

# Course 8

## An Introduction to the Kalman Filter



# Speakers

Greg Welch  
Gary Bishop



# Kalman Filters in 2 hours?



- Hah!
- No magic.
- Pretty simple to apply.
- Tolerant of abuse.
- Notes are a standalone reference.
- These slides are online at <http://www.cs.unc.edu/~tracker/ref/s2001/kalman/>

# Rudolf Emil Kalman



- Born 1930 in Hungary
- BS and MS from MIT
- PhD 1957 from Columbia
- Filter developed in 1960-61
- Now retired



# What is a Kalman Filter?



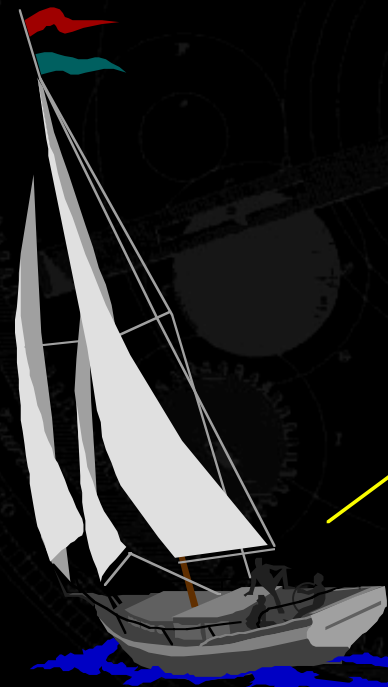
- Just some applied math.
- A linear system:  $f(a+b) = f(a) + f(b)$ .
- Noisy data in  $\rightarrow$  hopefully less noisy out.
- But delay is the price for filtering...
- Pure KF does not even adapt to the data.

# What is it used for?



- Tracking missiles
- Tracking heads/hands/drumsticks
- Extracting lip motion from video
- Fitting Bezier patches to point data
- Lots of computer vision applications
- Economics
- Navigation

# *A really simple example*





# Gary makes a measurement

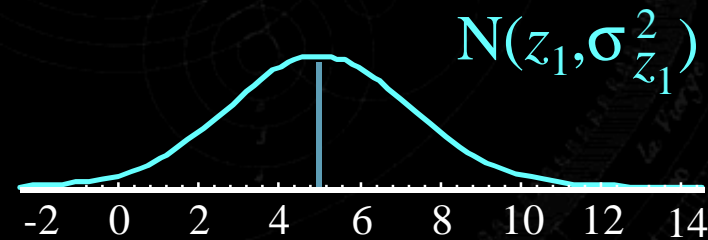


Conditional Density Function

$$z_1, \sigma_{z_1}^2$$

$$\hat{x}_1 = z_1$$

$$\hat{\sigma}_1^2 = \sigma_{z_1}^2$$





# Greg makes a measurement

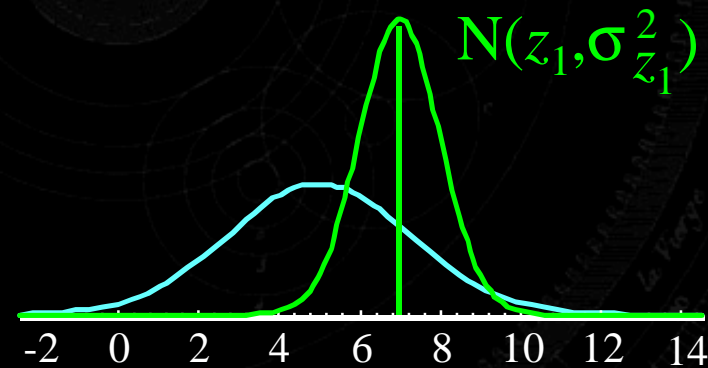


Conditional Density Function

$$z_2, \sigma_{z_2}^2$$

$$\hat{x}_2 = \dots?$$

$$\sigma_{\hat{x}_2}^2 = \dots?$$



# Combine estimates



$$\hat{x}_2 = \hat{x}_1 + K_2 (z_2 - \hat{x}_1)$$

$$K_2 = \frac{\sigma_1^2}{\sigma_1^2 + \sigma_{z_2}^2}$$

# Combine variances



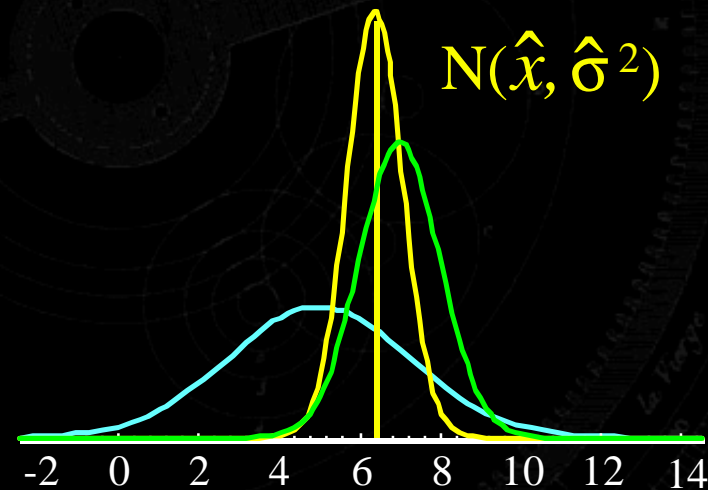
$$\frac{1}{\sigma_2^2} = \frac{1}{\sigma_1^2} + \frac{1}{\sigma_{z_2}^2}$$

# Combined Estimates



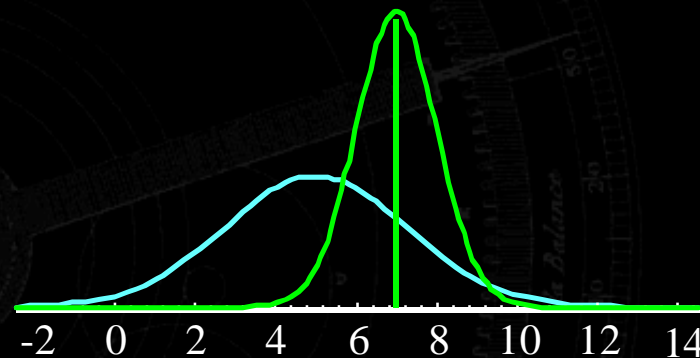
Conditional Density Function

$$\hat{x} = \hat{x}_2$$
$$\hat{\sigma}^2 = \sigma_2^2$$



Online weighted average!

# But suppose we're moving



- Not *all* the difference is error
- Some may be motion
- KF can include a motion model
- Estimate velocity and position

# Process Model



- Describes how the *state* changes over time
- The *state* for the first example was scalar
- The *process model* was “nothing changes”

A better model might be

- State is a 2-vector [ position, velocity ]
- $\text{position}_{n+1} = \text{position}_n + \text{velocity}_n * \text{time}$
- $\text{velocity}_{n+1} = \text{velocity}_n$

# Measurement Model



“What you see from where you are”  
not  
“Where you are from what you see”



# Predict → Correct



KF operates by

- Predicting the new state and its uncertainty
- Correcting with the new measurement

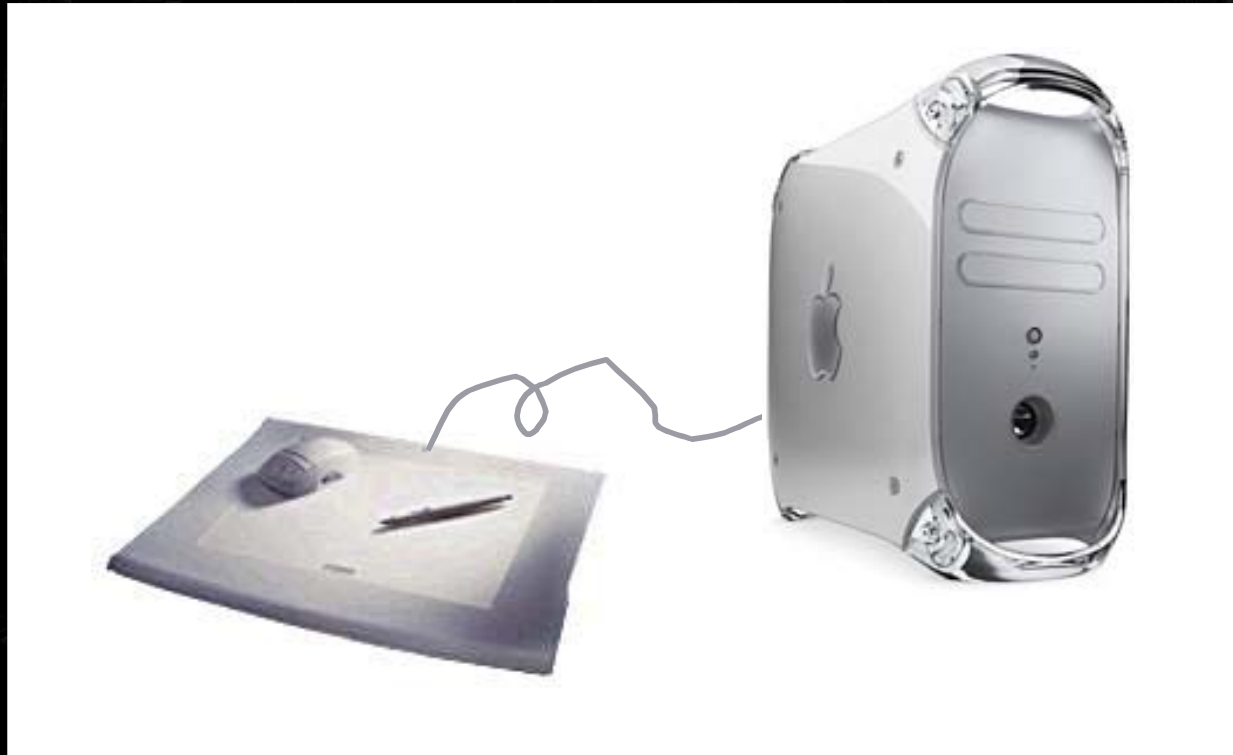
predict correct

# Example: 2D Position-Only

(Greg Welch)



# Apparatus: 2D Tablet



# Process Model



$$\begin{bmatrix} x_k \\ y_k \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_{k-1} \\ y_{k-1} \end{bmatrix} + \begin{bmatrix} \sim x_{k-1} \\ \sim y_{k-1} \end{bmatrix}$$

*state*<sub>k</sub>                      *state transition*                      *state*<sub>k-1</sub>                      *noise*<sub>k-1</sub>

$$\bar{x}_k = A \bar{x}_{k-1} + \bar{w}_{k-1}$$

# Measurement Model



$$\begin{bmatrix} u_k \\ v_k \end{bmatrix} = \begin{bmatrix} H_x & 0 \\ 0 & H_y \end{bmatrix} \begin{bmatrix} x_k \\ y_k \end{bmatrix} + \begin{bmatrix} \sim u_k \\ \sim v_k \end{bmatrix}$$

*measurement*  $\bar{z}_k$       *measurement*  $H$  *matrix*      *state*  $\bar{x}_k$       *noise*  $\bar{v}_k$

$$\bar{z}_k = H\bar{x}_k + \bar{v}_k$$

# Preparation



$$A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

State Transition

$$Q = E\{\bar{w} * \bar{w}^T\} = \begin{bmatrix} Q_{xx} & 0 \\ 0 & Q_{yy} \end{bmatrix}$$

**Process**  
Noise  
Covariance

$$R = E\{\bar{v} * \bar{v}^T\} = \begin{bmatrix} R_{xx} & 0 \\ 0 & R_{yy} \end{bmatrix}$$

**Measurement**  
Noise  
Covariance

# Initialization



$$\bar{x}_0 = H\bar{z}_0$$

$$P_0 = \begin{bmatrix} \varepsilon & 0 \\ 0 & \varepsilon \end{bmatrix}$$



# PREDICT



$$\bar{x}_k^- = A\bar{x}_{k-1}$$

$$P_k^- = AP_{k-1}A^T + Q$$

transition

uncertainty

# CORRECT



$$\bar{x}_k = \bar{x}_k^- + K(\bar{z}_k - H\bar{x}_k^-)$$
$$P_k = (I - KH)P_k^-$$

actual predicted

$$K = P_k^- H^T (HP_k^- H^T + R)^{-1}$$

“denominator”  
(measurement space)

# Summary



$$\bar{x}_k^- = A\bar{x}_{k-1}$$

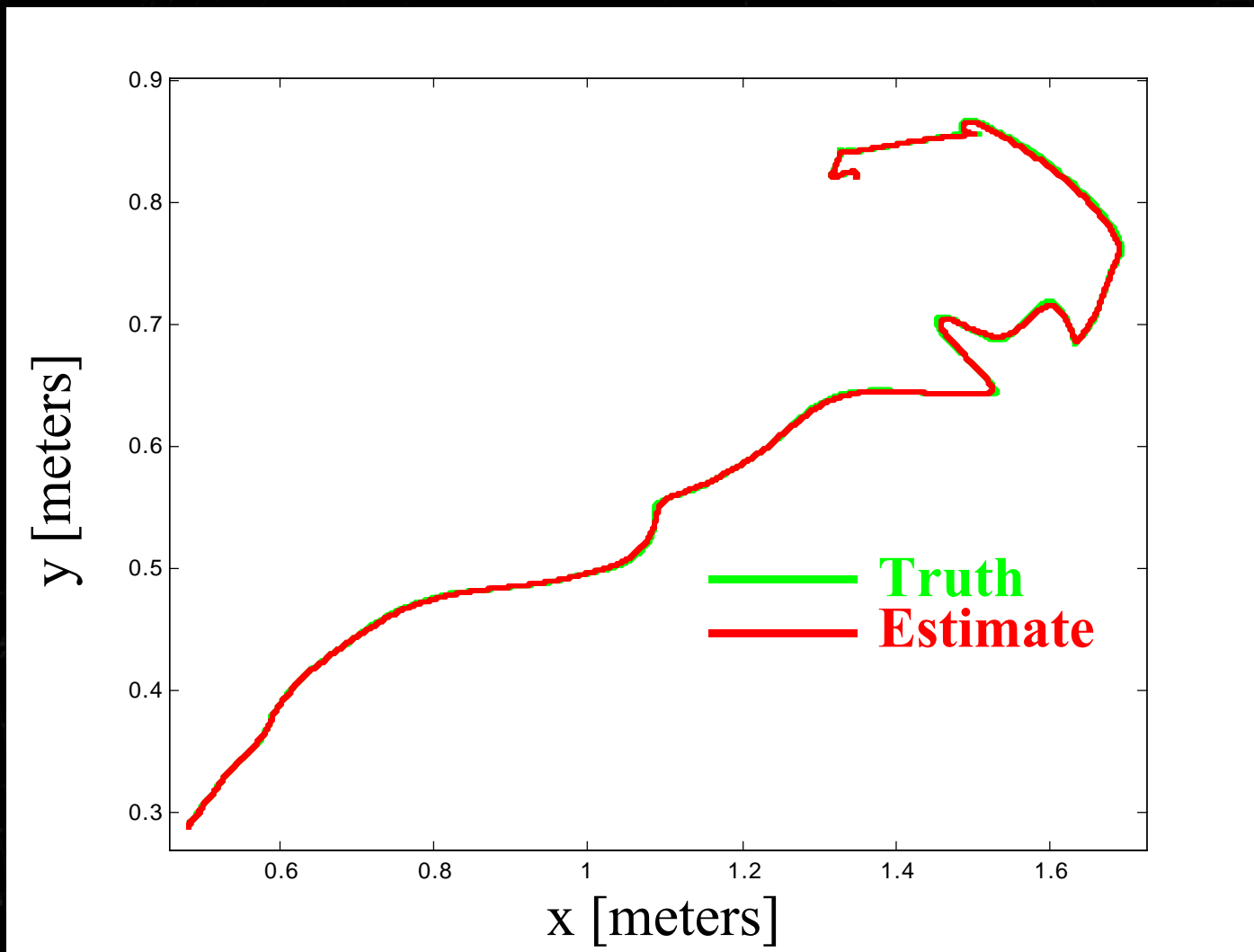
$$P_k^- = AP_{k-1}A^T + Q$$

$$K = P_k^- H^T (HP_k^- H^T + R)^{-1}$$

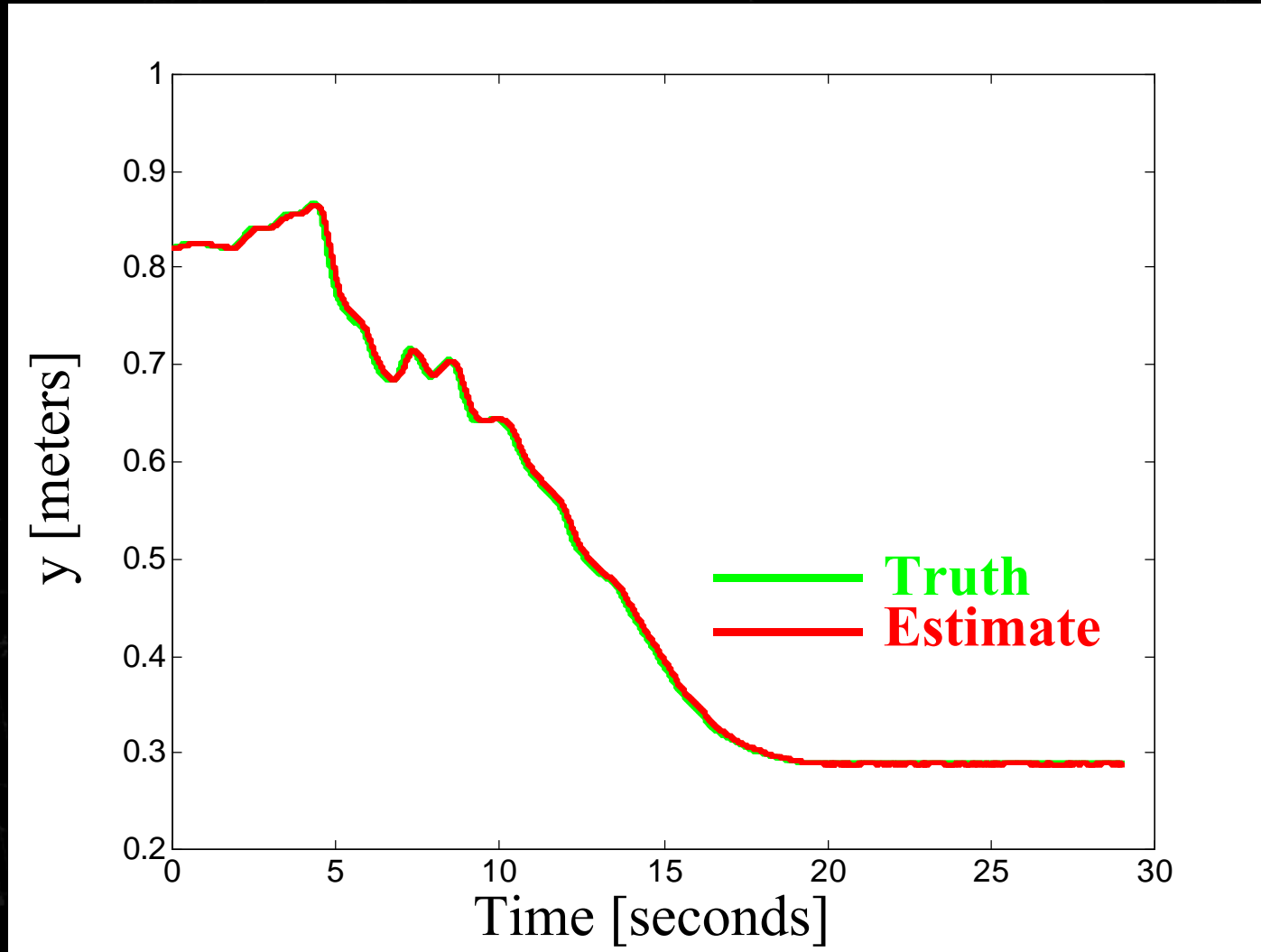
$$\bar{x}_k = \bar{x}_k^- + K(\bar{z}_k - H\bar{x}_k^-)$$

$$P_k = (I - KH)P_k^-$$

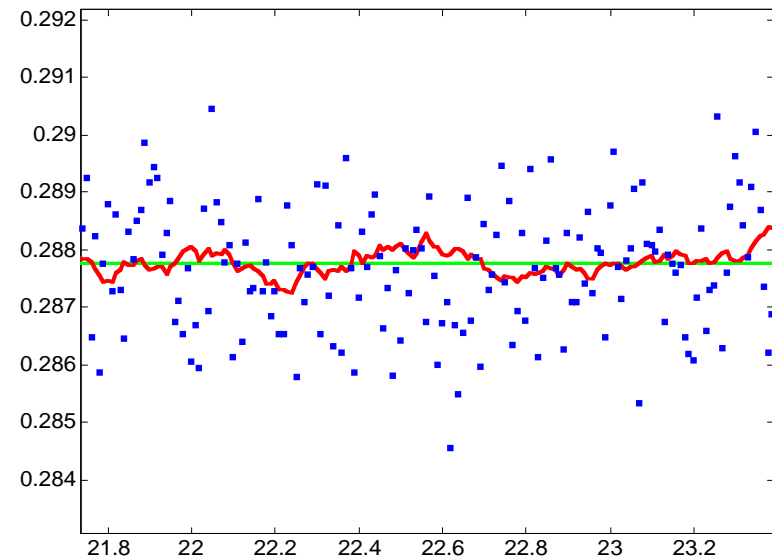
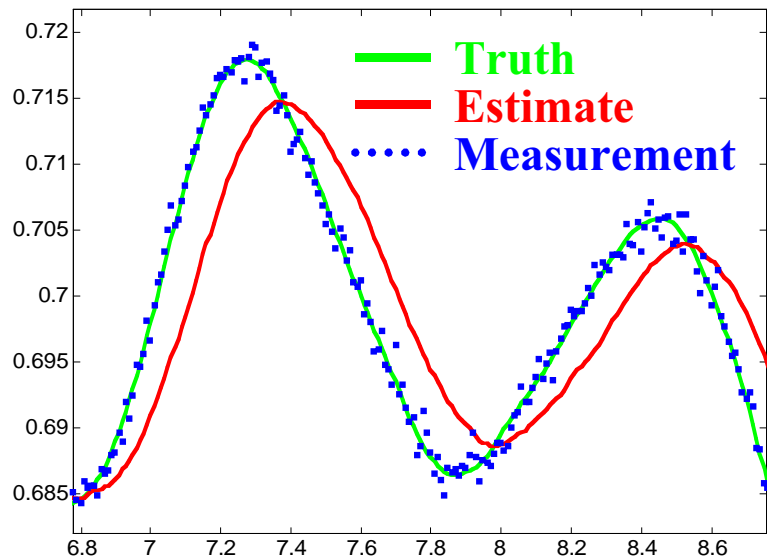
# Results: XY Track



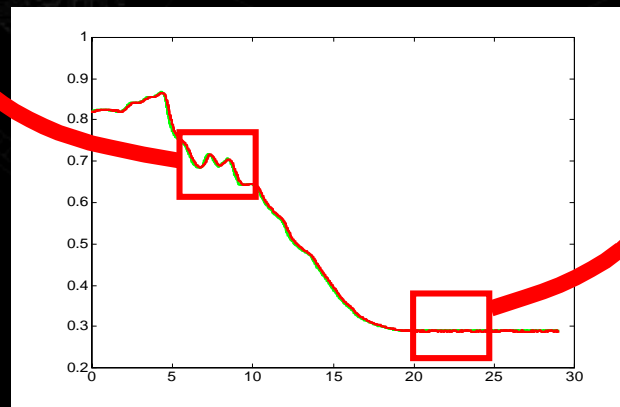
# Y Track: Moving then Still



# Motion-Dependent Performance



significant  
*latency* when  
moving...



...relatively  
*smooth*  
when not

# Example: 2D Position-Velocity (PV Model)





# Process Model (PV)



state transition

$$\begin{bmatrix} 1 & 0 & dt & 0 \\ 0 & 1 & 0 & dt \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

state

$$\begin{bmatrix} x \\ y \\ dx/dt \\ dy/dt \end{bmatrix}$$

# Measurement Model (Same)



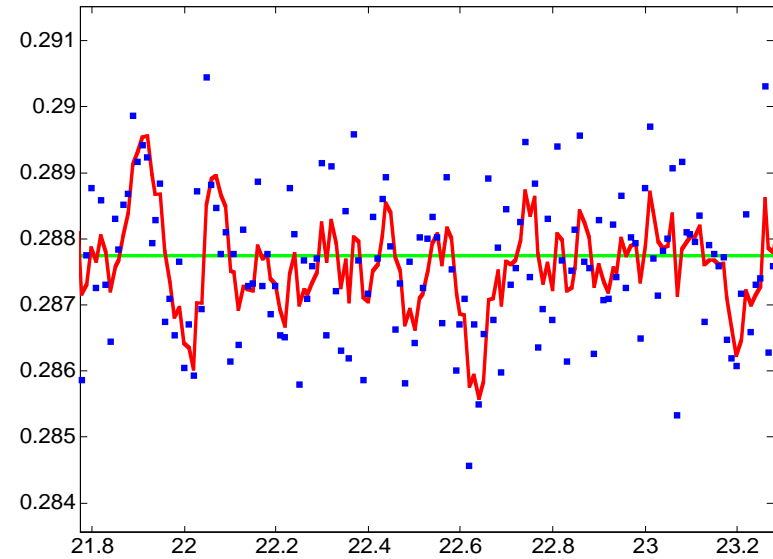
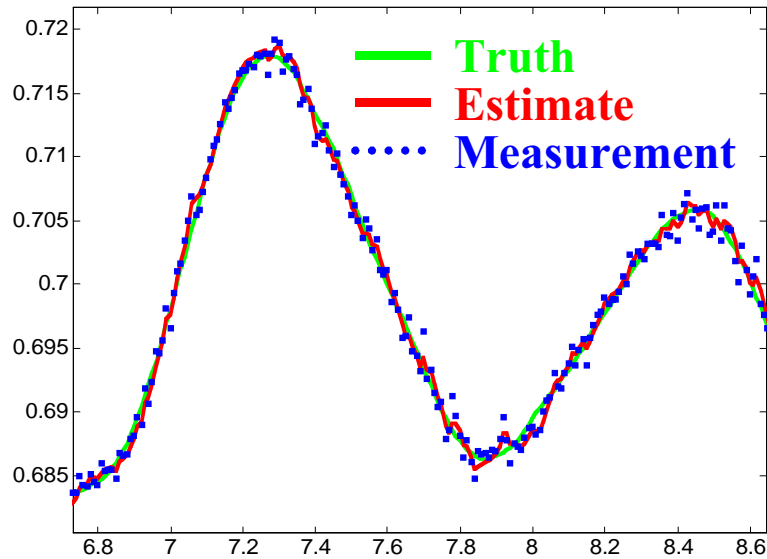
measurement matrix

$$\begin{bmatrix} H_x & 0 & 0 & 0 \\ 0 & H_y & 0 & 0 \end{bmatrix}$$

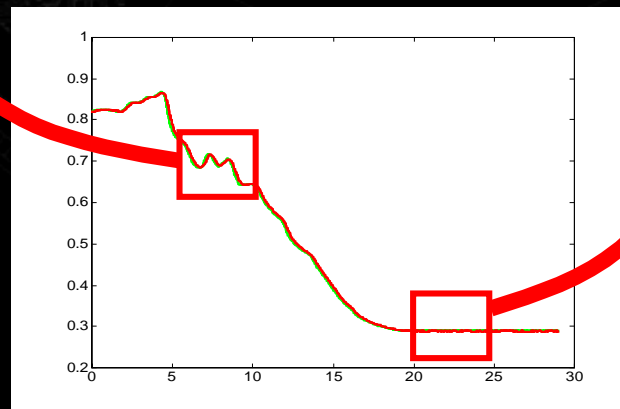
state

$$\begin{bmatrix} x \\ y \\ dx/dt \\ dy/dt \end{bmatrix}$$

# Different Performance



*improved  
latency when  
moving...*



*...relatively  
noisy  
when not*

# Example: 6D HiBall Tracker

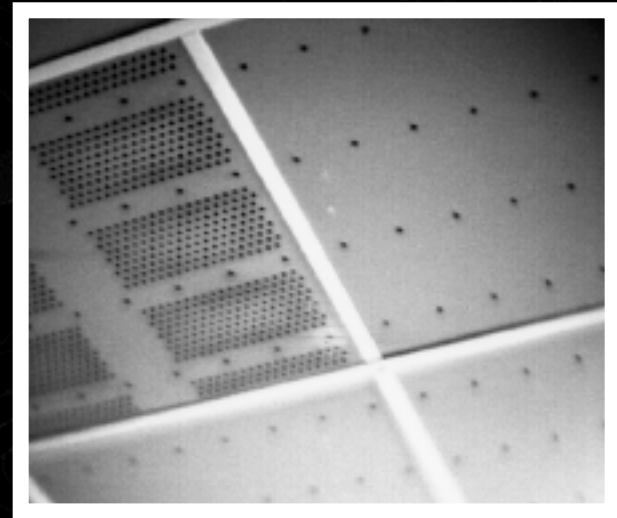
(x, y, z, roll, pitch, yaw)



# Apparatus



HiBall with six  
optical sensors



Ceiling panel  
with LEDs

# State Vector (PV)



$$\bar{x} = \left[ \bar{\tau} \quad \bar{\rho} \quad \frac{d\bar{\tau}}{dt} \quad \frac{d\bar{\rho}}{dt} \quad \bar{\lambda} \right]^T$$

$\bar{\tau}$  = translation (3D)

$\bar{\rho}$  = rotation (3D)

$\frac{d\bar{\tau}}{dt}$  = linear velocity (3D)

$\frac{d\bar{\rho}}{dt}$  = angular velocity (3D)

$\bar{\lambda}$  = LED position (3D)

# *Non-Linear* Measurement Model



$$\begin{bmatrix} c_x \\ c_y \\ c_z \end{bmatrix} = V \cdot \text{rotate}(\bar{\rho}) \cdot (\bar{\lambda} - \bar{\tau})$$

**view matrix**

$$\begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} c_x / c_z \\ c_y / c_z \end{bmatrix}$$

# SCAAT vs. MCAAT



- *Single or Multiple Constraint(s) at a Time*
- **Dimension of the measurement**
  - Nothing about KF mathematics restricts it
  - Can process in “batch” or sequential mode
- **SCAAT**
  - Estimate 15 parameters with 2D measurements
  - Temporal improvements
  - Autocalibration of LED positions



# HiBall Initialization



- Initialize pose using a brute-force (relatively slow) MCAAT approach
- Initial velocities = 0
- Initial process covariance  $P_0 = \sim \text{cm/degrees}$
- Transition to SCAAT Kalman filter

# Nonlinear Systems

(Gary Bishop)



# Kalman Filter assumes linearity



- Only matrix operations allowed
- Measurement is a linear function of state
- Next state is linear function of previous state
- Can't estimate gain
- Can't handle rotations (angles in state)
- Can't handle projection

# Extended Kalman Filter



## Nonlinear Process (Model)

- Process dynamics:  $A$  becomes  $a(x)$
- Measurement:  $H$  becomes  $h(x)$

## Filter Reformulation

- Use functions instead of matrices
- Use Jacobians to project forward, and to relate measurement to state

# Jacobian?



- Partial derivative of measurement with respect to state
- If measurement is a vector of length  $M$
- And state has length  $N$
- Jacobian of measurement function will be  $M \times N$  matrix of numbers (not equations)
- Often evaluating  $h(x)$  and  $Jacobian(h(x))$  at the same time cost only a little extra

# Tips



- Don't compute giant symbolic Jacobian with a symbolic algebra package
- Do use an automatic method during development
- Check out tools from optimization packages
- Differentiating your function line-by-line is usually pretty easy



# New Approaches



Several extensions are available that work better than the EKF in some circumstances

# System Identification

## Model Form and Parameters (Greg Welch)





# Measurement Noise (R)



# Sampled Process Noise (Q)



For continuous model

$$\frac{d\bar{x}}{dt} = F\bar{x} + Q_c$$

The sampled (discrete) Q is

$$Q_d = \int_0^{dt} e^{F\tau} Q_c e^{F^T \tau} d\tau$$

# Example: 2D PV Model



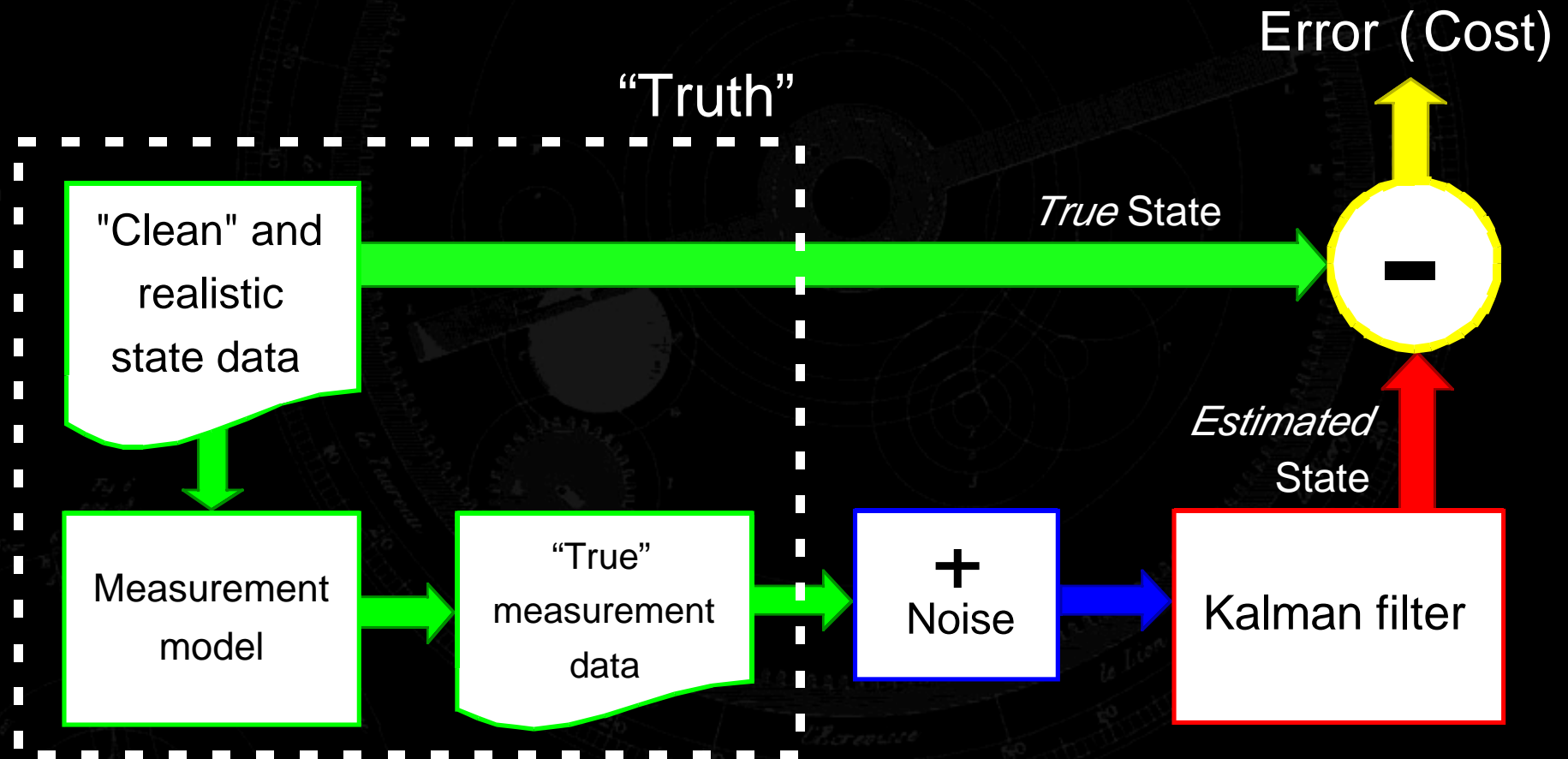
For continuous model

$$\frac{d\bar{x}}{dt} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \bar{x} + \begin{bmatrix} 0 & 0 \\ 0 & q \end{bmatrix}$$

The sampled (discrete) Q is

$$Q_d = \begin{bmatrix} dt^2 q / 3 & dt^2 q / 2 \\ dt^2 q / 2 & dt^2 q \end{bmatrix}$$

# Parameter Optimization

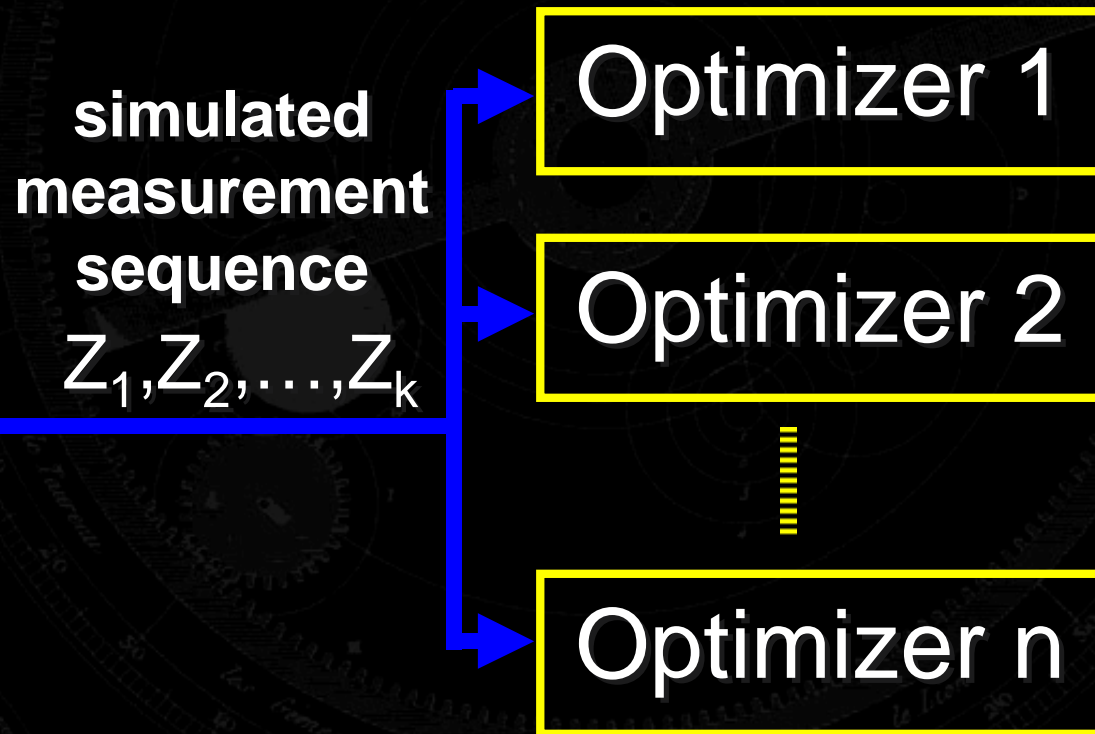


# Multiple-Model Configurations

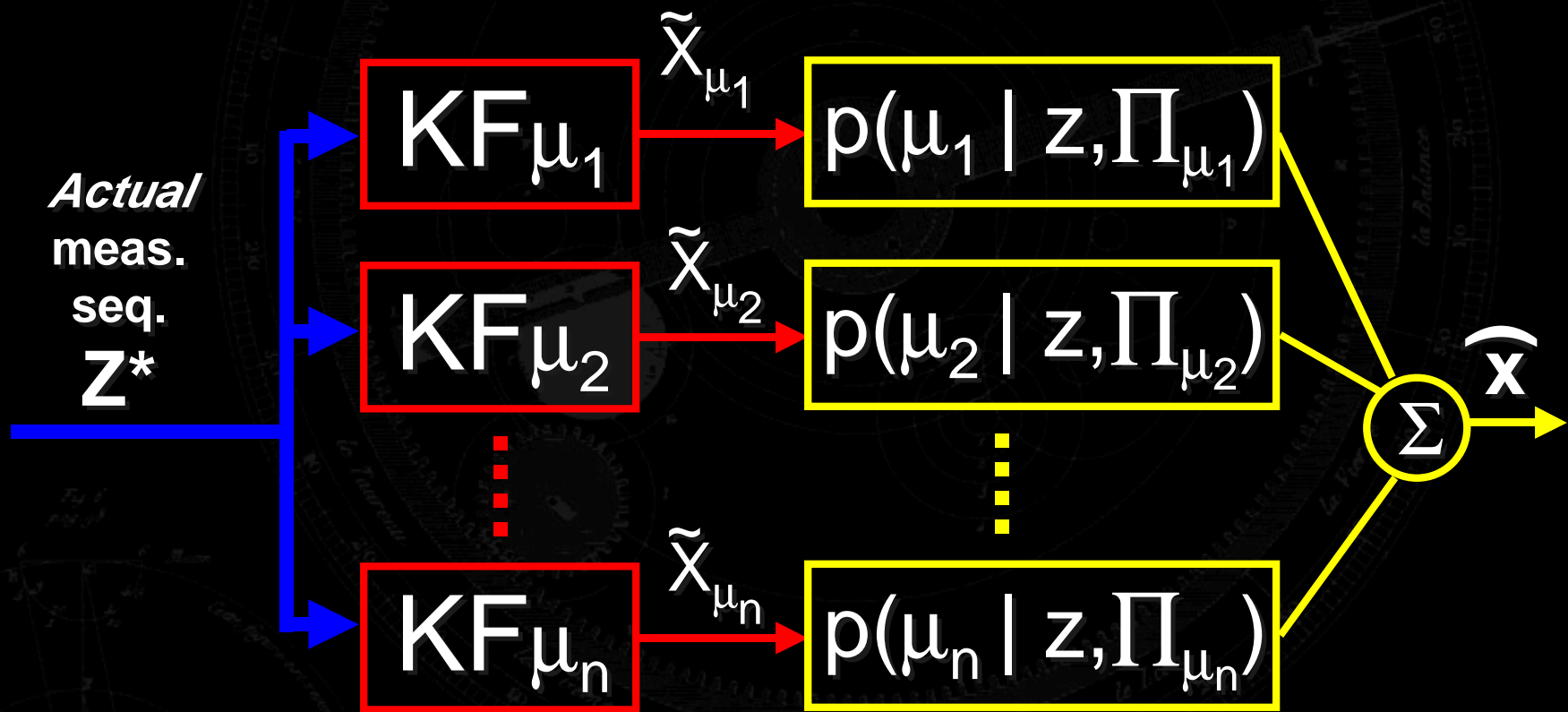
Off or On-Line Model Selection



# Off-Line Model Selection



# On-Line Multiple-Model Estimation



$$\Pi_{\mu_n} = \{ \bar{x}_k, P_k, H, R \}$$

# Probability of Model $\mu$



For model  $\mu$  with  $\Pi_\mu = \{x, P, H, R\}$

$$p(\mu|z, \Pi_\mu) = \frac{1}{(2\pi|C|)^{\frac{n}{2}}} e^{-\frac{1}{2}(z-Hx)^T C^{-1} (z-Hx)}$$

where

$$C = HPH^T + R$$

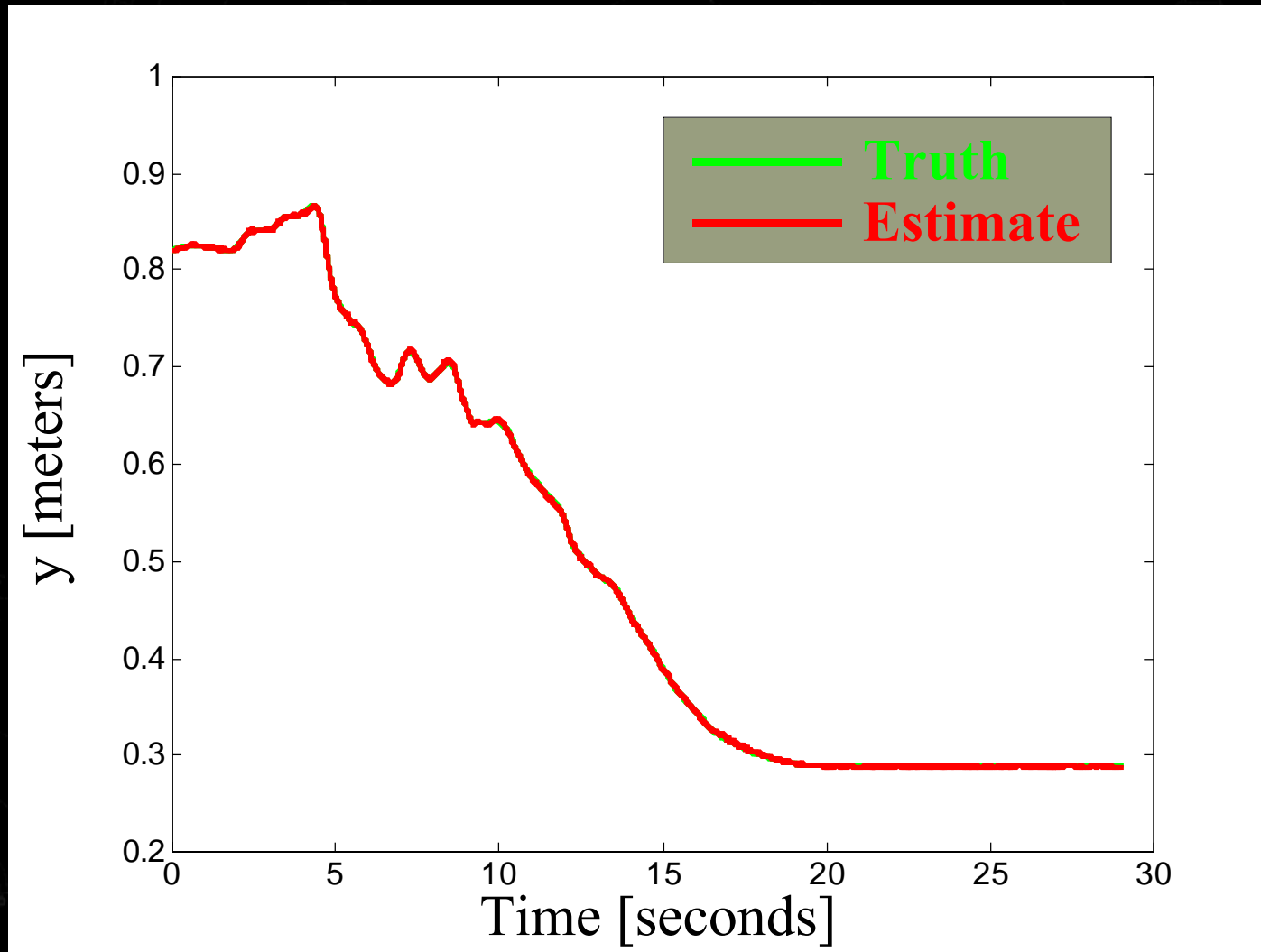


# Final Combined Estimate

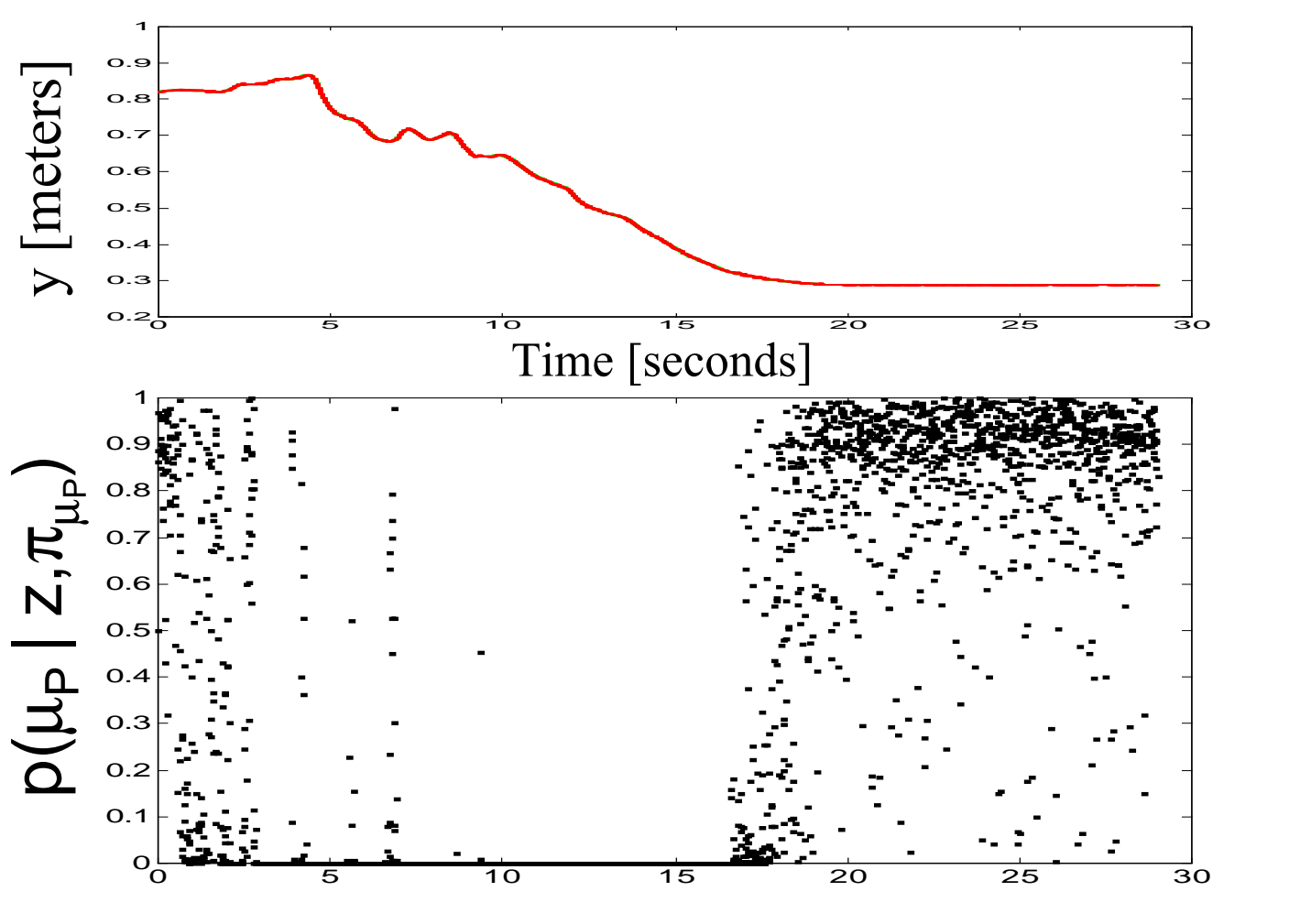


$$\hat{x} = \sum_{\mu} \mathcal{F}_{\mu} \frac{p(\mu|z, \Pi_{\mu})}{\sum_{\nu} p(\nu|z, \Pi_{\nu})}$$

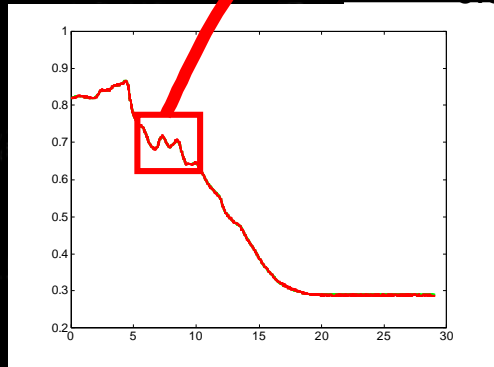
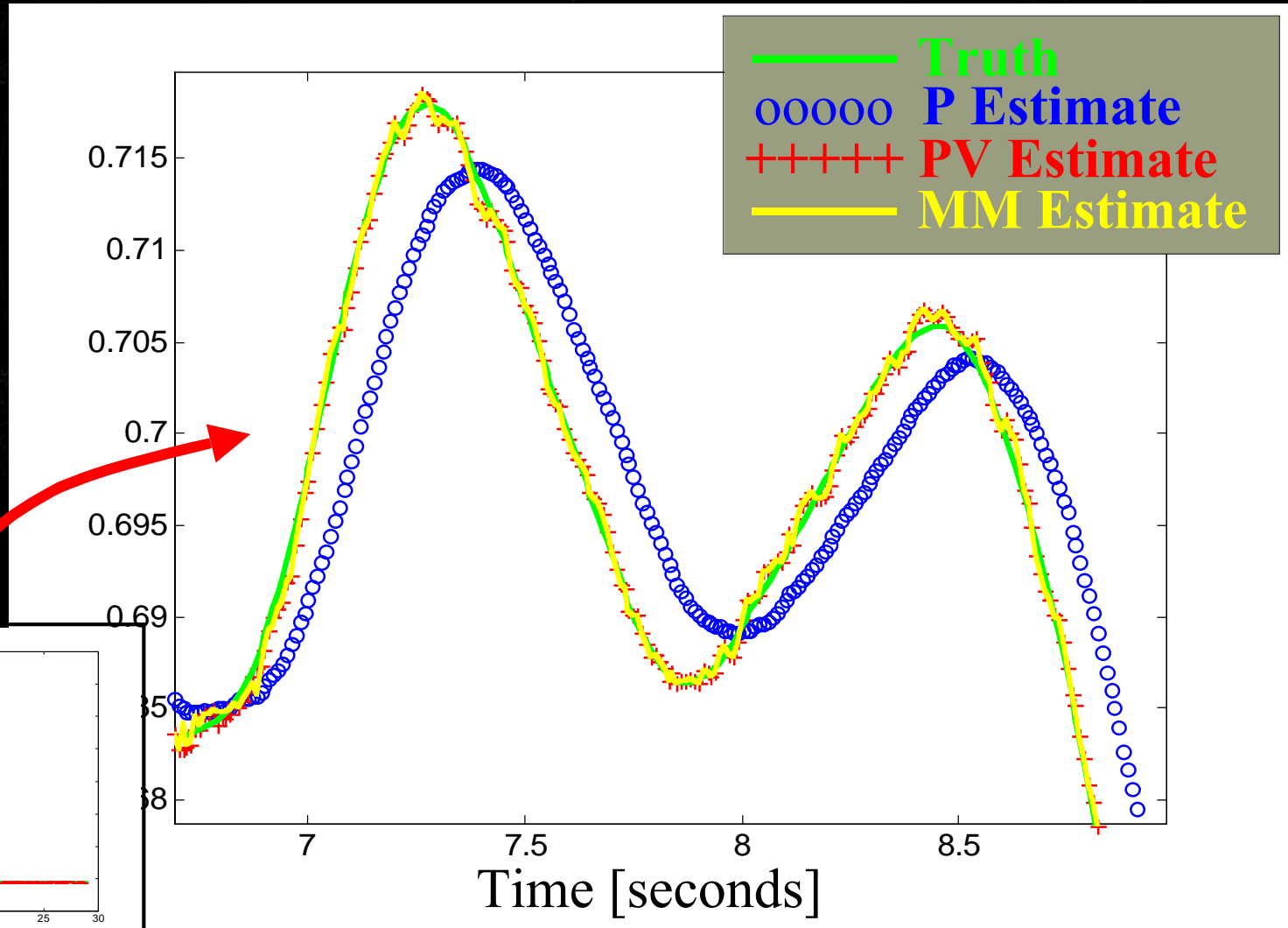
# Example: P/PV Multiple-Model



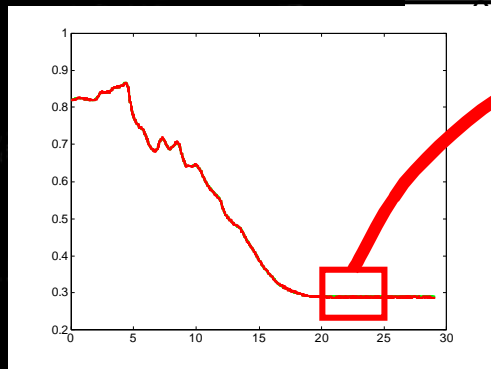
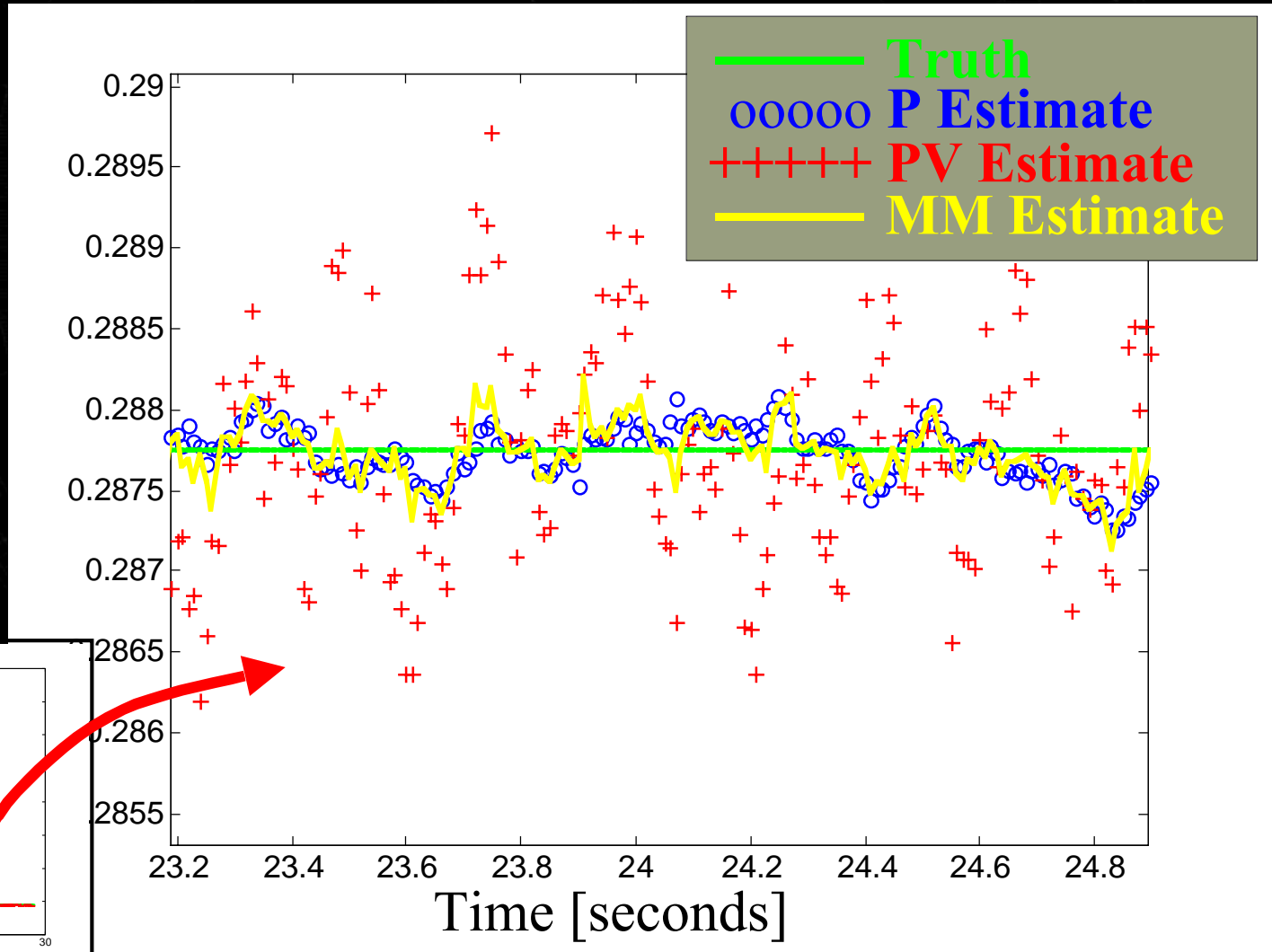
# MME Weighting



# Low-Latency During Motion



# Smooth When Still



# Conclusions

## Suggestions and Resources (Greg Welch)



# Many Applications (Examples)



- **Engineering**
  - Robotics, spacecraft, aircraft, automobiles
- **Computer**
  - Tracking, real-time graphics, computer vision
- **Economics**
  - Forecasting economic indicators
- **Other**
  - Telephone and electricity loads

# Kalman Filter Web Site



<http://www.cs.unc.edu/~welch/kalman/>

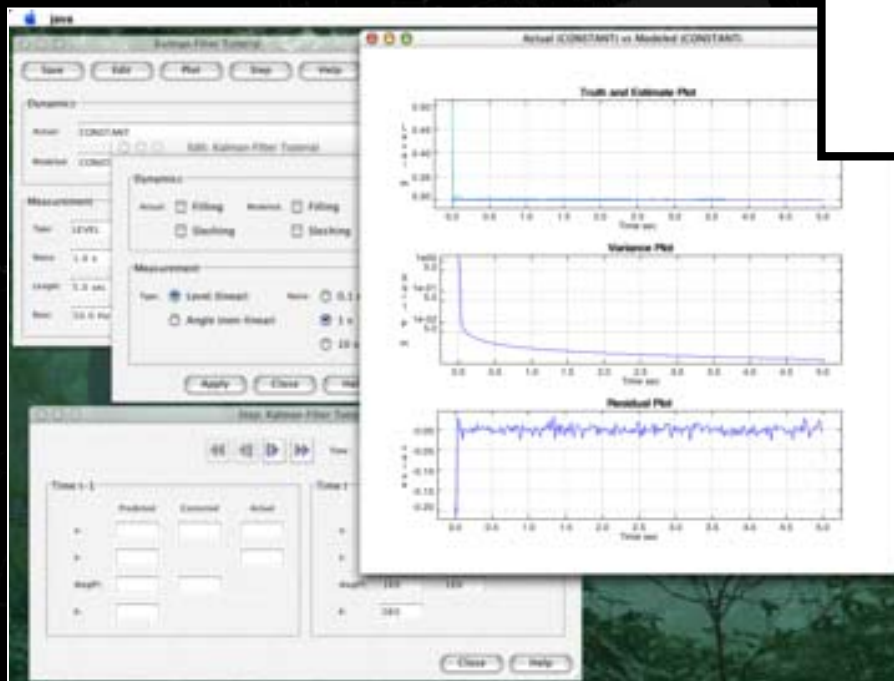
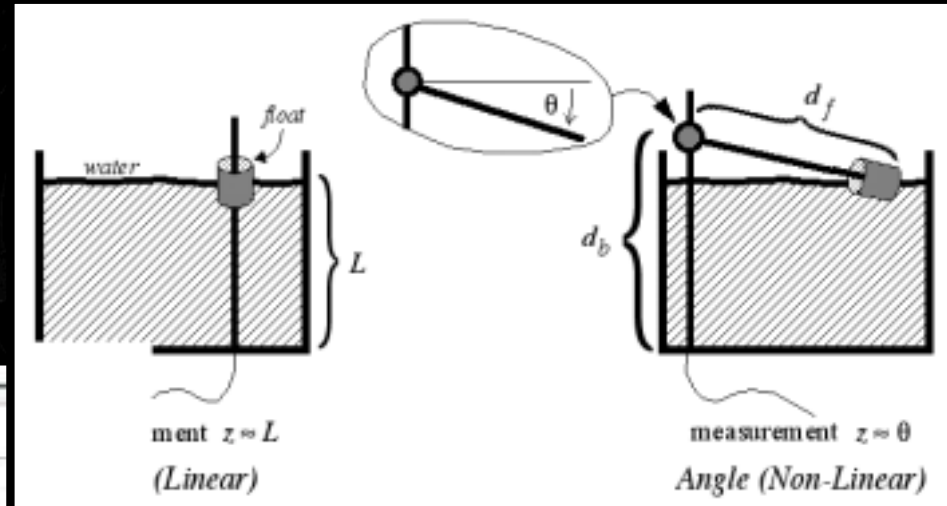
- **Electronic and printed references**
  - Book lists and recommendations
  - Research papers
  - Links to other sites
  - Some software
- **News**



# Java-Based KF Learning Tool



- On-line 1D simulation
- Linear and non-linear
- Variable dynamics



<http://www.cs.unc.edu/~welch/kalman/>

# KF Course Web Page



<http://www.cs.unc.edu/~tracker/ref/s2001/kalman/index.html>

( <http://www.cs.unc.edu/~tracker/> )

- Electronic version of course pack (updated)
- Java-Based KF Learning Tool
- KF web page
- *See also notes for Course 11 (Tracking)*

# Closing Remarks



- **Try it!**
  - Not too hard to understand or program
- **Start simple**
  - Experiment in 1D
  - Make your own filter in Matlab, etc.
- **Note: the Kalman filter “wants to work”**
  - Debugging can be difficult
  - Errors can go un-noticed

End

