A New Technique to Escape Local Minimum in Artificial Potential Field Based Path Planning

Min Gyu Park
Graduate School of Mechanical and Intelligent Systems Engineering, Pusan National University, Pusan 609-735, Korea
Min Cheol Lee*
School of Mechanical Engineering, Pusan National University, Pusan 609-735, Korea

The artificial potential field (APF) methods provide simple and efficient motion planners for practical purposes. However, these methods have a local minimum problem, which can trap an object before reaching its goal. The local minimum problem is sometimes inevitable when an object moves in unknown environments, because the object cannot predict local minima before it detects obstacles forming the local minima. The avoidance of local minima has been an active research topic in the potential field based path planing. In this study, we propose a new concept using a virtual obstacle to escape local minima that occur in local path planning. A virtual obstacle is located around local minima to repel an object from local minima. We also propose the discrete modeling method for the modeling of arbitrary shaped objects used in this approach. This modeling method is adaptable for real-time path planning because it is reliable and provides lower complexity.

Key Words : Virtual Obstacle, Path Planning, Artificial Potential Field, Local Minimum Problem, Discrete Modeling Method, Extra Potential

1. Introduction

The problem of moving an object, such as a mobile robot, in space while avoiding collisions with obstacles is known as obstacle avoidance or path planning. The goal of collision-free path planning is to find a continuous path for an object from the initial position to the goal position (Volpe and Khosla, 1990 ; McFetridge and Yousef-Ibrahim, 1998). Many algorithms for path planning have been studied and developed over the past twenty years (Im et al., 2002 ; Sacks, 2002 ; Kang and Lim, 1999 ; Han et al., 2001). The previous related works can be classified into complete and heuristic (incomplete) techniques (Janabi-Sharifi and Vinke, 1993). Complete algorithms are based on exact configuration representations with complete information about the free space and goal. They have been developed for parts bounded by algebraic curve segments. The basic problem with the complete algorithms is that they are computationally intractable (Rimon and Koditschek, 1992). On the other hand, heuristic techniques provide lower complexity. Among heuristic approaches, the APF method provides simple and effective motion planners for practical purposes (Lee and Park, 1991). The applications of APF for obstacle avoidance was first developed by Khatib (Khatib, 1986). This approach uses two types of potentials, which are a repulsive potential field to force an object away from obstacles or forbidden regions and an attractive potential field to drive the object to its center. The object moves under the action of a force that is equal to the negative gradient of that potential,

* Corresponding Author,
E-mail : mclee@pusan.ac.kr
TEL : +82-51-510-2439; **FAX** : +82-51-512-9835
School of Mechanical Engineering, Pusan National University, Pusan 609-735, Korea. (Manuscript **Received** November 2, 2002; **Revised** June 7, 2003)

and it is driven from the position with the higher potential to that with the lower.

Path planning using the APF is decomposed into two levels — local and global (Singh et al., 2000). The job of local planning is to react to sensory data as quickly as possible for avoiding hazards of various kinds. Global planning requires a complete specification of the environment to determine how to move the object to reach the goal. Global methods have several disadvantages. For example, the algorithms for these methods cannot be applied to the path planning process in unknown environments because it requires complete information on the environment before path planning. Even though complete information may be known about the environment, the computational complexity of this approach limits its real-time applications to only very simple cases, because their computation time increases exponentially with the degrees of freedom of objects (Kim and Khosla, 1992). Therefore, global planning is suited only for off-line path planning in known environments. A viable alternative to global planning methods is provided by local ones. The local potential field methods capture local information in real-time to keep the object away from the local obstacles in the cartesian space of the object. Consequently, the local methods may avoid complexity of the global ones.

However, a major problem in local path planning using an APF approach is the local minimum, which can trap an object before reaching its goal. The local minimum problem is sometimes inevitable in local path planning, because the object can detect only local information on obstacles. In other words, the object cannot predict local minima before experiencing the environment. Avoidance of a local minimum has been an active research topic in the potential field based path planning (Volpe and Khosla, 1990; McFetridge and Yousef-Ibrahim, 1998; Janabi-Sharifi and Vinke, 1993; Lee and Park, 1991; Kim and Khosla, 1992; Rimom and Koditschek, 1992; Cho and Kwon, 1996) However, the previous solutions were limited to simple formations of obstacles or available for path planning in known environments.

In this research, a virtual obstacle concept is proposed as an idea to escape a local minimum. The virtual obstacle is located around the local minimum point to repel the object from this point. This technique is useful for local path planning in unknown environments. The discrete modeling method is also proposed for the simple modeling of objects with an arbitrary shape. This modeling method is reliable and provides less complexity for real-time path planning.

This paper is organized as follows: In Section 2, the artificial potential approach is introduced and the local minimum problem is discussed. In Section 3, the discrete modeling method is proposed. In Section 4, the virtual obstacle concept is proposed to overcome the local minimum problem. In Section 5, the proposed approach is evaluated through simulations. This paper concludes in Section 6.

2. Potential Theory and Local Minimum Problem

2.1 Artificial potential field approach

APF approaches are based on a gradient descent search method, which is directed towards minimizing the potential function. Obstacles that have to be avoided are surrounded by repulsive potential fields, and the goal point is surrounded by an attractive potential field. The attractive potential is generally a bowl-shaped energy well which drives an object to its center if the environment is unobstructed. However, in an obstructed environment, repulsive potential energy hills that repel the objects are added to an attractive potential field at obstacle locations, as shown in Fig. 1. The object experiences a force that is equal to the negative gradient of the potential. This force drives the object downhill until the object reaches the position with minimum energy.

In this section, we review the attributes of the attractive potential function and the repulsive potential function adopted in this study. The attractive potential function used in this study is the conical well proposed by Andrews (Andrews and Hogan, 1983). This function is quadratic

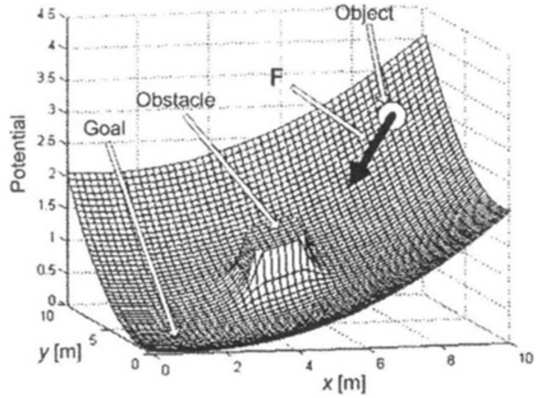


Fig. 1 Repulsive potential added to an attractive potential and distributed force

within a given range and the value of the function increases linearly in the outer range. Therefore, it is adaptable for path planning in wide environments (Volpe and Khosla, 1990). The conical well U_{att} is described by

$$U_{att}(\mathbf{x}) = \begin{cases} k_a|\mathbf{x}-\mathbf{x}_d|^2 & \text{if } |\mathbf{x}-\mathbf{x}_d| \leqq d_a \\ k_a(2d_a|\mathbf{x}-\mathbf{x}_d|-d_a^2) & \text{if } |\mathbf{x}-\mathbf{x}_d| > d_a \end{cases} \quad (1)$$

where $\mathbf{x}$ represents the position vector of the object, $\mathbf{x}_d$ represents the position vector of the goal, d_a is the radius of the quadratic range, and k_a is the proportional gain of the function. The attractive force $\mathbf{F}_{att}$ may be obtained by the negative gradient of this attractive potential :

$$\mathbf{F}_{att}(\mathbf{x}) = -\nabla U_{att} = \begin{cases} -2k_a(\mathbf{x}-\mathbf{x}_d) & \text{if } |\mathbf{x}-\mathbf{x}_d| \leqq d_a \\ -2d_a k_a \dfrac{\mathbf{x}-\mathbf{x}_d}{|\mathbf{x}-\mathbf{x}_d|} & \text{if } |\mathbf{x}-\mathbf{x}_d| > d_a. \end{cases} \quad (2)$$

The conical well provides a force with constant magnitude for distances larger than d_a.

The second category of potentials, the repulsive potential, is necessary to repel the object away from obstacles that obstruct the object's path of motion in the global attractive potential field. These potential functions have a limited range of influence. This prevents an obstacle from affecting the motion of an object when it is far away from the obstacle (Volpe and Khosla, 1990). The following repulsive potential function is the FIRAS function proposed by Khatib. This function uses the shortest distance to an obstacle as

$$U_{rep}(\mathbf{x}) = \begin{cases} \dfrac{1}{2}k_r\left(\dfrac{1}{\rho}-\dfrac{1}{\rho_0}\right)^2 & \text{if } \rho \leqq \rho_0 \\ 0 & \text{if } \rho > \rho_0 \end{cases} \quad (3)$$

where ρ_0 represents a potential field's distance limit of influence and ρ is the shortest distance to an obstacle. The selection of the distance ρ_0 depends on the maximum speed of the object and the control period (Khatib, 1986). The repulsive force is driven as

$$\mathbf{F}_{rep}(\mathbf{x}) = -\nabla U_{rep} = \begin{cases} k_r\left(\dfrac{1}{\rho}-\dfrac{1}{\rho_0}\right)\dfrac{1}{\rho^2}\dfrac{\partial\rho}{\partial\mathbf{x}} & \text{if } \rho \leqq \rho_0 \\ 0 & \text{if } \rho > \rho_0 \end{cases} \quad (4)$$

where $\partial\rho/\partial\mathbf{x}$ can be represented as

$$\frac{\partial\rho}{\partial\mathbf{x}} = \left(\frac{\partial\rho}{\partial x}\ \frac{\partial\rho}{\partial y}\right)^T = \frac{\mathbf{x}-\mathbf{x}_o}{\rho} \quad (5)$$

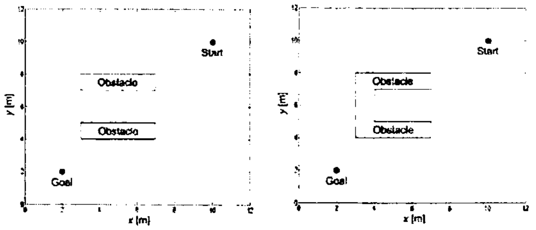
where $\mathbf{x}_o$ is the position vector of the closest obstacle in the xy-coordinate system (Khatib, 1986).

The global potential can be obtained by adding together the sum of the attractive potential and repulsive potential. The distributed force $\mathbf{F}(\mathbf{x})$ is obtained by the negative gradient of a global potential. The principle of superposition can be applied to get $\mathbf{F}(\mathbf{x})$ as

$$\begin{aligned} \mathbf{F}(\mathbf{x}) &= -\nabla U(\mathbf{x}) \\ &= -\nabla U_{att}(\mathbf{x}) - \nabla U_{rep}(\mathbf{x}) \\ &= \mathbf{F}_{att}(\mathbf{x}) + \mathbf{F}_{rep}(\mathbf{x}). \end{aligned} \quad (6)$$

2.2 Local minimum problem in unknown environments

In unknown environments, the object initially does not have any information about the environment, and it has a limited sensing range to detect obstacles. In this study, it is assumed that the object can detect obstacles up to 1.5 m from itself. The environment in Fig. 2(a) does not contain a local minimum, so objects may successfully reach the goal using the APF approach. In the environment of Fig. 2(b), however, objects may be trapped in a local minimum. In this case,



(a) Open aisle (b) Closed aisle

Fig. 2 Two types of obstacles with aisle shapes

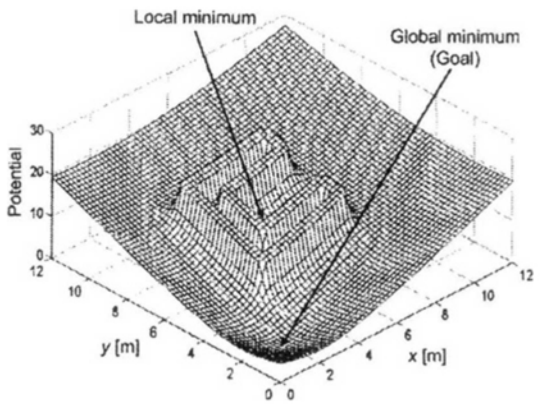


Fig. 3 The potential field of the closed aisle

the global potential has the formation in Fig. 3. The object cannot move anywhere in the local minimum, because the local minimum is a point where the potential gradient becomes zero. The local minimum problem is sometimes inevitable in local path planning. In Fig. 2, objects can detect only the obstacle located in 1.5 m from itself. Therefore, the object cannot judge whether the deep aisle-shaped obstacle has a dead-end (Fig. 2(b)) or not (Fig. 2(a)) before going into the aisle.

3. Discrete Modeling Method

2.1 Continuous modeling of objects and its problem

The discrete modeling method simplifies the modeling of arbitrary objects. In this section, a continuous modeling method and its problems are discussed before proposing the discrete modeling method.

Consider the dynamics of the object shown in

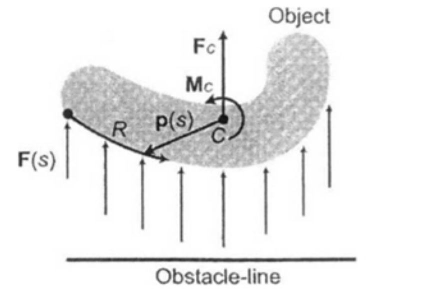


Fig. 4 Forces acting on an arbitrary shaped object

Fig. 4, where C is the center of mass. The object is subject to distributed force $\mathbf{F}(s)$. To get the velocity of the object, we should obtain the total force $\mathbf{F}_C$ and the total moment $\mathbf{M}_C$, which act at C. They are obtained by the line integral of force and moment along R as follows :

$$\mathbf{F}_C = \oint_R \mathbf{F}(s)\,ds \tag{7}$$

$$\mathbf{M}_C = \oint_R (\mathbf{p}(s) \times \mathbf{F}(s))\,ds \tag{8}$$

where the integration around R is the boundary curve of the object and is the arc length of R. To solve Eqs. (7) and (8), the boundary curve R should be defined as a continuous function in a global coordinate system. However, it is very difficult to describe arbitrary-shaped objects as a continuos function. Even though the function is obtained, these models of objects are not adaptable for real-time path planning because they are computationally intensive.

3.2 Discrete modeling of an object

To solve the problem of the continuous modeling method, we propose a discrete modeling method that lets us easily get a total force and a total torque acted on the center of mass in arbitrary shaped objects. Fig. 5 shows the example of an arbitrary shaped object. The object has a local coordinate system fixed on it. The point C is the center of mass and the origin of the local coordinate system. In the discrete modeling method, the object is divided into finite segments and each segment has the object skeleton point p_i, which is given by the designer. To analyze the dynamics of the object, we should get the position vector

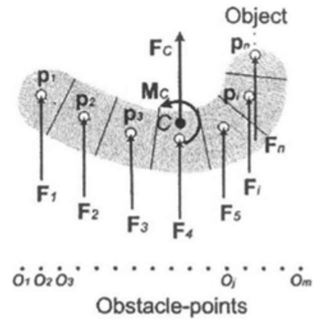


Fig. 5 Discrete modeling and forces acting on object skeleton points

of the object skeleton points relative to O, which is the origin of the global coordinate system. The position vector of the object skeleton points can be obtained by

$$\mathbf{p}_{i/O}=\mathbf{p}_{i/C}+\mathbf{x}_{C/O} \tag{9}$$

where $\mathbf{x}_{C/O}$ is the position vector of C relative to O and the set of $\mathbf{p}_{i/C}$ should be initially defined by the user.

In Fig 5, each object skeleton point is under the action of the force generated in the potential field. These forces can be represented as the total force $\mathbf{F}_C$ and the total moment $\mathbf{M}_C$ acting on the center of mass. $\mathbf{F}_C$ and $\mathbf{M}_C$ are obtained by

$$\mathbf{F}_C=\sum_{i=1}^{n}\mathbf{F}(\mathbf{p}_{i/O}) \tag{10}$$

$$\mathbf{M}_C=\sum_{i=1}^{n}(\mathbf{p}_{i/C}\times\mathbf{F}(\mathbf{p}_{i/O})). \tag{11}$$

Consequently, we can get the linear acceleration and the angular acceleration of the object by Newton's 2nd Law as follows:

$$\dot{\mathbf{v}}_C=\frac{\mathbf{F}_C}{\sum_{i=1}^{n}m_i} \tag{12}$$

$$\dot{\boldsymbol{w}}_C=\frac{\mathbf{M}_C}{\sum_{i=1}^{n}m_i(\mathbf{p}_{i/C}\cdot\mathbf{p}_{i/C})} \tag{13}$$

where m_i is the mass of each segment.

The linear velocity of the object in the discrete control system with a control period T can be derived as

$$\begin{aligned}\mathbf{v}'_C(t+T)&=\mathbf{v}_C(t)+\Delta\mathbf{v}_C(t)\\&=\mathbf{v}_C(t)+T\dot{\mathbf{v}}_C(t)\end{aligned} \tag{14}$$

$$\mathbf{v}_C=\begin{cases}\mathbf{v}'_C & \text{if } |\mathbf{v}'_C|\leqq v_{\max}\\ v_{\max}\dfrac{\mathbf{v}'_C}{|\mathbf{v}'_C|} & \text{if } |\mathbf{v}'_C|>v_{\max}.\end{cases} \tag{15}$$

Because the velocity of the object has an upper limit in the real world, the maximum magnitude of the linear velocity is set to $v_{\max}$ when $|\mathbf{v}'_C|$ is greater than $v_{\max}$. In the same way, the angular velocity with the maximum magnitude of $w_{\max}$ is obtained by

$$\begin{aligned}\boldsymbol{w}'_C(t+T)&=\boldsymbol{w}_C(t)+\Delta\boldsymbol{w}_C(t)\\&=\boldsymbol{w}_C(t)+T\dot{\boldsymbol{w}}_C(t)\end{aligned} \tag{16}$$

$$\boldsymbol{w}_C=\begin{cases}\boldsymbol{w}'_C & \text{if } |\boldsymbol{w}'_C|\leqq w_{\max}\\ w_{\max}\dfrac{\boldsymbol{w}'_C}{|\boldsymbol{w}'_C|} & \text{if } |\boldsymbol{w}'_C|>w_{\max}.\end{cases} \tag{17}$$

In the path planning of real objects, these velocities may be used as control inputs. In simulations, however, the position of the object should be derived. The position vector $\mathbf{x}_{C/O}$ and the angle $\theta_{C/O}$ in the global coordinate system is expressed as

$$\begin{aligned}\mathbf{x}_{C/O}(t+T)&=\mathbf{x}_{C/O}(t)+\Delta\mathbf{x}_{C/O}(t)\\&=\mathbf{x}_{C/O}(t)+T\mathbf{v}_C(t)\end{aligned} \tag{18}$$

$$\begin{aligned}\theta_{C/O}(t+T)&=\theta_{C/O}(t)+\Delta\theta_{C/O}(t)\\&=\theta_{C/O}(t)+T\boldsymbol{w}_C(t)\cdot\boldsymbol{k}\end{aligned} \tag{19}$$

where T is the sampling period used in simulations.

To get arbitrary points on the object in the global coordinate system, it requires the transformation matrix between the global coordinate system and the local coordinate system. The point $\{x_{i/C}\ y_{i/C}\}^T$ in the local coordinate system can be transformed into the point $\{x_{i/O}\ y_{i/O}\}^T$ in the global coordinate system by following this transformation equation:

$$\begin{Bmatrix}x_{i/O}\\ y_{i/O}\end{Bmatrix}=\begin{bmatrix}\cos\theta_{C/O} & -\sin\theta_{C/O} & x_{C/O}\\ \sin\theta_{C/O} & \cos\theta_{C/O} & y_{C/O}\end{bmatrix}\begin{Bmatrix}x_{i/C}\\ y_{i/C}\\ 1\end{Bmatrix} \tag{20}$$

where $\{x_{C/O}\ y_{C/O}\}^T$ is the position of C in the global coordinate system.

In this study, we defined two types of objects as shown in Fig. 6 and Fig. 7. The object skeleton points of these object are defined in Table 1. These objects will be used for simulations in Section 5.

Table 1 Object skeleton points for two objects

Bar-shaped object	L-shaped object
	$\mathbf{p}_{1/C} = -0.5143\hat{\mathbf{i}} + 1.2857\hat{\mathbf{j}}$
$\mathbf{p}_{1/C} = -0.8\hat{\mathbf{i}}$	$\mathbf{p}_{2/C} = -0.5143\hat{\mathbf{i}} + 0.6857\hat{\mathbf{j}}$
$\mathbf{p}_{2/C} = -0.4\hat{\mathbf{i}}$	$\mathbf{p}_{3/C} = -0.5143\hat{\mathbf{i}} + 0.0857\hat{\mathbf{j}}$
$\mathbf{p}_{3/C} = 0$	$\mathbf{p}_{4/C} = -0.5143\hat{\mathbf{i}} + 0.5143\hat{\mathbf{j}}$
$\mathbf{p}_{4/C} = 0.4\hat{\mathbf{i}}$	$\mathbf{p}_{5/C} = 0.0857\hat{\mathbf{i}} + 0.5143\hat{\mathbf{j}}$
$\mathbf{p}_{5/C} = 0.8\hat{\mathbf{i}}$	$\mathbf{p}_{6/C} = 0.6857\hat{\mathbf{i}} + 0.5143\hat{\mathbf{j}}$
	$\mathbf{p}_{7/C} = 1.2857\hat{\mathbf{i}} + 0.5143\hat{\mathbf{j}}$

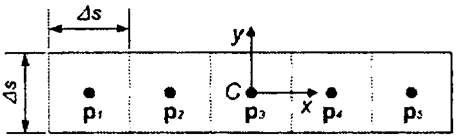


Fig. 6 Discrete modeling of a bar-shaped object

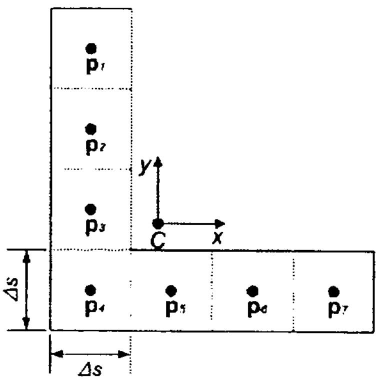
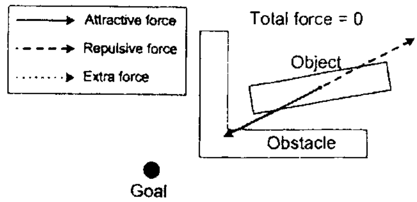


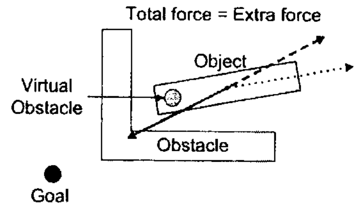
Fig. 7 Discrete modeling of an L-shaped object

4. Virtual Obstacle Concept and Extra Potential Function

A virtual obstacle is a new concept to escape a local minimum when an object is trapped in the local minimum. In the conventional APF method, the local minimum is formed when an attractive force is equal to a repulsive force as shown in Fig. 8(a). A virtual obstacle has the role of repelling the object from a local minimum. Fig. 8 (b) illustrates the mechanism of the proposed APF method with a virtual obstacle. The virtual obstacle is generated when the object is trapped in a local minimum, and then it make an extra force that repel the object from a local minimum point. To judge whether the object is trapped in the



(a)



(b)

Fig. 8 (a) Conventional artificial forces versus (b) Proposed artificial forces with virtual obstacle

local minimum or not, the following criterion is defined :

Local-minimum-criterion

When $t \geqq T_a$, if $|\mathbf{x}_C(t) - \mathbf{x}_C(t - T_a)| \leqq S_a$ then the object is trapped in a local minimum, where $\mathbf{x}_C$ represents the position vector of the object, T_a is the time interval, and S_a is set to the minimum distance that the object moves for T_a in the non-local minimum condition. S_a should be set to a very small value because the distance between $\mathbf{x}_C(t)$ and $\mathbf{x}_C(t - T_a)$ has a very small value when the object is trapped in a local minimum.

When an object is trapped in a local minimum, a virtual obstacle is located at the trapping point to repel the object from the local minimum point. The position vector of the trapping point is defined as $\mathbf{x}_{TP}$, which satisfies the following identical equation :

$$\begin{aligned} \mathbf{F}_{att}(\mathbf{x}_{TP}) \cdot (-\mathbf{F}_{rep}(\mathbf{x}_{TP})) = MAX\{ & \mathbf{F}_{att}(\mathbf{p}_1) \cdot (-\mathbf{F}_{rep}(\mathbf{p}_1)), \\ & \mathbf{F}_{att}(\mathbf{p}_2) \cdot (-\mathbf{F}_{rep}(\mathbf{p}_2)), \\ & \cdots, \\ & \mathbf{F}_{att}(\mathbf{p}_n) \cdot (-\mathbf{F}_{rep}(\mathbf{p}_n))\} \end{aligned} \tag{21}$$

where $\mathbf{p}_i$ is the object skeleton points discussed in Section 3.2. The trapping point is selected among the object skeleton points, and the inner product of the attractive force and the negative repulsive force has the maximum value at this point as shown in Fig. 9. Therefore, the trapping point may has a major influence on trapping the object, and the object should then be far away from this point.

The virtual obstacle has the extra potential to repel the object from the trapping point. The extra potential U_{ext} (Fig. 10) is defined as

$$U_{ext}(\mathbf{x}) = \begin{cases} -\dfrac{k_e}{2d_e}|\mathbf{x}-\mathbf{x}_{TP}|^2 & \text{if } |\mathbf{x}-\mathbf{x}_{TP}| \leqq d_e \\ -k_e\left(|\mathbf{x}-\mathbf{x}_{TP}| - \dfrac{d_e}{2}\right) & \text{if } |\mathbf{x}-\mathbf{x}_{TP}| > d_e \end{cases} \tag{22}$$

where d_e is the range of the quadratic part in the extra potential. This quadratic part is required for differentiation at the trapping point. The extra potential has a maximum value at the trapping point, but it decreases with the distance from the trapping point. Therefore, this potential can repel an object from the virtual obstacle. The extra force $\mathbf{F}_{ext}$ is obtained by the negative gradient of an extra potential as follows :

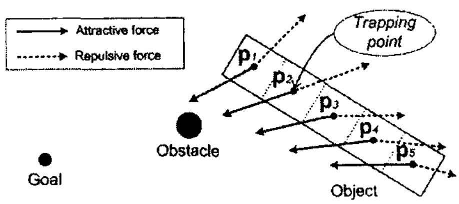


Fig. 9 Searching for a trapping point

$$\mathbf{F}_{ext}(\mathbf{x}) = -\nabla U_{ext} = \begin{cases} \dfrac{k_e}{d_e}(\mathbf{x}-\mathbf{x}_{TP}) & \text{if } |\mathbf{x}-\mathbf{x}_{TP}| \leqq d_e \\ k_e\dfrac{\mathbf{x}-\mathbf{x}_{TP}}{|\mathbf{x}-\mathbf{x}_{TP}|} & \text{if } |\mathbf{x}-\mathbf{x}_{TP}| > d_e. \end{cases} \tag{23}$$

If d_e is set to a very small value, the extra force can be redefined as

$$\mathbf{F}_{ext}(\mathbf{x}) = -\nabla U_{ext} \approx \begin{cases} 0 & \text{if } |\mathbf{x}-\mathbf{x}_{TP}| = 0 \\ k_e\dfrac{\mathbf{x}-\mathbf{x}_{TP}}{|\mathbf{x}-\mathbf{x}_{TP}|} & \text{if } |\mathbf{x}-\mathbf{x}_{TP}| > 0. \end{cases} \tag{24}$$

$U_1(\mathbf{x})$ having a global potential without an extra potential and $U_2(\mathbf{x})$ containing an extra potential are defined as follows :

$$U_1(\mathbf{x}) = U_{att}(\mathbf{x}) + U_{rep}(\mathbf{x}) \tag{25}$$

$$U_2(\mathbf{x}) = U_1(\mathbf{x}) + U_{ext}(\mathbf{x}) = U_{att}(\mathbf{x}) + U_{rep}(\mathbf{x}) + U_{ext}(\mathbf{x}). \tag{26}$$

The distributed forces are expressed as

$$\mathbf{F}_1(\mathbf{x}) = \mathbf{F}_{att}(\mathbf{x}) + \mathbf{F}_{rep}(\mathbf{x}) \tag{27}$$

$$\mathbf{F}_2(\mathbf{x}) = \mathbf{F}_1(\mathbf{x}) + \mathbf{F}_{ext}(\mathbf{x}) = \mathbf{F}_{att}(\mathbf{x}) + \mathbf{F}_{rep}(\mathbf{x}) + \mathbf{F}_{ext}(\mathbf{x}). \tag{28}$$

Figure 11 shows the extra potential added to the original global potential. In this formation of potential, the object can escape from a local minimum because the trapping point has a higher potential than its neighbors. The extra potential is applied while an object is in a local minimum area. The local minimum area means the region

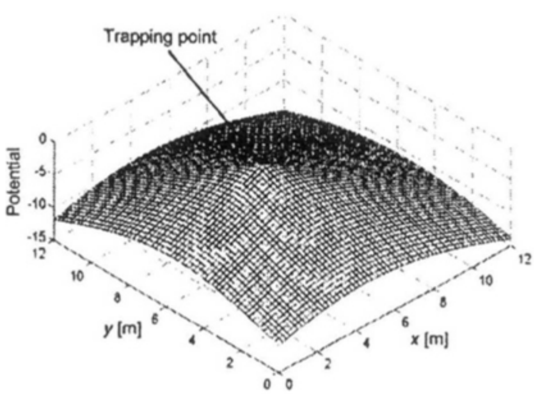


Fig. 10 Extra potential by a virtual obstacle

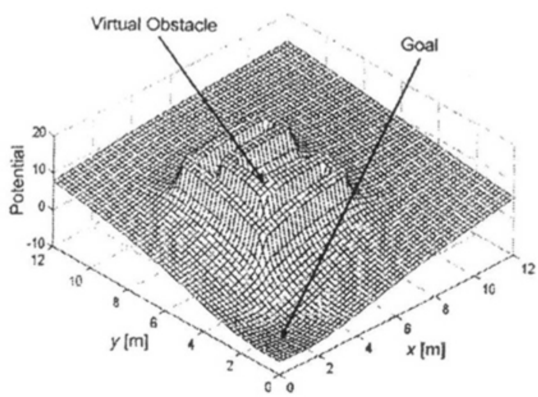


Fig. 11 Global potential with a virtual obstacle

that the object may return to when the virtual obstacle is cleared.

When the object is in a local minimum area, it may move away from the local minimum by the virtual obstacle, and also it may move away from its goal because the direction of the goal is similar to that of the trapping point. The object may move to its goal only after it escapes the local minimum area. Therefore, we define the following criterion to judge whether the object escapes the local minimum area or not:

Escape-local-minimum-area-criterion

When $t-t_{TP}\geqq T_b$, if $|\mathbf{x}_c(t)-\mathbf{x}_d|\leqq|\mathbf{x}_c(t-T_b)-\mathbf{x}_d|$ then it is assumed that the object escaped the local minimum, where t_{TP} is the time when the object is located at a trapping point, T_b is the time interval from the previous to current time to get the change of distance to goal, and this conditional expression means that the object moves to the goal direction.

The whole path planning algorithm is as follows:

Path-planning-algorithm

Step 1.

$t=0$.

$\mathbf{x}_C(0)=\mathbf{x}_{START}$.

$\mathbf{v}_C(0)=0$.

$\boldsymbol{w}_C(0)=0$.

$Local-Minimum-Flag=0$.

Step 2.

Sensing obstacles.

$t=t+T$.

Calculate $\mathbf{p}_{i/O}$ by Eq. (9).

If $Local-Minimum-Flag=0$,

$\mathbf{F}(\mathbf{p}_{i/O})=\mathbf{F}_1(\mathbf{x})$.

Or else if $Local-Minimum-Flag=1$,

$\mathbf{F}(\mathbf{p}_{i/O})=\mathbf{F}_2(\mathbf{x})$.

Calculate $\mathbf{F}(\mathbf{p}_{i/O})$ by Eq. (27) or (28).

Calculate $\mathbf{F}_C(t)$ and $\mathbf{M}_C(t)$ by Eqs. (10) and (11).

Calculate $\dot{\mathbf{v}}_C(t)$, $\dot{\boldsymbol{w}}_C(t)$ by Eqs. (12) and (13).

Calculate $\mathbf{v}_C(t)$, $\boldsymbol{w}_C(t)$ by Eqs. (14) and (17).

Calculate $\mathbf{x}_{C/O}(t)$, $\theta_{C/O}(t)$ by Eqs. (18) and (19).

Step 3.

Local-minimum-criterion.

If the object is trapped by a local minimum,

then $Local-Minimum-Flag=1$.

Search for the trapping point $\mathbf{x}_{TP}$ to satisfy Eq. (21).

Step 4.

Escape-local-minimum-area-criterion.

If the object escapes local minimum area,

then $Local-Minimum-Flag=0$.

Step 5.

If $|\mathbf{x}_C-\mathbf{x}_d|\leqq Tolerance$

then path planning is completed,

Or else return to Step 2.

5. Simulations

We performed various simulations to evaluate the discrete modeling method and the virtual obstacle approach. It is assumed that an object initially does not have any information on the environment, and it can detect obstacles up to 1.5 m from itself. Table 2 shows the simulation conditions. The values of parameters are adequately set by a trial and error method. Two types of objects are used in simulations: a bar-shaped object and an L-shaped object shown in Section 3.2. The simulations of Figs. 12(a) and 12(b) do not have any local minimum, so the object can successfully reach the goal only by the APF approach. In Fig. 12(c), the obstacle has the shape of a closed aisle. Therefore, the object is trapped in a local minimum when the APF approach is applied. In the same environment, Fig. 13 shows that the object can escape the local

Table 2 Simulation conditions

Control period: $T=0.1$ sec
Maximum linear velocity: $v_{\max}=0.3$ m/sec
Maximum angular velocity: $w_{\max}=10$ deg/sec
Maximum sensing range of an object $=1.5$ m
Parameter for an attactive potential: $k_a=1$, $d_a=1$
Parameter for a repulsive potential: $k_r=4$, $\rho_0=2$
Parameter for an extra potential: $k_e=2$

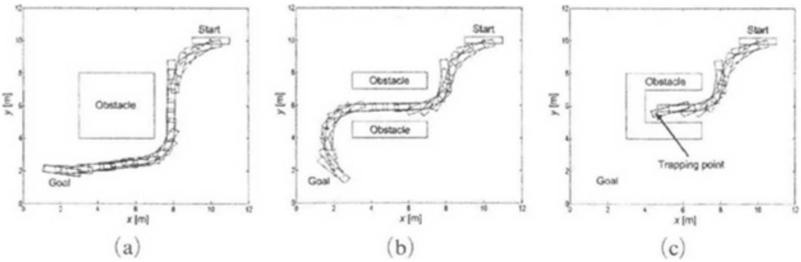


Fig. 12 Path planning by APF method. (a) Rectangular obstacle. (b) Open aisle. (c) Closed aisle (Fail)

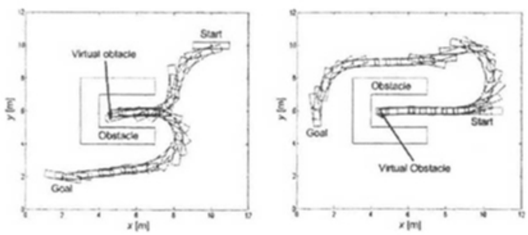


Fig. 13 Path planning by the APF method with a virtual obstacle

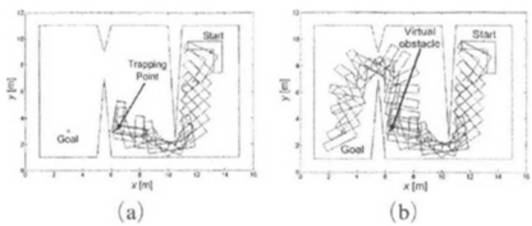


Fig. 14 Path planning of an L-shaped object by (a) the APF method and (b) the APF method with a virtual obstacle

minimum by the virtual obstacle approach, and it can successfully reach its goal. These results of the simulations show that this technique is useful for concave obstacles and for deep aisle-shaped obstacles. In the simulation of Fig. 14(a), by only using the APF approach, the L-shaped object fails to reach its goal because it is trapped in a local minimum. However, the object can successfully reach its goal by the virtual obstacle approach, as shown in Fig. 14(b). Also, the object can move without collision in the narrow aisles because the object is effectively modeled by the discrete modeling method. To evaluate the generality of the proposed algorithm, simulations are done in some environments with randomly generated obstacles as shown in Fig. 15. The results

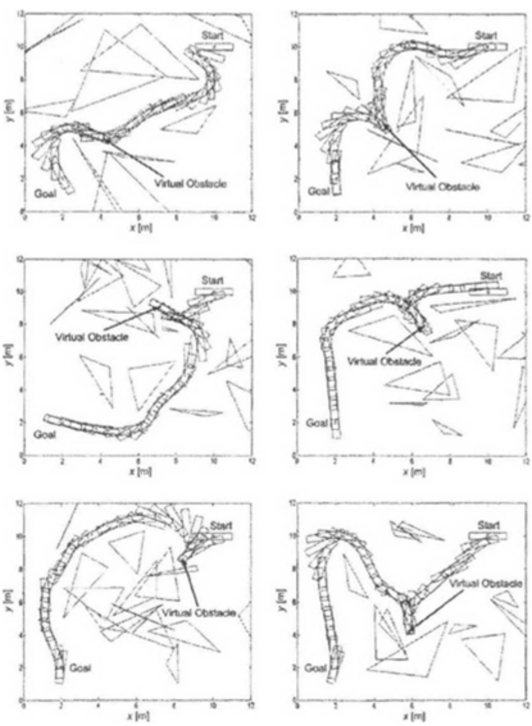


Fig. 15 Path planning in randomly generated environments

of the simulations show that the proposed path planner has good generality.

6. Conclusions

In this study, we proposed the virtual obstacle concept to escape local minima in local path planning based on the APF approach. The virtual obstacle with the extra potential is located at the trapping point when objects are trapped in a local minima. The extra potential is added to the global potential, and it repels the object from the local minimum. The major advantage of the proposed path planner is that it is simple and efficient to solve the local minimum problem. The simulation results show that this technique is useful for path planning in various environments. The discrete modeling method was also proposed to get a simple model of arbitrary-shaped objects. This method is useful for real-time path planning because it can simplify the complex shapes of objects.

Acknowledgment

The authors would like to thank the Ministry of Science and Technology of Korea for its financial support through a grant (M1-0203-00-0017-02J0000-00910) under the NRL (National Research Laboratory) project.

References

Andrews, J. R. and Hogan, N., 1983, "Impedance Control as a Framework for Implementing Obstacle Avoidance in a Manipulator," *Control of Manufacturing Process and Robotic System*, David E. Hardt and Wayne J. Book, Editors, ASME, pp. 243~251.

Cho, W. J. and Kwon, D. S., 1996, "A Sensor-Based Obstacle Avoidance for a Redundant Manipulator Using a Velocity Potential Function," *IEEE Int. workshop on Robot and Human Communication*, pp. 306~310.

Han, K. B., Kim, H. Y. and Baek, Y. S., 2001, "Corridor Navigation of the Mobile Robot Using Image Based control," *KSME International Journal*, Vol. 15, No. 8, pp. 1097~1107.

Im, K. Y., Oh, S. Y. and Han, S. J., 2002, "Evolving a Modular Neural Network-Based Behavioral Fusion Using Extended VFF and Environment Classification for Mobile Robot Navigation" *IEEE Transactions on Evolutionary Computation*, Vol. 6, Issue. 4, pp. 413~419.

Janabi-Sharifi, F. and Vinke, D., 1993, "Integration of the Artificial Potential Field Approach with Simulated Annealing for Robot Path Planning," *Proceedings of the 1993 IEEE International Symposium on Intelligent Control*, pp. 536~541.

Kang, S. K. and Lim, J. H., 1999, "Sonar Based Position Estimation System for an Autonomous Mobile Robot Operating in an Unknown Environment," *KSME International Journal*, Vol. 13, No. 4, pp. 339~349.

Khatib, O., 1986, "Real-Time Obstacle Avoidance for Manipulators and Mobile Robots," *International Journal of Robotics Research*, Vol. 5, No. 1, pp. 90~98.

Kim, J. O. and Khosla, P. K., 1992, "Real-Time Obstacle Avoidance Using Harmonic Potential Functions," *IEEE Trans. on Robotics and Automation*, Vol. 8, No. 3, pp. 338~349.

Lee, S. H. and Park, J., 1991, "Cellular Robotic Collising-Free Path Planning," *Fifth International Conference on Advanced Robotics*, 'Robots in Unstructured Environments,' Vol. 1, pp. 539~544.

McFetridge, L. and Yousef-Ibrahim, M., 1998, "New Technique of Mobile Robot Navigation Using a Hybrid Adaptive Fuqqy-Potential Field Approach," *Computers & Industrial Engineering*, Vol. 35, Issues 3-4, pp. 471~474.

Rimon, E. and Koditschek, D. E., 1992, "Exact Robot Navigation Using Artificial Potential Functions," *IEEE Trans. on Robotics and Automation*, Vol. 8, No. 5, pp. 501~508.

Sacks, E., 2002, "Path Planning with Configuration Spaces and Compliant Motion," Purdue University Technical Report, CSD-TR00-011.

Singh. S., Simmons, R., Smith, T., Stentz, A., Verma, V., Yahja, A. and Schwehr, K., 2000, "Recent Progress in Local and Global Traversability for Planetary Rovers," *In Proceedings International Conference on Robotics and Autonomous*, Vol. 2, pp. 1194~1200.

Volpe, R. and Khosla, P., 1990, "Manipulator Control with Superquadric Artivicial Potential Functions: Theory and Experiments," *IEEE Trans. on System, Man and Cybernetics*, Vol. 20, No. 6, pp. 1423~1436.