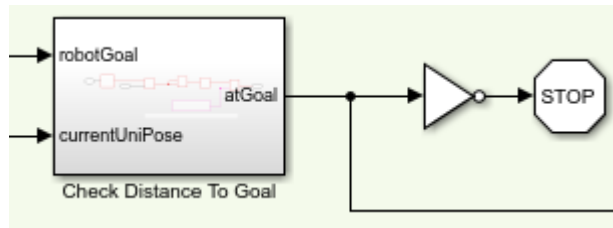
Control

Pure Pursuit



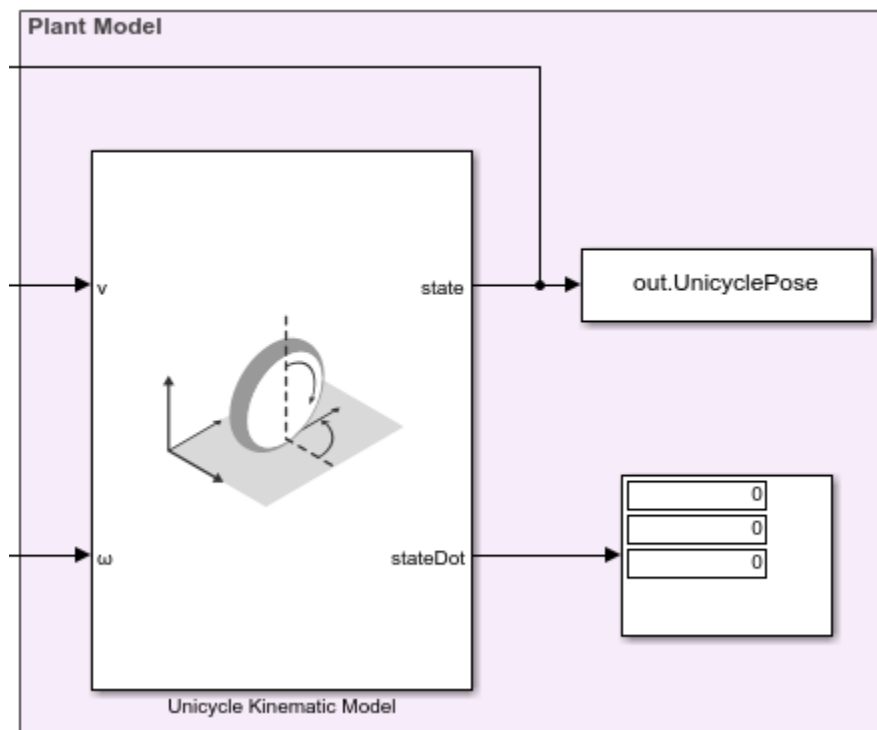
The **Pure Pursuit** controller block generates the linear velocity and angular velocity commands based on the waypoints and the current pose of the robot.

Check if Goal is Reached



The **Check Distance to Goal** subsystem calculates the current distance to the goal and if it is within a threshold, the simulation stops.

Plant Model



The **Unicycle Kinematic Model** block creates a vehicle model to simulate simplified vehicle kinematics. The block takes linear and angular velocities as command inputs from the **Pure Pursuit** controller block, and outputs the current position and velocity states.

Run the Model

To simulate the model

```
simulation = sim('pathPlanningUnicycleSimulinkModel.slx');
```

Visualize The Motion of Robot

After simulating the model, visualize the robot driving the obstacle-free path in the map.

```
map = binaryOccupancyMap(simpleMap)
```

```

map =
  binaryOccupancyMap with properties:

    GridLocationInWorld: [0 0]
      XWorldLimits: [0 27]
      YWorldLimits: [0 26]
      DataType: 'logical'
      DefaultValue: 0
      Resolution: 1
      GridSize: [26 27]
      XLocalLimits: [0 27]
      YLocalLimits: [0 26]
      GridOriginInLocal: [0 0]
      LocalOriginInWorld: [0 0]

robotPose = simulation.UnicyclePose
robotPose = 428x3

    5.0000    5.0000         0
    5.0000    5.0000   -0.0002
    5.0001    5.0000   -0.0012
    5.0006    5.0000   -0.0062
    5.0031    5.0000   -0.0313
    5.0156    4.9988   -0.1569
    5.0707    4.9707   -0.7849
    5.0945    4.9354   -1.1140
    5.1075    4.9059   -1.1828
    5.1193    4.8759   -1.2030
    :

numRobots = size(robotPose, 2) / 3;
thetaIdx = 3;

% Translation
xyz = robotPose;
xyz(:, thetaIdx) = 0;

% Rotation in XYZ euler angles
theta = robotPose(:,thetaIdx);
thetaEuler = zeros(size(robotPose, 1), 3 * size(theta, 2));
thetaEuler(:, end) = theta;

for k = 1:size(xyz, 1)
    show(map)
    hold on;

    % Plot Start Location
    plotTransforms([startLoc, 0], eul2quat([0, 0, 0]))
    text(startLoc(1), startLoc(2), 2, 'Start');

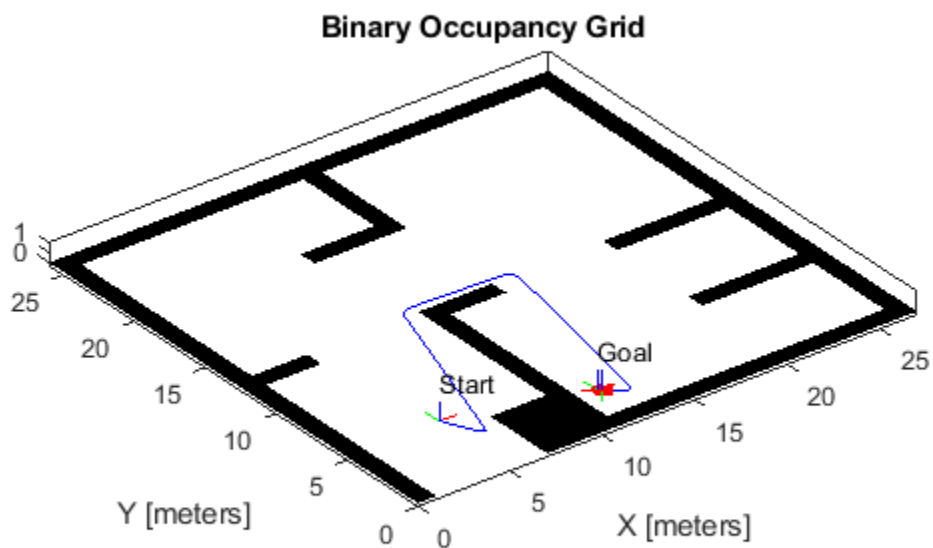
    % Plot Goal Location
    plotTransforms([goalLoc, 0], eul2quat([0, 0, 0]))
    text(goalLoc(1), goalLoc(2), 2, 'Goal');

    % Plot Robot's XY locations
    plot(robotPose(:, 1), robotPose(:, 2), '-b')

```

```
% Plot Robot's pose as it traverses the path
quat = eul2quat(thetaEuler(k, :), 'xyz');
plotTransforms(xyz(k,:), quat, 'MeshFilePath',...
    'groundvehicle.stl');

pause(0.01)
hold off;
end
```



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Plan Path for a Differential Drive Robot in Simulink

This example demonstrates how to execute an obstacle-free path between two locations on a given map in Simulink®. The path is generated using a probabilistic road map (PRM) planning algorithm (`mobileRobotPRM`). Control commands for navigating this path are generated using the **Pure Pursuit** controller block. A differential drive kinematic motion model simulates the robot motion based on those commands.

Load the Map and Simulink Model

Load the occupancy map, which defines the map limits and obstacles within the map. `exampleMaps.mat` contain multiple maps including `simpleMap`, which this example uses.

```
load exampleMaps.mat
```

Specify a start and end location within the map.

```
startLoc = [5 5];  
goalLoc = [20 20];
```

Model Overview

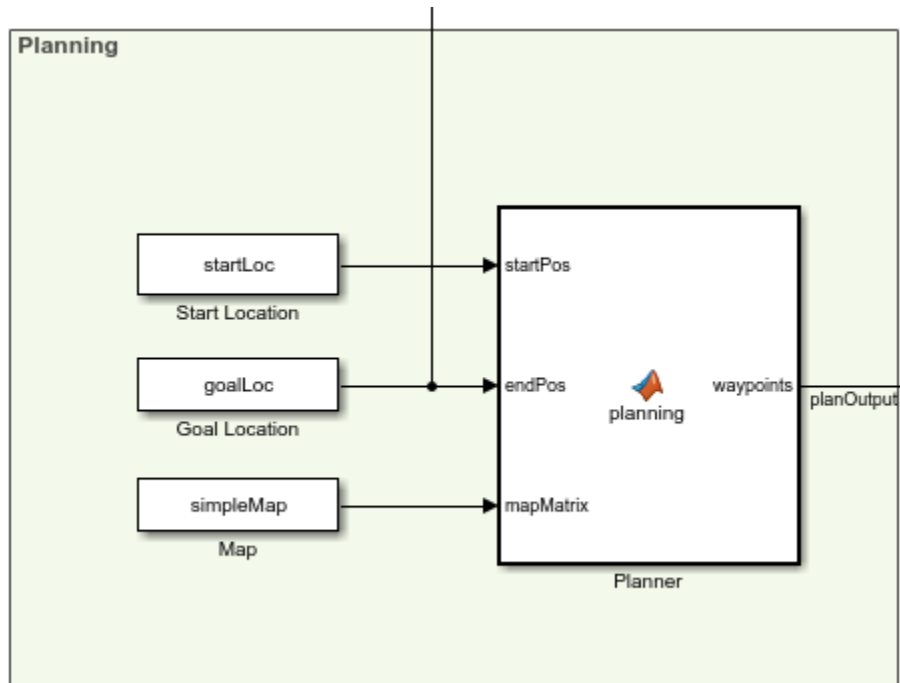
Open the Simulink model.

```
open_system('pathPlanningSimulinkModel.slx')
```

The model is composed of three primary parts:

- **Planning**
- **Control**
- **Plant Model**

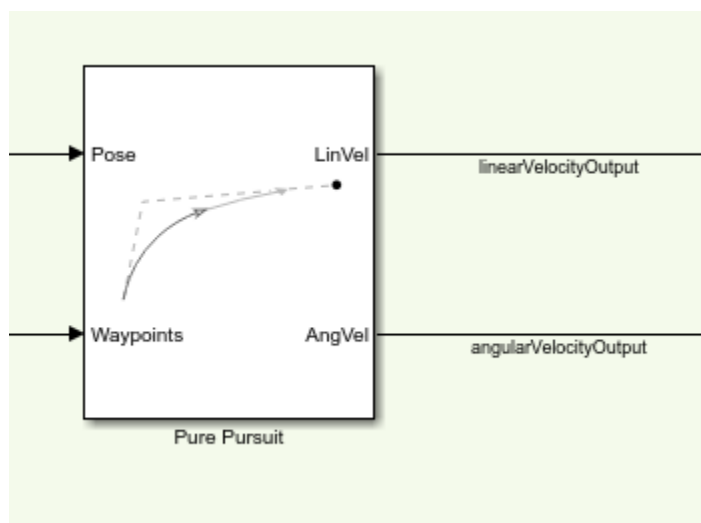
Planning



The **Planner** MATLAB® function block uses the `mobileRobotPRM` path planner and takes a start location, goal location, and map as inputs. The block outputs an array of waypoints that the robot follows. The planned waypoints are used downstream by the **Pure Pursuit** controller block.

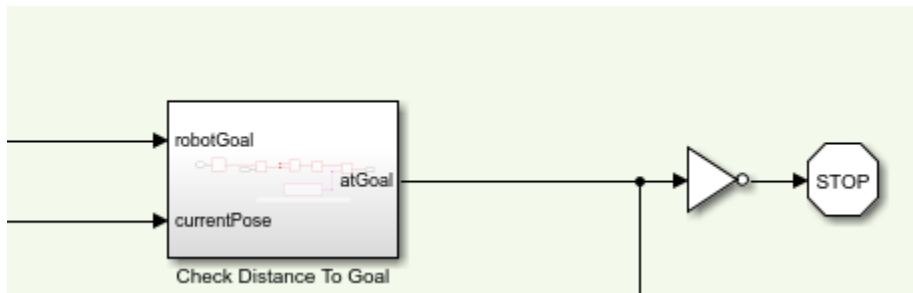
Control

Pure Pursuit



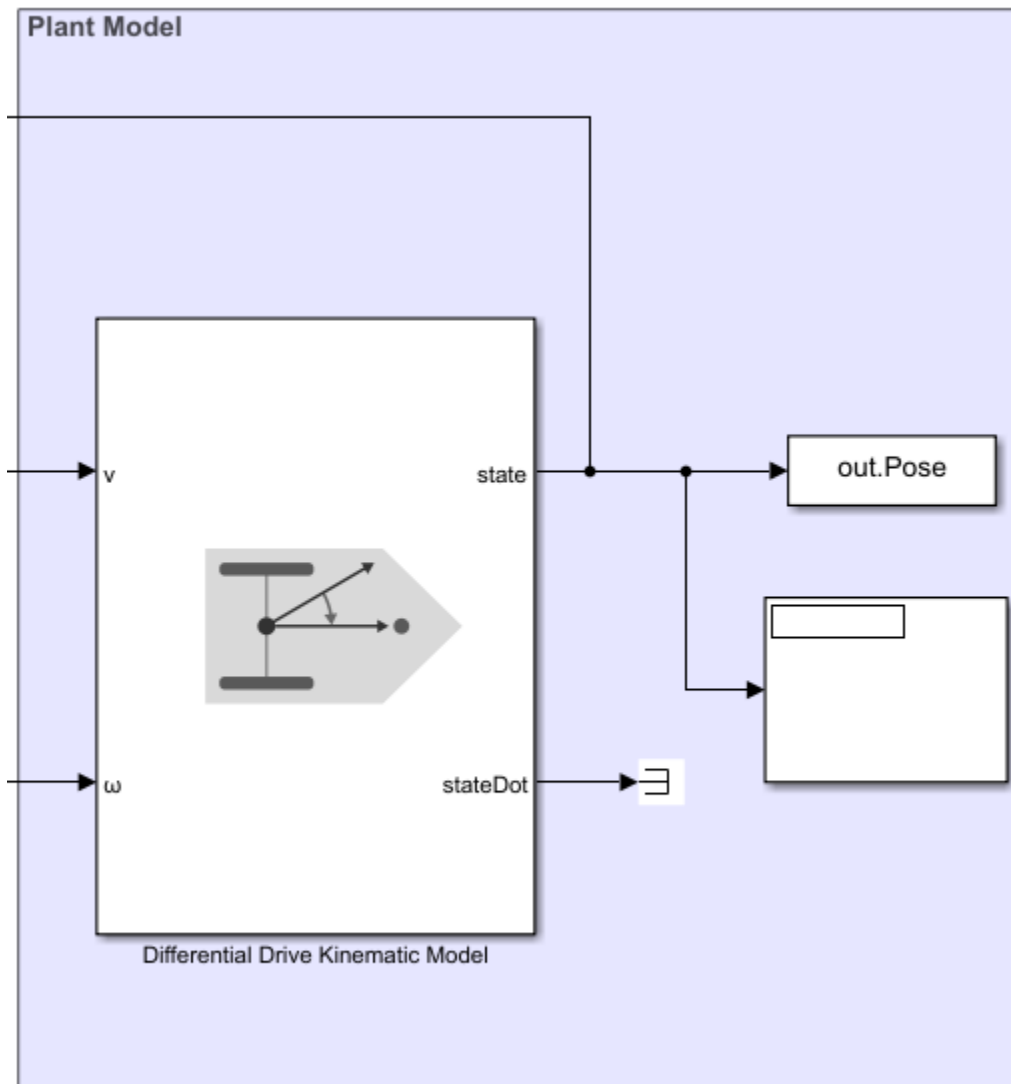
The **Pure Pursuit** controller block generates the linear velocity and angular velocity commands based on the waypoints and the current pose of the robot.

Check if Goal is Reached



The **Check Distance to Goal** subsystem calculates the current distance to the goal and if it is within a threshold, the simulation stops.

Plant Model



The **Differential Drive Kinematic Model** block creates a vehicle model to simulate simplified vehicle kinematics. The block takes linear and angular velocities as command inputs from the **Pure Pursuit** controller block, and outputs the current position and velocity states.

Run the Model

```
simulation = sim('pathPlanningSimulinkModel.slx');
```

Visualize The Motion of Robot

After simulating the model, visualize the robot driving the obstacle-free path in the map.

```
map = binaryOccupancyMap(simpleMap);
robotPose = simulation.Pose;
thetaIdx = 3;

% Translation
xyz = robotPose;
xyz(:, thetaIdx) = 0;

% Rotation in XYZ euler angles
theta = robotPose(:,thetaIdx);
thetaEuler = zeros(size(robotPose, 1), 3 * size(theta, 2));
thetaEuler(:, end) = theta;

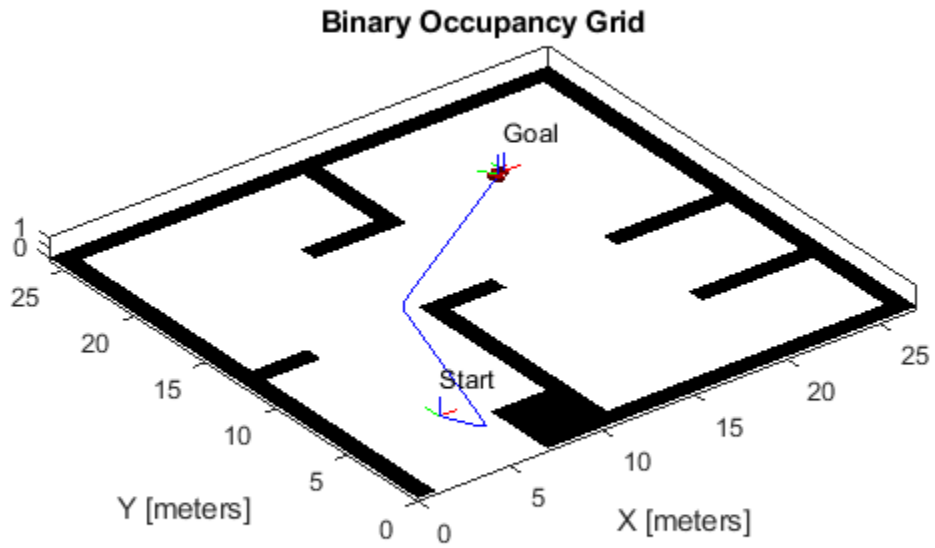
% Plot the robot poses at every 10th step.
for k = 1:10:size(xyz, 1)
    show(map)
    hold on;

    % Plot the start location.
    plotTransforms([startLoc, 0], eul2quat([0, 0, 0]))
    text(startLoc(1), startLoc(2), 2, 'Start');

    % Plot the goal location.
    plotTransforms([goalLoc, 0], eul2quat([0, 0, 0]))
    text(goalLoc(1), goalLoc(2), 2, 'Goal');

    % Plot the xy-locations.
    plot(robotPose(:, 1), robotPose(:, 2), '-b')

    % Plot the robot pose as it traverses the path.
    quat = eul2quat(thetaEuler(k, :), 'xyz');
    plotTransforms(xyz(k,:), quat, 'MeshFilePath',...
        'groundvehicle.stl');
    light;
    drawnow;
    hold off;
end
```



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Plan Path for a Bicycle Robot in Simulink

This example demonstrates how to execute an obstacle-free path between two locations on a given map in Simulink®. The path is generated using a probabilistic road map (PRM) planning algorithm (`mobileRobotPRM`). Control commands for navigating this path are generated using the **Pure Pursuit** controller block. A bicycle kinematic motion model simulates the robot motion based on those commands.

Load the Map and Simulink Model

Load map in MATLAB workspace

```
load exampleMaps.mat
```

Enter start and goal locations

```
startLoc = [5 5];  
goalLoc = [12 3];
```

The imported maps are : `simpleMap`, `complexMap` and `ternaryMap`.

Open the Simulink Model

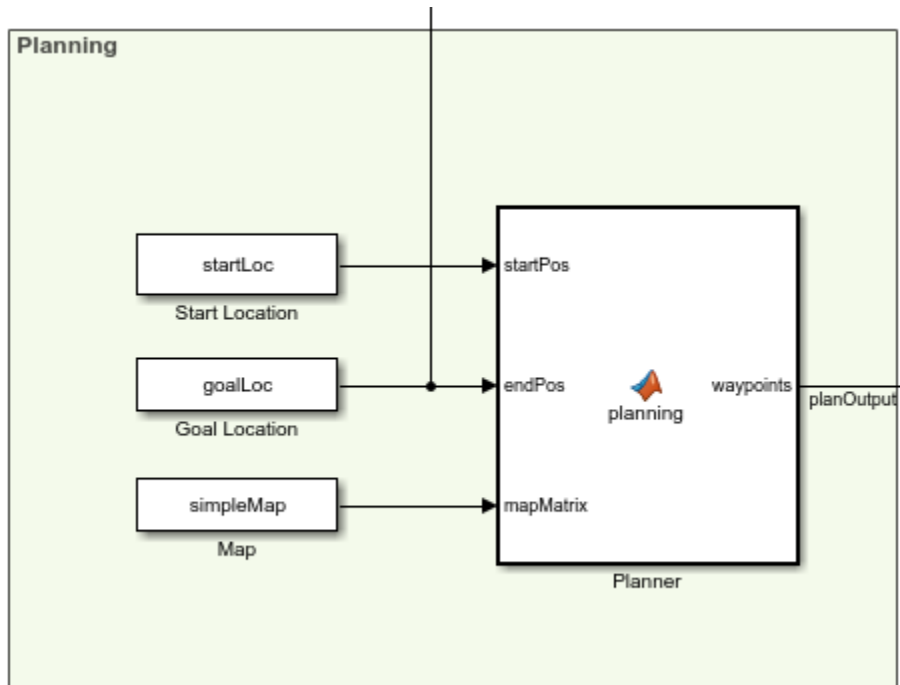
```
open_system('pathPlanningBicycleSimulinkModel.slx')
```

Model Overview

The model is composed of four primary operations :

- **Planning**
- **Control**
- **Plant Model**

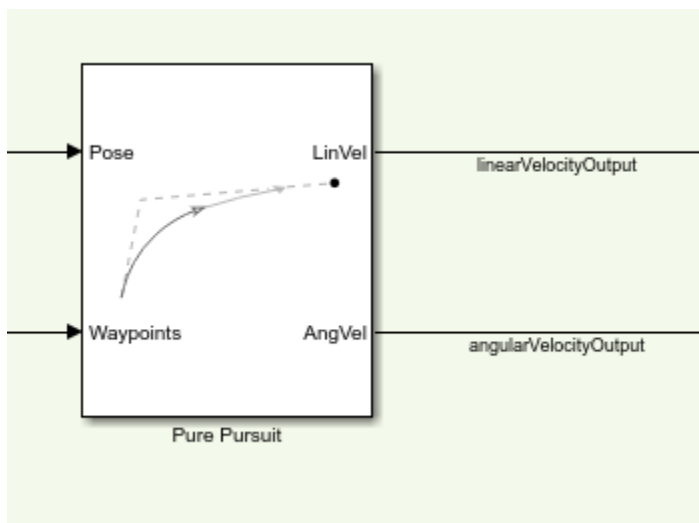
Planning



The **Planner** MATLAB® function block uses the `mobileRobotPRM` path planner and takes a start location, goal location, and map as inputs. The block outputs an array of waypoints that the robot follows. The planned waypoints are used downstream by the **Pure Pursuit** controller block.

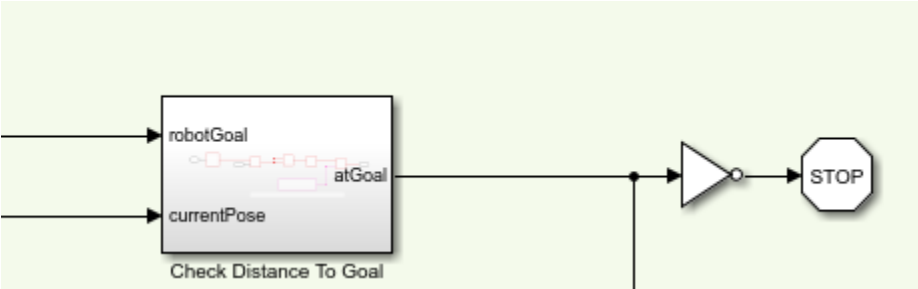
Control

Pure Pursuit



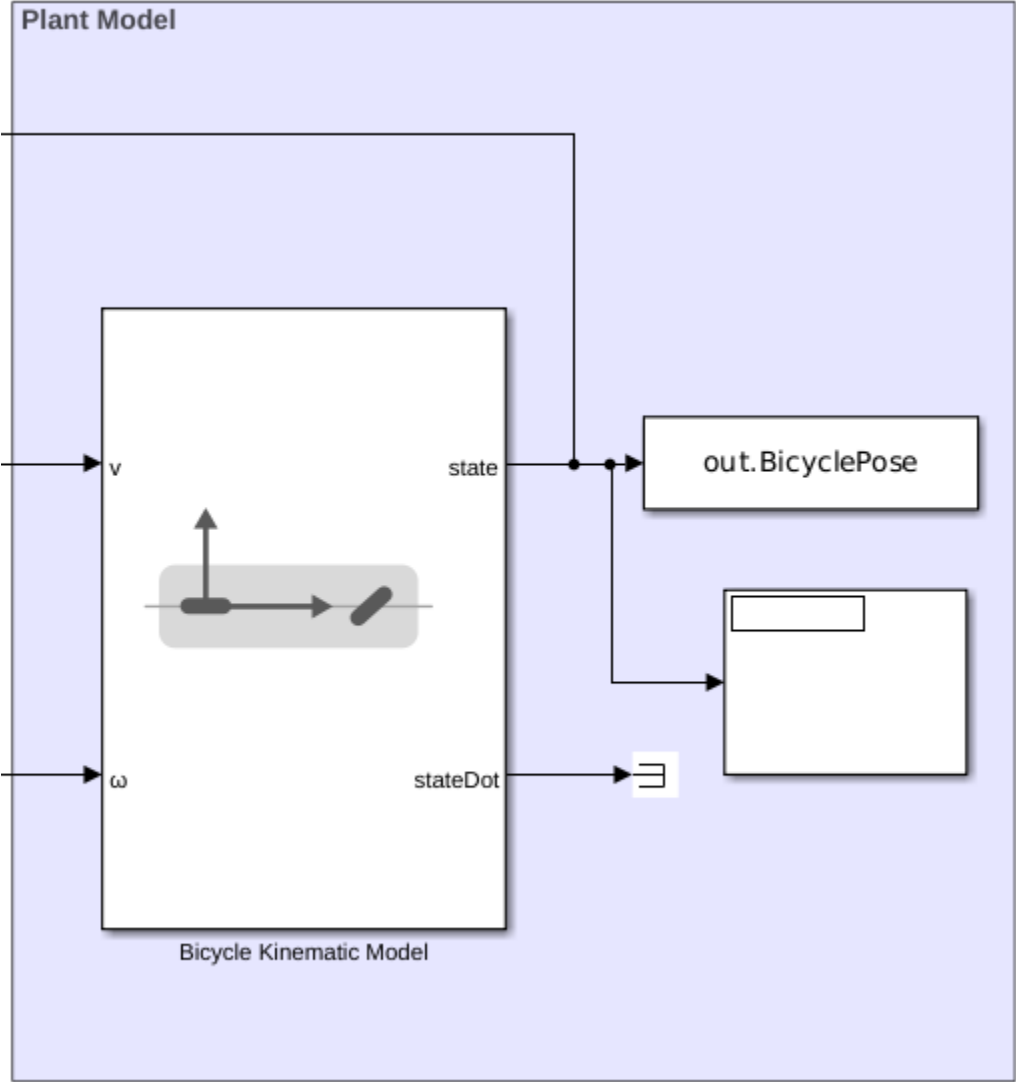
The **Pure Pursuit** controller block generates the linear velocity and angular velocity commands based on the waypoints and the current pose of the robot.

Check if Goal is Reached



The **Check Distance to Goal** subsystem calculates the current distance to the goal and if it is within a threshold, the simulation stops.

Plant Model



The **Bicycle Kinematic Model** block creates a vehicle model to simulate simplified vehicle kinematics. The block takes linear and angular velocities as command inputs from the **Pure Pursuit** controller block, and outputs the current position and velocity states.

Run the Model

To simulate the model

```
simulation = sim('pathPlanningBicycleSimulinkModel.slx');
```

Visualize The Motion of Robot

To see the poses :

```
map = binaryOccupancyMap(simpleMap)
```

```
map =  
  binaryOccupancyMap with properties:
```

```
  GridLocationInWorld: [0 0]  
    XWorldLimits: [0 27]  
    YWorldLimits: [0 26]  
      DataType: 'logical'  
  DefaultValue: 0  
    Resolution: 1  
    GridSize: [26 27]  
  XLocalLimits: [0 27]  
  YLocalLimits: [0 26]  
  GridOriginInLocal: [0 0]  
  LocalOriginInWorld: [0 0]
```

```
robotPose = simulation.BicyclePose
```

```
robotPose = 362x3
```

```
  5.0000    5.0000         0  
  5.0001    5.0000   -0.0002  
  5.0007    5.0000   -0.0012  
  5.0036    5.0000   -0.0062  
  5.0181    4.9997   -0.0313  
  5.0902    4.9929   -0.1569  
  5.4081    4.8311   -0.7849  
  5.5189    4.6758   -1.1170  
  5.5366    4.6356   -1.1930  
  5.5512    4.5942   -1.2684  
  :
```

```
numRobots = size(robotPose, 2) / 3;  
thetaIdx = 3;
```

```
% Translation
```

```
xyz = robotPose;  
xyz(:, thetaIdx) = 0;
```

```
% Rotation in XYZ euler angles
```

```
theta = robotPose(:, thetaIdx);  
thetaEuler = zeros(size(robotPose, 1), 3 * size(theta, 2));
```

```

thetaEuler(:, end) = theta;

for k = 1:size(xyz, 1)
    show(map)
    hold on;

    % Plot Start Location
    plotTransforms([startLoc, 0], eul2quat([0, 0, 0]))
    text(startLoc(1), startLoc(2), 2, 'Start');

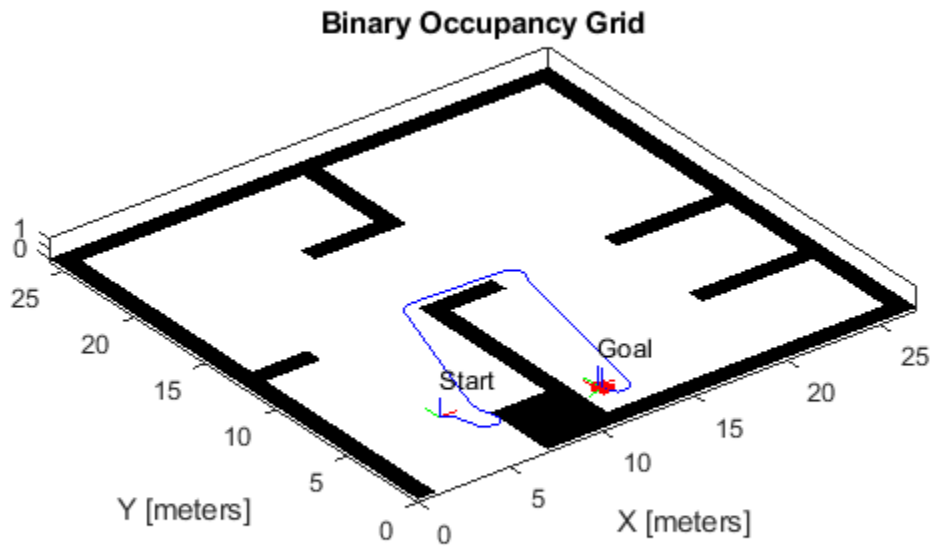
    % Plot Goal Location
    plotTransforms([goalLoc, 0], eul2quat([0, 0, 0]))
    text(goalLoc(1), goalLoc(2), 2, 'Goal');

    % Plot Robot's XY locations
    plot(robotPose(:, 1), robotPose(:, 2), '-b')

    % Plot Robot's pose as it traverses the path
    quat = eul2quat(thetaEuler(k, :), 'xyz');
    plotTransforms(xyz(k,:), quat, 'MeshFilePath',...
        'groundvehicle.stl');

    pause(0.01)
    hold off;
end

```



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Plot Ackermann Drive Vehicle in Simulink

This example shows how to plot the position of an Ackermann Kinematic Model block and change its vehicle velocity and steering angular velocity in real-time.

Open the Simulink model.

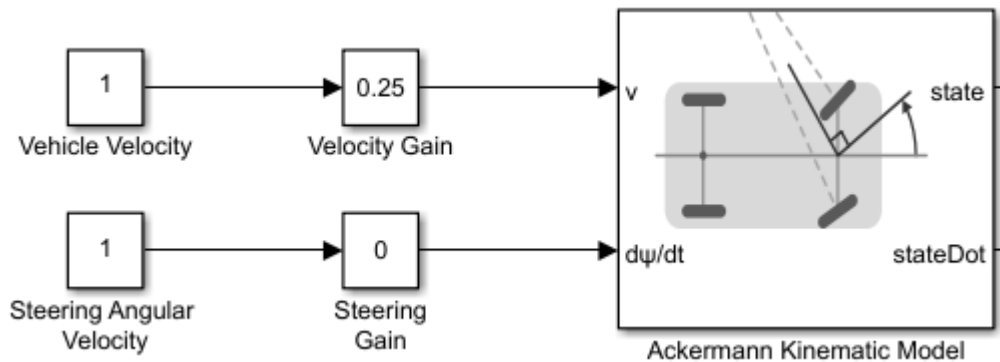
```
open_system("plotAckermannDriveSimulinkModel.slx");
```

Ackermann Kinematic Block

The Ackermann Kinematic Model block parameters are the default values, but it is important to note two parameters for this example, the **Vehicle speed range** and **Maximum steering angle**. Both parameters limit the motion of the vehicle. The lower bound of the **Vehicle speed range** parameter is set to $-\infty$ and the upper bound is set to ∞ , so the vehicle velocity can be any real value you set. The **Maximum steering angle** is set to $\pi/4$, so there's a max turning radius that the vehicle can achieve.

Vehicle and Steering Velocity

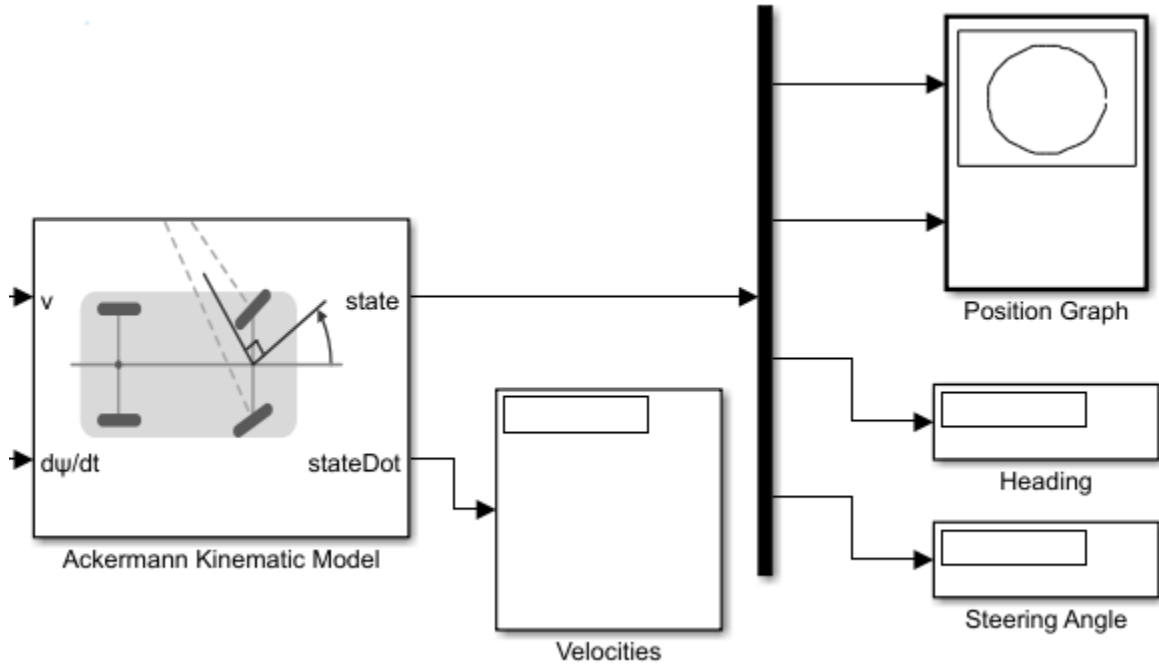
The Ackermann Kinematic Model block takes two inputs, vehicle velocity and steering angular velocity. This model uses **Slider Gain** blocks to change the inputs.



These values can be any real values within the parameter constraints set in the Ackermann Kinematic Model block.

Graphing the Output

Using a demux block, the x and y signals of the `state` output connect to a **XY Graph** block. The signals of `stateDot` and the other two signals of `state` connect to **Display** blocks.



Run the Model

- Set the model run time to `inf`.
- Click **Play** to run the model. The graph will appear and you can see the path of the vehicle.
- Open the **Slider Gain** blocks and adjust the values of the blocks to see their affects on the path of the vehicle.
- Adjust the graph limits as needed.
- Observe the **Steering Angle** display as you adjust the value of the **Steering Gain**.

Follow Joint Space Trajectory in Simulink

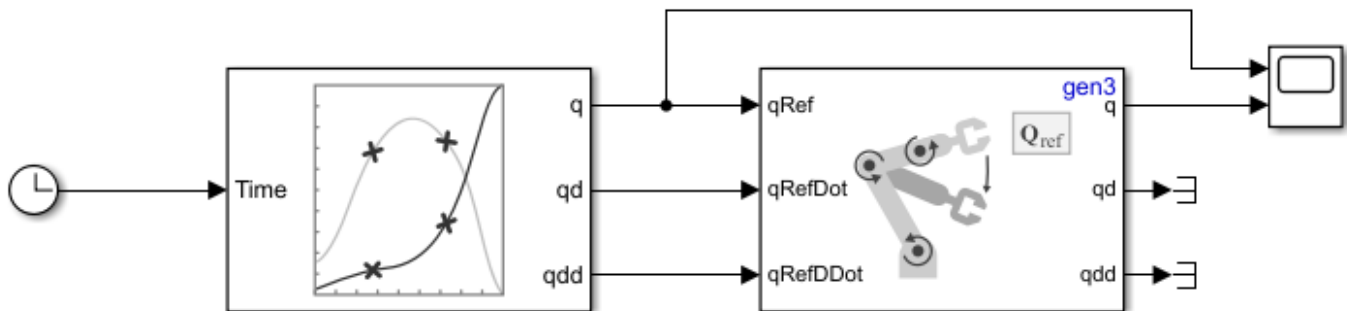
This example shows how to use a **Joint Space Motion Model** block to follow a trajectory in Simulink.

This example uses the Kinova Gen3 manipulator robot to follow the trajectories. Load the Gen3 manipulator using `loadrobot` and save the `RigidBodyTree` output as `gen3`. Open the Simulink model.

```
[gen3,metadata] = loadrobot("kinovaGen3");
```

Open the simulink model.

```
open_system("followJointSpaceTrajectoryModel.slx");
```

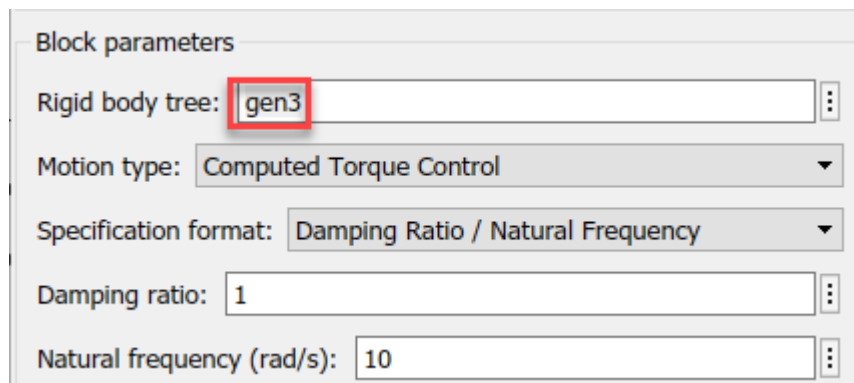


Plan Trajectory

The **Polynomial Trajectory** block generates a trajectory from a set of waypoints specified in the **Waypoints** parameter in joint space. This example uses five time points, specified row vector and also the Kinova Gen3 has seven degrees of freedom, so the waypoints matrix must be a 7-by-5 size matrix. The block is set up to generate a new set of waypoints every simulation.

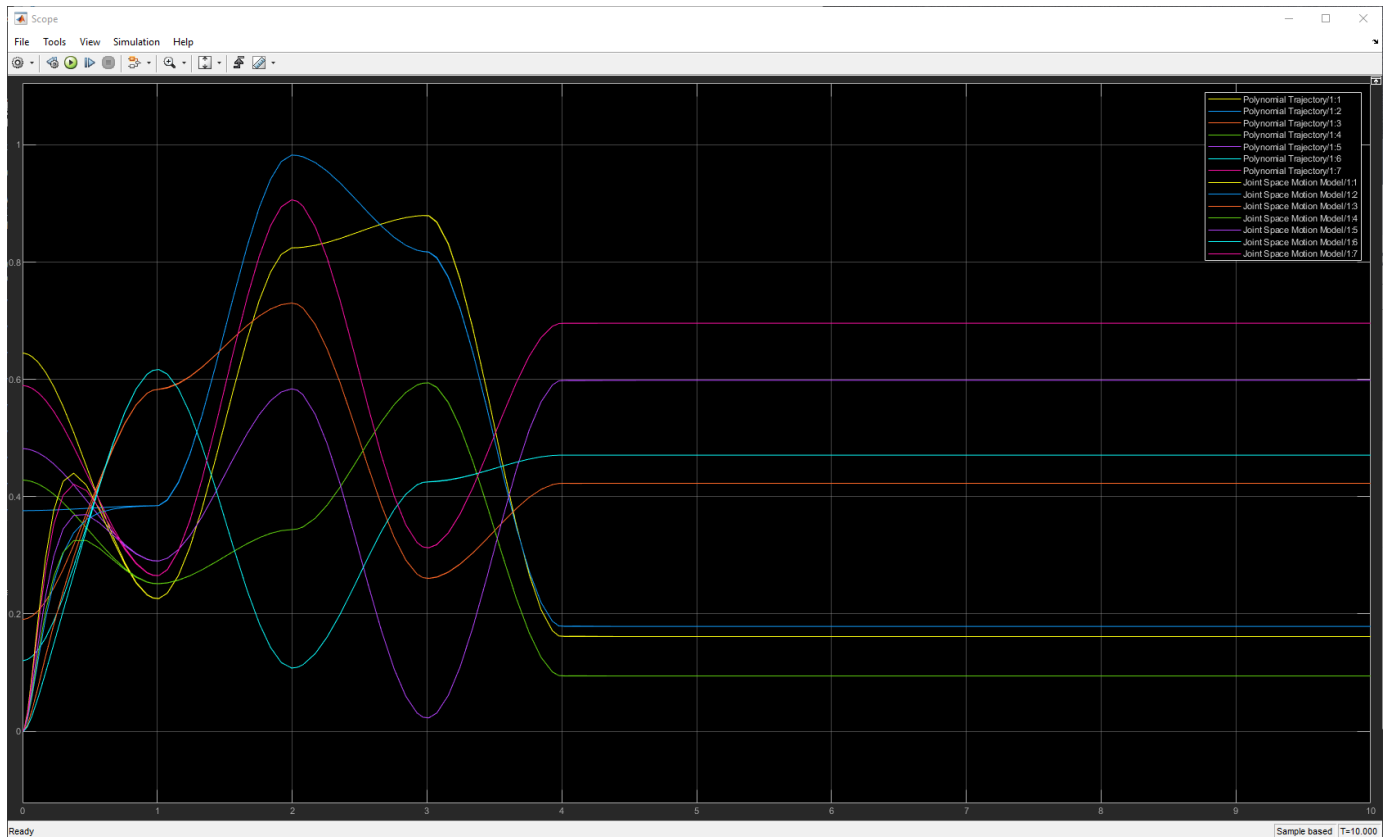
Motion Model

The Joint Space Motion Model uses a `RigidBodyTree`, `gen3`, to calculate the joint positions to reach the random trajectory generated by the **Polynomial Trajectory** block. Leave the other block parameters as default.

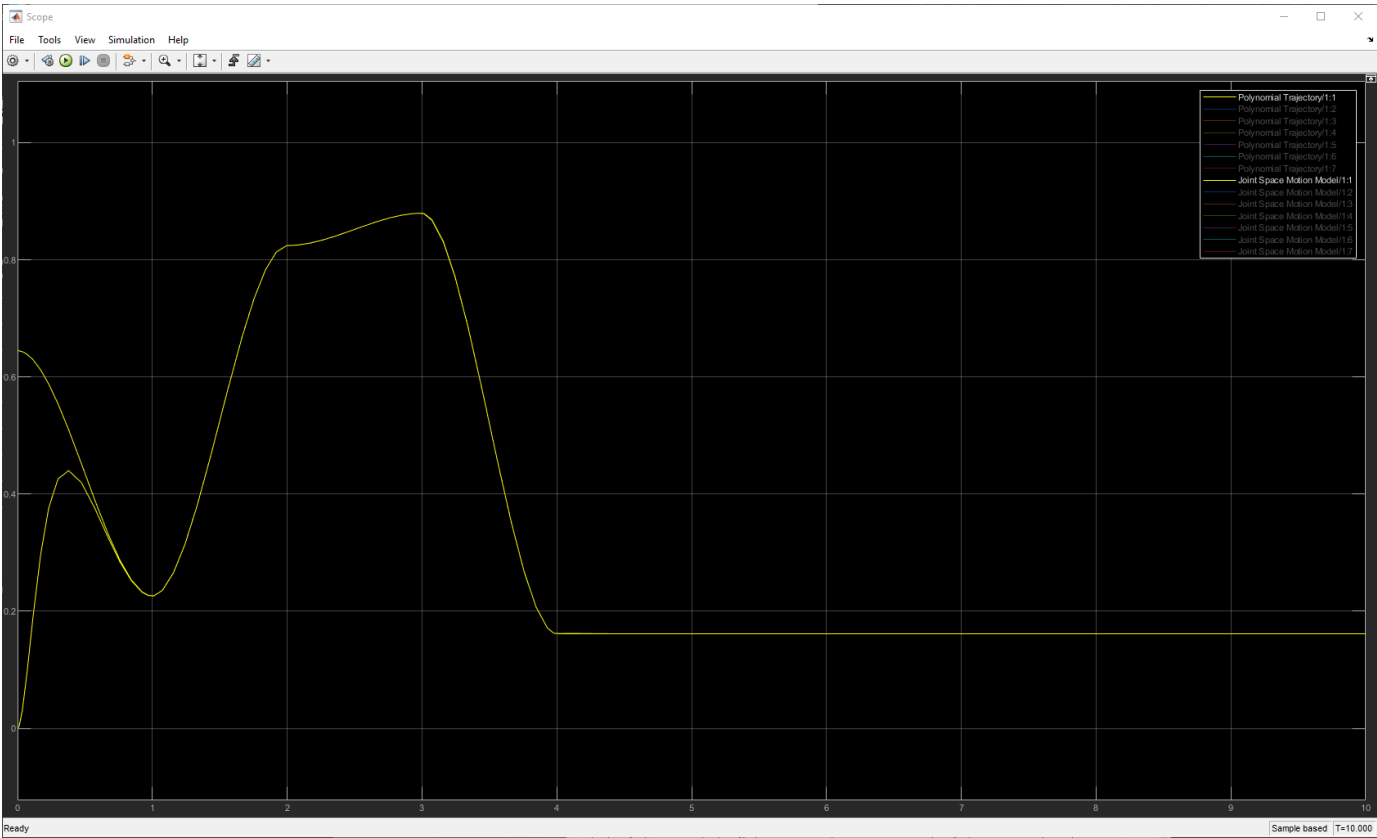


Visualize Results

The joint target positions and the calculated joint values from the **Joint Space Motion Model** connect to a **Scope** block. Using the legend, you can select a smaller set of signals to compare with better clarity.



Observe that the signals for the first joint start separated, and overlap when time is equal to 1s. So from the initial configuration, the first joint was able to follow the trajectory.



Follow Task Space Trajectory in Simulink

This example shows how to use a Task Space Motion Model to follow a task space trajectory.

Load Robot and Simulink Model

This example uses a Kinova Gen3 manipulator robot. Load the model using `loadrobot`.

```
[gen3,metadata] = loadrobot("kinovaGen3", 'DataFormat', 'column');
initialConfig = homeConfiguration(gen3);
targetPosition = trvec2tform([0.6 -0.1 0.5])
```

```
targetPosition = 4x4
```

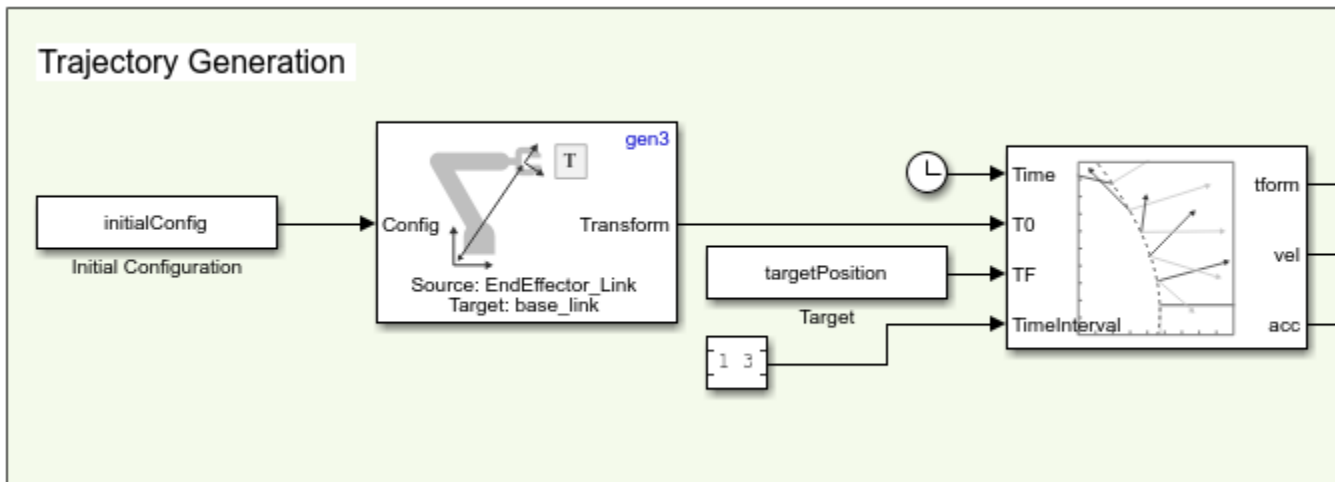
```
    1.0000    0    0    0.6000
    0    1.0000    0    -0.1000
    0    0    1.0000    0.5000
    0    0    0    1.0000
```

Open the Simulink model.

```
open_system("followTaskSpaceTrajectoryModel.slx")
```

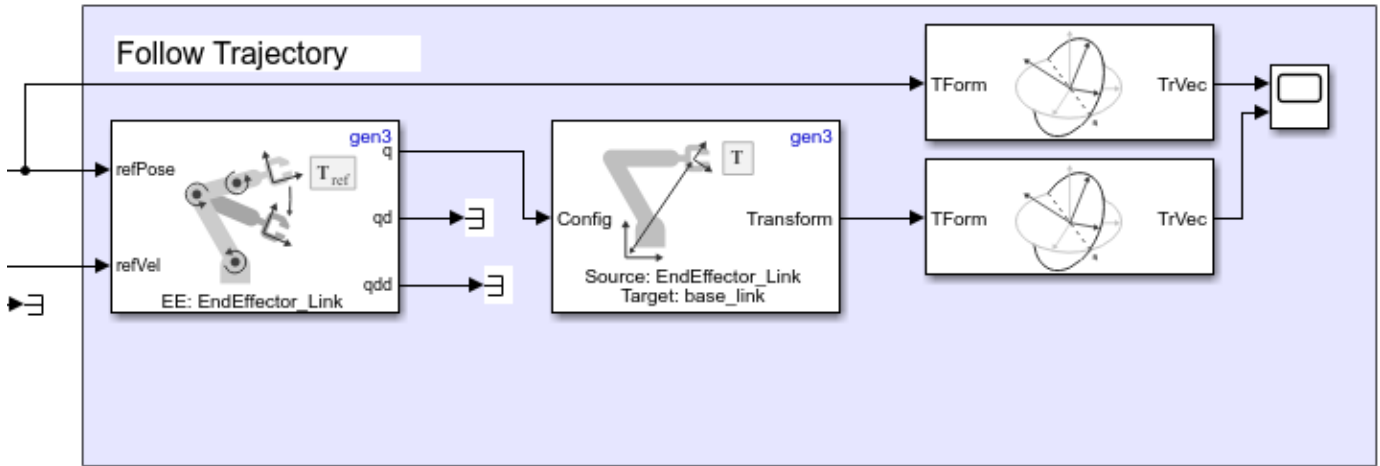
Trajectory Generation

The **Transform Trajectory** block creates a trajectory between the initial homogeneous transform matrix of the end effector of the Gen3, and the target position over a 3 second time interval.



Follow Trajectory

The Joint Space Motion Model uses a RigidBodyTree, `gen3`, to calculate the joint positions to follow the trajectory. The joint positions are converted to homogeneous transform matrices and then the converted to a translation vector so that it is easier to visualize.



Visualize Results

The joint target positions and the calculated joint values from the **Task Space Motion Model** connect to a **Scope** block. Using the legend, you can select a smaller set of signals to compare with better clarity. Observe that the x, y, and z positions of the end effector match closely with the x, y, and z positions of the trajectory to the target position.

