An Effective Improved Artificial Potential Field Based Regression Search Method for Autonomous Mobile Robot Path Planning

Guanghui Li, Yusuke Tamura, Atsushi Yamashita and Hajime Asama

Department of Precision Engineering
The University of Tokyo
Hongo 7-3-1, Bunkyo-ku, Tokyo, Japan

guanghui@robot.t.u-tokyo.ac.jp, tamura@robot.t.u-tokyo.ac.jp, yamashita@robot.t.u-tokyo.ac.jp and asama@robot.t.u-tokyo.ac.jp

***Abstract* - Path planning field for autonomous mobile robot is an optimization problem that involves computing a collision-free path between initial location and goal location. In this paper, we present an effective improved artificial potential field based regression search (Improved APF-based RS) method which can obtain a global sub-optimal/optimal path efficiently without local minima and oscillations in the environment contains known, partial known/unknown, static and dynamic environments. We redefine potential functions to eliminate oscillations and local minima problems, and utilize improved wall-following method for robot to escape non-reachable target problem. Due to the planned path by improved APF is not the shortest/approximate shortest trajectory, we develop a regression search method (RS method) to optimize the planned path. The optimization path is calculated by connecting the sequential points which produced by improved APF. Amount of simulations demonstrate that the improved APF method very easily escape from local minima, oscillations and non-reachable target problem. Moreover, the simulation results confirm that our proposed path planning approach could always calculate a more shorter/near-optimal, collision-free and safety path to its destination compare with general APF. That proves our improved APF-based RS method very feasibility and efficiency to solve path planning which is a NP-hard problem for autonomous mobile robot.**

Index Terms* – *Autonomous mobile robot. Path planning. Artificial potential field. Bidirectional artificial potential field. Regression search method.

I. INTRODUCTION

During the last few decades, mechatronics and automation has become an extremely quickly growing field that affecting almost all aspects of our daily life. Especially, robotics have become a major part of this trend, since robotic scientists have investigated on service mobile robots which could be able to operate within human-robot coexistent environments to execute different complex works, such as transportation of heavy objects, surveillance, rescue, and guiding people in exhibitions and museums. Autonomous mobile robot path planning or navigation is one of the most important applications for intelligent robot control systems and has attracted remarkable attention from number of researchers. Path planning is aimed at enabling robots with the capabilities of automatically deciding and executing a sequence of collision-free and safety motions in order to achieve a certain tasks in a given environment. Therefore, the basic function of path planning problem is to computer a valid and feasible solution. Nowadays, path planning problem is transformed into an optimization problem with the development of computer technology and modern control methodology. That is robot searches for an optimal or approximal optimal path with respect to the problem objectives. As described in many interesting researches, two importance features that distinguish these algorithms are whether the environment is known or unknown and whether it is static or dynamic.

Known environments are those in which all information about obstacles and targets are known a priori, the motion of robot is designed based on the given information. Examples of successful algorithms for path planning in this kind of environment include sub-goal network, cell decomposition, A* and D* algorithm, traditional artificial potential field, and many others. Usually, robot under known environment can calculate an optimal/sub-optimal path. However, in unknown environments, robot does not have any previous knowledge about the environment or only partial information is available about the obstacles and targets. Therefore, robot must plan a path based on the available information or the only sense information within the range of those sensors, in other words, it cannot plan a global optimal path in a single attempt. In recent years, lots of researchers have achieved important investigation results in such environments, for instance, fuzzy logic method, neural networks, rapidly-exploring random tree algorithm, ant colony optimization algorithm, and so on.

As mentioned above, autonomous intelligent mobile robot path planning in known environment is considered to be static. In contrast, the following conditions that make environments dynamic, e.g. the target moves continuously during robot approaching, moving obstacles, dynamic obstacles appearing randomly, and all of them. This paper presents a new approach for autonomous mobile robot path planning/navigation in the environment contains known, partial known/unknown, static and dynamic environments. Herein, we propose an effective improved artificial field based regression search methodology (Improved APF-based RS method) for autonomous mobile robot path planning which can program a valid, feasible and shorter solution from the location of robot to the position of target. We firstly modify the potential functions of traditional artificial potential field and improve the wall-following method to resolve the intrinsic fatal problems of previous methods, and then utilize the proposed regression search algorithm to shorten the planned path. At the end of this paper, the validity and efficiency of our proposed methodology is demonstrated by number of simulation experiments.

The remainder of this paper is organized as follows. The next section discusses related works, classic and heuristic approaches for autonomous mobile robot path planning. Mainly focus on discussing and analyzing the problems of traditional and variable artificial potential field methods. In section III, we first introduce the conventional artificial potential field method briefly, and then present our improved artificial potential field (Improved APF) to deal with local minima and oscillations problems by modifying potential functions and applying improved wall-following method in unknown/partial known environments. Finally, we utilize regression search method to shorten the path which planned by our Improved APF method. To demonstrate our proposed method, amount of simulations are done in section IV, we prove the proposed Improved APF method can completely resolve the problems of previous conventional methods. The performance and efficiency of our proposed Improved APF-based RS method and conventional methods are compared under the same conditions of static environment, moving target, dynamic obstacle, and local sensing information for robot. In section VI, the influence of parameter setting under our method is discussed. And we analyze the necessity by implementing bidirectional Improved APF method to deal with autonomous mobile robot path planning problem. Finally, section V draws conclusions and sketches the future work.

II. THE RELATED WORKS

Large part of autonomous mobile robot path planning is pertaining to scheduling and routing, and is well-known to be NP-hard (NP-complete) problem. Path planning algorithms are classified as classic and heuristic approaches (Masehian and Sedighizadeh, 2007). Classic algorithms aim to calculate an optimal solution if one exists, or prove that there is no feasible path. On the other hand, heuristic algorithms attempt to find search for a good quality solution in a short time. Classic algorithms are usually computationally expensive. However heuristic algorithms may fail to find a good solution for difficulty problem. The following we will introduce certain related works about classic and heuristic algorithms.

A. Classic Algorithms

Currently, the developed classic methods are variations of a few general approaches, like roadmap, cell decomposition, artificial potential fields, and mathematical programming. Most autonomous mobile robot path planning problems can be solved using classic algorithms. These approaches are not necessarily mutually exclusive, but combination of them is often used in developing a more reliable path. In roadmap approach (Oh et al., 2004), feasible paths are mapped onto a network of one-dimensional lines, and then search for a desired path in such network. But the searched path is limited to the network, and path planning becomes a graph-searching problem. The well-known roadmaps include visibility graph, voronoi diagram, and sub-goal network. Visibility graph algorithm (Tarjan, 1981) can compute the shortest distance/optimal path, this approach do not consider the size of mobile robot that lead robot too close to the vertexes of obstacle, even collision with obstacles, and the computational time for path planning is too long. Voronoi diagram (Takahashi and Schilling, 1989) and sub-goal network (Avneesh et al., 2008) algorithms are the improved methods of visibility graph. Additionally, a number of researchers have been demonstrated that the cell decompositions (Cai and Ferrai, 2009) are the simplest methods for mobile robot path planning, but are inefficient for computational memory and planning time according to the size of cells.

However, most of classic approaches, such as roadmaps and cell decomposition are based on the free configuration space (C-space) concept. In addition to their lack of adaptively and robustness, thus conventional approaches are not suitable for dynamic environments because of utilizing a sequential search algorithm to generate a single solution which may become infeasible when a change in the environment, a new solution has to be generated from scratch. Expect for, the greater the dimension of free C-space, the more complex the path planning problem will be.

B. Heuristic Algorithms

A* algorithm calculates a shortest path (with minimum cost) in a given map by keep track of an open list and a closed list (Nilsson, 2000). A* algorithm is a kind of classical heuristic search algorithm, while applied A* algorithm for robot path planning in the free C-space, due to the search space is too large, that the search efficiency of A* algorithm is low and planed path is relative optimal to cell decomposition. D* algorithm (Stentz, 1995) almost the same as A* algorithm, but there is no heuristic, searches by expending out equally in every direction, it may search much large area before the goal is reached, thus D* is slower than A*, however, it performs better when the goal is unknown.

Genetic algorithm can obtain the best feasible path for mobile robot path planning in an uncertain environment after number of iterations. While the structure of genetic algorithm are very complex that result in taking a long time to process and affecting the real-time performance of the robot during path planning (Sedighi et al., 2004). When dealing with dynamic environment most genetic algorithm does not control the population diversity due to premature convergence, and it is very easy fall into local optimization. Some researchers suggest that combine genetic algorithm with simulated annealing (Blackowiak and Rajan, 1995) can resolve these problems. In paper (Elshamli et al., 2004), they develop a genetic algorithm for dynamic path planning method which takes into consideration path safety and smoothness.

In addition, some scholars have researched robot navigation algorithms based on ant colony optimization algorithms (Garcia et al., 2009) and improved ant colony optimization (Dorigo and Gambardella, 1997) algorithms. While the convergence speed of both algorithm is far from satisfying the real-time requirement of global dynamic planning. Paper (Zhua et al., 2011) develops a new robot navigation algorithm for dynamic unknown environments by dynamic path re-computation and an improved scout ant algorithm. The simulation results indicate that their algorithm has good effect, high real-time performance, and is very suitable for real-time navigation in complex and dynamic environments.

Many other heuristic path planning methods, such as neural networks, particle swarm optimization, fuzzy logic and Tabu search algorithms are implemented. However, the time complexity of all heuristic algorithms will increase greatly when the environment becomes larger and more complex. For example, the path planning algorithm based on the genetic algorithm may produce many invalid paths and may fail when the number of obstacles increases. Furthermore, deadlock and oscillation happen easily in the rolling window method, and stagnation is a general problem of ant colony optimization algorithm.

C. *Artificial Potential Field (APF)*

The artificial potential field (APF) is firstly introduced by Khatib (Khatib, 1986). The potential function can be defined over free C-space as the sum of attractive potential pulls robot toward the goal configuration, and repulsive potential pushes robot away from obstacles. Artificial potential field is one of the most important classic methods for autonomous mobile robot, and nowadays there are still many researchers are studying it all over the world. Artificial potential field has often represented a good quality to achieve a fast and reactive response to dynamic environment. However, this method has been widely demonstrated that it suffer from unavoidable drawbacks which are very likely for robot to get trapped into a local minimum and oscillations. Paper (Sgorbissa and Zaccaria, 2012) describes a hybrid approach, which integrates a priori knowledge of environment with local perceptions in order to execute the assigned tasks efficiently and safely. The results indicate that this method guarantees the robot can never be trapped in deadlocks even when operating within a partially unknown dynamic environment. In spite of its good properties, the navigation system described in this paper has typical drawback that is the system is relying on local perceptions and navigation strategies. Another improved artificial potential field is proposed in (Zhang et al., 2011) utilizing quantum particle swarm optimization for rapid global searching and realizing the optimal path planning. They employ quantum particle swarm optimization to modify the parameters of artificial potential field to adapt different environment and dynamical obstacles. To address the local minima problem in the traditional artificial potential field, a method composed of robot regression and potential field filling is proposed (Qi et al., 2008; Shi et al., 2010). The similar methods propose in (Zhang et al., 2006; Yu et al., 2011), before calculating the resultant force that is put on an object in the potential field, they build links among closed obstacles to optimize the planed solution. Other kinds of improved artificial potential fields are investigated, such as in (He et al., 2011), they introduce the relative distance between robot and target into repulsive force function and modify the repulsion direction to ensure the global minimum is at the position of target. Donnart and Meyer (1996) research the learning reactive and planning rules into mobile robot path planning. The main distribution of (Sheng et al., 2010; Yang et al., 2011) is that apply virtual local target to guide robot escapes local minimum.

While the all mentioned above artificial potential field and its improved methods still suffer from many drawbacks, such as high time complexity in high dimensions that result in these methods could not deal with real-time path planning, and some methods do not completely solve local minima, oscillations and non-reachable target problem which makes them inefficient in practice. Moreover, the path under previously methods is not optimal/near-optimal, but only feasible for autonomous mobile robot to adapt the given environment. In other words, robot move along the planed path will consume more energy and costs. As described in (Elshamli et al., 2004), the common path planning problem criteria may include the distance of planned path, computational time, and robot travelled energy. That means all these methods are not handle the common criterions very well. In this paper, we present an effective Improved APF-based RS method which can obtain a shorter planned path without local minima, oscillatory movements and non-reachable target problem. That is we utilize the simplest path planning algorithm to very rapidly plan an effective and shorter distance path for autonomous mobile robot.

III. THE PROPOSED PATH PLANNING METHOD

A. *Traditional Artificial Potential Field*

The basic idea of artificial potential field method assumes that robot as a point moves in an abstract artificial force field. The artificial potential field in environment is composed of attractive potential of target and repulsive potential of obstacles. Attractive potential is produce by target and direct to target point, while repulsive potential is the synthesis repulsive potential of different obstacles and the direction of the synthesis repulsive potential is away from obstacles. Therefore, the potential function (1) is the artificial potential field of robot which is defined as the resultant of attractive potential and repulsive potential. Robot controls its movement toward the target point along the direction of artificial potential field. Under the method of artificial potential field, robot could find a collision-free path by searching the route along the decline direction of potential function.

The coordinate of robot is $q=(x, y)^T$, thus the artificial potential field is defined as:

$$U(q) = U_{att}(q) + U_{rep}(q) \tag{1}$$

Where: $U(q)$ is artificial potential field. $U_{att}(q)$ is attractive potential. $U_{rep}(q)$ is repulsive potential.

The negative gradient of artificial potential field is defined as artificial force which is the steepest descent direction for guiding robot to target point. Attractive force is the negative gradient of attractive potential, and repulsive force is the negative gradient of repulsive potential.

Thus, the artificial force of robot is:

$$F(q) = -\nabla U(q) = -\nabla U_{att}(q) - \nabla U_{rep}(q) = F_{att}(q) + F_{rep}(q) \quad (2)$$

Where: $F(q)$ is artificial force. $F_{att}(q)$ is attractive force. $F_{rep}(q)$ is repulsive force.

The attractive potential between robot and target is constructed to pull robot to the goal area. The attractive potential created by the goal is given by

$$U_{att}(q) = \frac{1}{2}k(q-q_g)^2 = \frac{1}{2}k\rho_{goal}^2(q) \quad (3)$$

Where: k is a positive coefficient for artificial potential field. $q_g=(x_g, y_g)^T$ is the location vector of target. $\rho_{goal}(q)=\|q-q_g\|$ is the Euclidean distance from the location of robot to the position of target.

The attractive force on robot is calculated as the negative gradient of attractive potential and takes the following form:

$$F_{att}(q) = -\nabla U_{att}(q) = -\frac{1}{2}k\nabla\rho_{goal}^2(q) = -k(q-q_g) \quad (4)$$

$F_{att}(q)$ is a vector directed toward q_g with magnitude linearly related to the distance from q to q_g. The components of $F_{att}(q)$ are the minus directional derivatives of the attractive potential along the x and y directions. Therefore, when the attractive potential takes effect, the components can be written as:

$$\begin{aligned} F_{att-x}(q) &= -k(x-x_g) \\ F_{att-y}(q) &= -k(y-y_g) \end{aligned} \quad (5)$$

Where: F_{att-x} is the attractive force on the x direction. F_{att-y} is the attractive force on the y direction.

Robot should be repelled from obstacles, but when robot is far from obstacles, we do not want obstacles to affect robot's motion. Khatib uses Eq. (6) as the repulsive potential field.

$$U_{rep}(q) = \begin{cases} 0 & ,\rho(q) \ge \rho_0 \\ \frac{1}{2}\eta\left(\frac{1}{\rho(q)} - \frac{1}{\rho_0}\right)^2 & ,\rho(q) \le \rho_0 \end{cases} \quad (6)$$

Where: η is a positive scaling factor. Let $q_c=(x_c, y_c)$ be unique configuration in obstacle closest to q. $\rho(q)=\|q-q_c\|$ is the shortest distance between robot and obstacle. ρ_0 is the largest impact distance of single obstacle. There is no impact for robot when the distance between robot and obstacle is greater than ρ_0. Similarly, the repulsive force is the negative gradient of repulsive potential function, as follows:

$$F_{rep}(q) = -\nabla U_{rep}(q) = \begin{cases} 0 & ,\rho(q) \ge \rho_0 \\ \eta\left(\frac{1}{\rho(q)} - \frac{1}{\rho_0}\right)\left(\frac{1}{\rho^2(q)}\right)\nabla\rho(q) & ,\rho(q) \le \rho_0 \end{cases} \quad (7)$$

$$F_{rep}(q) = \begin{cases} 0 & ,\rho(q) \ge \rho_0 \\ \eta\left(\frac{1}{\rho(q)} - \frac{1}{\rho_0}\right)\left(\frac{1}{\rho^2(q)}\right)\frac{q-q_c}{\|q-q_c\|} & ,\rho(q) \le \rho_0 \end{cases} \quad (8)$$

F_{rep-x} and F_{rep-y} are the Cartesian components of the repulsive force F_{rep}. When the repulsive potential acting on robot takes effect, the components can be written as:

$$F_{rep-x}(q) = \begin{cases} 0 & ,\rho(q) \ge \rho_0 \\ \eta\left(\frac{1}{\rho(q)} - \frac{1}{\rho_0}\right)\left(\frac{1}{\rho^2(q)}\right)\frac{x-x_c}{\|q-q_c\|} & ,\rho(q) \le \rho_0 \end{cases} \quad (9)$$

$$F_{rep-y}(q) = \begin{cases} 0 & ,\rho(q) \ge \rho_0 \\ \eta\left(\frac{1}{\rho(q)} - \frac{1}{\rho_0}\right)\left(\frac{1}{\rho^2(q)}\right)\frac{y-y_c}{\|q-q_c\|} & ,\rho(q) \le \rho_0 \end{cases} \quad (10)$$

While there are many obstacles in the environment, the total repulsive potential field is the sum of all obstacles' repulsive potential field. The total artificial potential field can be expressed as function (11).

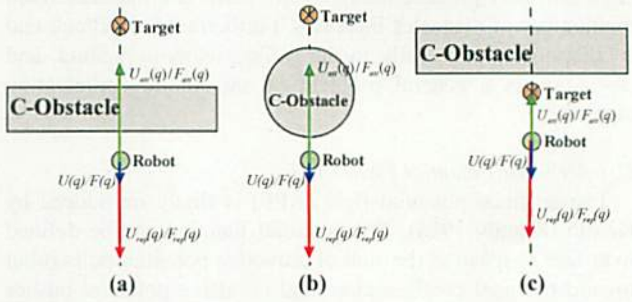
$$U(q) = U_{att}(q) + \sum_{i=1}^{n} U_{rep}(q) \quad (11)$$

Where: $i=1, 2, \ldots, n$ (n is the number of obstacles).

The total artificial force field is:

$$F(q) = F_{att}(q) + \sum_{i=1}^{n} F_{rep}(q) \quad (12)$$

Figure 1 Problems of traditional artificial potential field, (a) and (b) are local minima and oscillations, (c) is non-reachable target problem



Notes: (a) When the position of robot and target are collinear or almost collinear, and there is an obstacle between them, it is very easy to become collinear reverse or almost collinear reverse of attractive potential/force and repulsive potential/force. In such case, local minima and oscillations occur. (b) When the attractive potential/force and repulsive potential/force is equivalent or almost equivalent and collinear reverse or almost collinear reverse, the artificial potential/force field of robot is almost zero, then it will cause robot to be trapped in local minima and oscillations. (c) When the position of target is very close to obstacles, the repulsive potential/force will be much greater than the attractive potential/force, that means under this condition, robot will never arrive at the location of target, e.g. non-reachable target problem.

Although the traditional artificial potential field method can plan smooth path effectively, it has fatal problems. The traditional artificial potential field method used in the path planning may suffer from the local minimum and oscillations problem instead of the desired global minimum. We definite the local minima and oscillations problem as:

$$|U(q)| = \left|U_{att}(q) + \sum_{i=1}^{n} U_{rep}(q)\right| \le \varepsilon \quad (13)$$

or

$$|F(q)| = \left|F_{att}(q) + \sum_{i=1}^{n} F_{rep}(q)\right| \le \varepsilon \quad (14)$$

Eq. (13) means that for any small ε greater than zero, the resultant of attractive potential and repulsive potential at point q is smaller than ε. Similarly, Eq. (14) means that for any small ε greater than zero, the resultant of attractive force and repulsive force at point q is smaller than ε. If the artificial potential field or artificial force field satisfies the Eq. (13) or Eq. (14), robot is considered to be trapped in a local minima and oscillations. That is, when the attractive potential/force and repulsive potential/force is equivalent or almost equivalent and collinear reverse or almost collinear reverse, the artificial potential/force field of robot is almost zero, then it will cause robot to be trapped in local minima and oscillations (Figure 1 (a) and (b)). And when the position of target is very close to obstacles, robot could not reach the target (Figure 1 (c)).

B. *Improved Artificial Potential Field (Improved APF)*

B.1. Redefine attractive potential function

As Eq. (3)/Eq. (4) presented, the attractive potential/force is in proportion to distance $\rho_{goal}(q)$ (Shown in figure 2(a)). The value of attractive potential/force is decided by their distance between robot and target, which proposed by the traditional attractive potential function. While when $\rho_{goal}(q)$ is very great, the attractive potential/force will become very great too. In other words, when robot is very far away target, it is easily leading robot move too close toward the obstacles (Amato, 2004). Therefore, in the real environment shown in Figure 3, robot has the risk of collision to obstacles when we take account the error of path planning. Thus, the attractive potential and attractive force are modified as function (15) and (16) (Li et al., 2012).

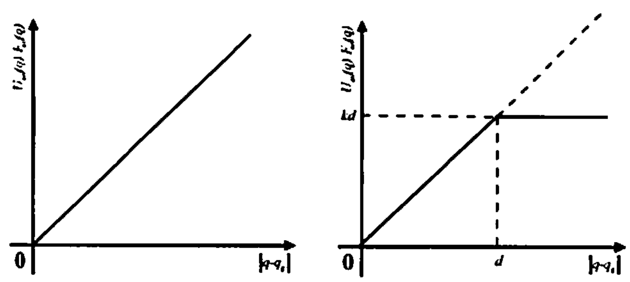
$$U_{att}(q) = \begin{cases} \frac{1}{2}k\rho_{goal}^{2}(q) & ,\rho_{goal}(q) \le d \\ kd\rho_{goal}(q) & ,\rho_{goal}(q) \ge d \end{cases} \quad (15)$$

and

$$F_{att}(q) = \begin{cases} -k(q-q_g) & ,\|q-q_g\| \le d \\ -kd\frac{(q-q_g)}{\|q-q_g\|} & ,\|q-q_g\| \ge d \end{cases} \quad (16)$$

Where, d is positive coefficient for attractive potential and force.

Figure 2 Attractive potential function, (a) Traditional attractive potential function, (b) Improved attractive potential function

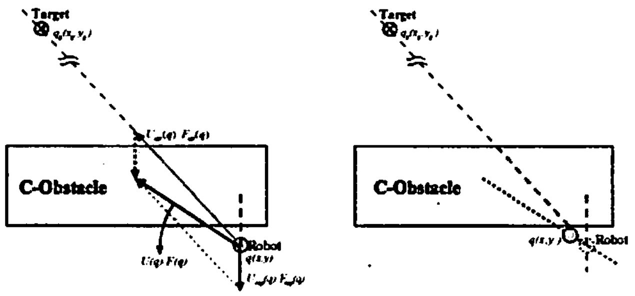


(a) Traditional attractive potential function **(b) Improved attractive potential function**

Notes: (a) Traditional artificial potential field define the relationship between attractive potential/force and distance from robot to target is proportion. That means the value of attractive potential/force increases linearly according to the distance increasing. (b) In improved artificial potential field, we consider the risk of collision and real robot path planning error, and modify the attractive potential/force function: set a threshold d, if the distance is less than d, the value of attractive potential/force increases linearly according to the distance increasing like traditional artificial potential field defined. Otherwise, the attractive potential/force is a constant.

When the distance $\rho_{goal}(q)$ is less than d, the redefined attractive potential and force are the same as conventional defined. Otherwise, the attractive potential and force are a constant which illustrate in figure 2(b). We redefined the attractive potential function as Eq. (15) and (16) to guarantee robot avoids collision toward obstacles, since when robot moves near any obstacles, the repulsive potential/force from obstacles is greater enough than kd to push robot away from obstacles.

Figure 3 Attractive potential field, (a) At $T=t$, (b) At $T=t'$



(a) T=t **(b) T=t'**

Notes: When target is too far away from robot, result in the attractive force is too much greater than repulsive force even though robot is very close to obstacle. Then at the next step, robot moves along the direction of resultant force to obstacle closer. In real path planning, robot has the risk of collision toward obstacles, especially take account error.

B.2. Redefine repulsive potential function

As many papers described, when target is very close to obstacle, result in the repulsive potential/force is too much greater than attractive potential/force:

$$|U_{att}(q)| << \left|\sum_{i=1}^{n} U_{rep}(q)\right| \quad (17)$$

or

$$|F_{att}(q)| << \left|\sum_{i=1}^{n} F_{rep}(q)\right| \quad (18)$$

such that robot impossible arrive at the position of target in such circumstance, this condition named non-reachable target problem (shown in figure 1(c)) which is undesirable for robot path planning problem. In this paper, we redefine potential function and utilize function (19) and (20) to resolve robot non-reachable target problem, we named this redefined potential function as repulsive potential/force instantaneous disappearance if (a) and (b) as follows is simultaneously satisfied:

(a) $\rho(q) \le d_{Ob}$

(b) $\rho_{goal} \le d_{gr}$

Where d_{Ob} and d_{gr} are positive coefficients, respectively.

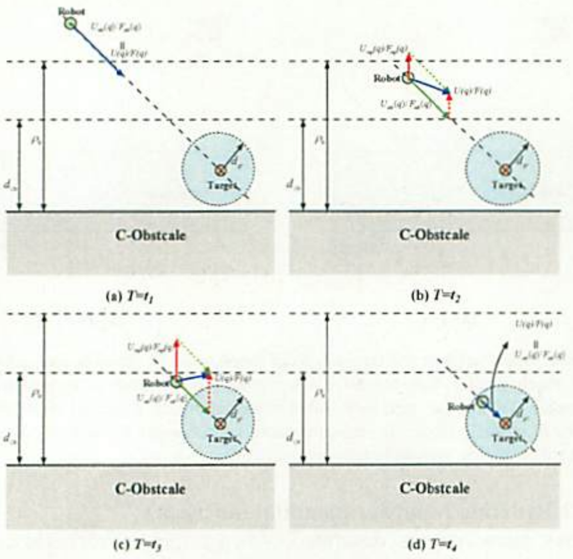
That is, once robot detects the distance between target and obstacle is less than d_{Ob}, and simultaneously the distance between target and robot is less than d_{gr}, robot only move along the attractive potential/force instead of considering the resultant of attractive potential/force and repulsive potential/force until robot arrives at the location of target (As shown in figure 4). Since when (a) and (b) are satisfied, there is no repulsive potential/force, robot is only attracted by target.

$$U(q)=\begin{cases} U_{att}(q) & ,\rho(q)\le d_{Ob} \ \ and \ \ \rho_{goal}\le d_{gr} \\ U_{att}(q)+U_{rep}(q) & ,Otherwise \end{cases} \quad (19)$$

and

$$U(q)=\begin{cases} F_{att}(q) & ,\rho(q)\le d_{Ob} \ \ and \ \ \rho_{goal}\le d_{gr} \\ F_{att}(q)+F_{rep}(q) & ,Otherwise \end{cases} \quad (20)$$

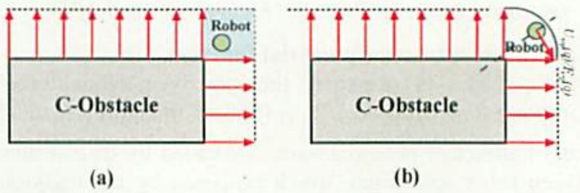
Figure 4 Illustration of redefined artificial potential field, (a) At $T=t_1$, (b) At $T=t_2$, (c) At $T=t_3$, (d) At $T=t_4$



Notes: (a) $\rho(q)$ is greater than ρ_0, the artificial potential field of robot is only attractive potential, while repulsive potential is zero. Robot moves along the direction of attractive force. (b) $\rho(q)$ is less than ρ_0, the artificial potential field of robot is the resultant of attractive potential and repulsive potential. Robot moves along the direction of resultant force. (c) $\rho(q)$ is less than ρ_0 and d_{Ob}, but $\rho(q)$ is greater than d_{gb}, this does not satisfy requirement of non-reachable target problem. Thus, the artificial potential field of robot is the resultant of attractive potential and repulsive potential. Robot moves along the direction of resultant force. (d) $\rho(q)$ is less than ρ_0 and d_{Ob}, simultaneously $\rho(q)$ is less than d_{gb}, the requirements of non-reachable target problem are satisfied, as a result, non-reachable target problem emerges. Thus, in this condition, the repulsive potential instantaneous disappear, the artificial potential field of robot is only the attractive potential. Robot moves along the direction of resultant force to arrive at the location of target. This modified artificial potential field is very effective to deal with such non-reachable target problem.

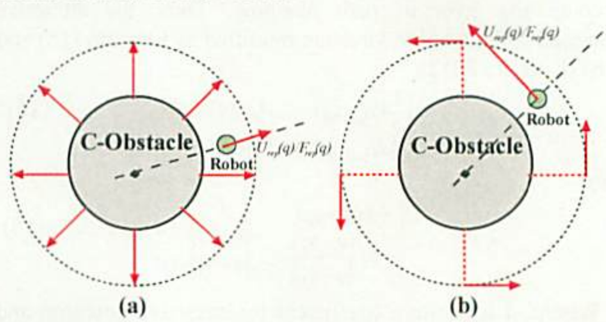
All previous proposed artificial potential field and improved artificial potential field methods do not explicitly define the repulsive potential/force about vertex of polygonal obstacles. As described by general artificial potential field, the direction of repulsive potential/force for polygonal obstacles is the perpendicular of polygon side and away from the obstacles as Figure 5 (a) shown, thus it will be unreasonable due to there is no repulsive potential/force near the area of vertex of polygonal obstacles (Zhang et al., 2006). Therefore, we define the repulsive potential/force about vertex of polygonal obstacles like Figure 5 (b) and the direction is the tangential line of semicircle (Uyanik, 2010). Similarly, we change the direction of repulsive potential/force which is caused by circular obstacles (Figure 6) to solve the problems of general artificial potential field: local minima and oscillatory movements.

Figure 5 Repulsive potential of polygonal obstacle, (a) Repulsive potential defined by traditional artificial potential field, (b) Repulsive potential defined by our Improved APF



Notes: (a) Traditional artificial potential field define the repulsive potential of polygonal obstacle is vertical polygonal side and away from obstacle. Near the vertex, there is no repulsive potential, this is unreasonable. (b) Improved APF, We redefine the repulsive potential, and its direction is the tangent of semicircle.

Figure 6 Repulsive potential of circular obstacle, (a) Traditional artificial potential field, (b) Our Improved APF

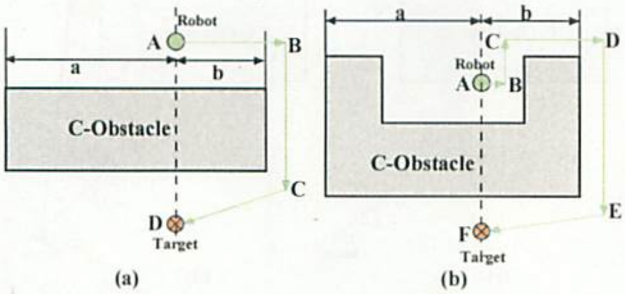


Notes: (a) Traditional artificial potential field define the direction of repulsive of circular obstacle is vertical and away from obstacle. Such defined repulsive potential is easy to cause local minima and oscillations. (b) Improved APF, we change the direction of repulsive potential for circular obstacle, is the tangential of the circle.

B.3. Improved wall-following

The artificial potential field method used in the robot path planning may suffer from the local minima and oscillations problem when the Eq. (13) or (14) is satisfied as the above mentioned. During path planning, once the local minima and oscillatory movements occurs like Figure 1 (a) and (b) shown, we employ wall-following method which was presented in (Sheng et al., 2010) to guide robot escapes from local minima, and this method can resolve oscillations. However, the previously proposed wall-following method need detail information of each obstacle that is this method only can solve local minima and oscillations in known environment. The illustration of wall-following method in figure 7(a), since robot has the information about obstacles, robot compares the distance from the location of robot to the two sides of obstacle, if b<a, then robot moves along A-B-C-D toward the position of target to eliminate local minima and oscillatory movements. Similarly, as presented in figure 7(b), robot moves along A-B-C-D-E-F toward the position of target to escape local minima and oscillatory movements. The wall-following method can successfully resolve the two key problems: local minima and oscillations which caused by general artificial potential field method in known environment, nevertheless, for the partial or unknown environment, robot has not the complete information about obstacles, result in robot cannot know which side is closer. In other words, the wall-following method is not suitable for the partial/unknown environment, thus we should modify the previous wall-following meth to adapt partial/unknown environments.

Figure 7 The wall-following in known environment, (a) polygonal obstacle, (b) U-shape obstacle



Notes: In complete environments, robot knows information about obstacles, when local minima occurs, robot compares the distance from the location of itself and two sides of obstacle, then selects the shorter distance side to wall-following.

Herein, we improve the wall-following method to deal with local minima and oscillations problem of Improved APF when robot moves in a partial/unknown environment. We utilize the latest five steps to determine the moving tendency of robot, and combine the wall-following method to assistant robot to move out of local minima and oscillatory movements. The orders of our proposed improved wall-following method are as follows.

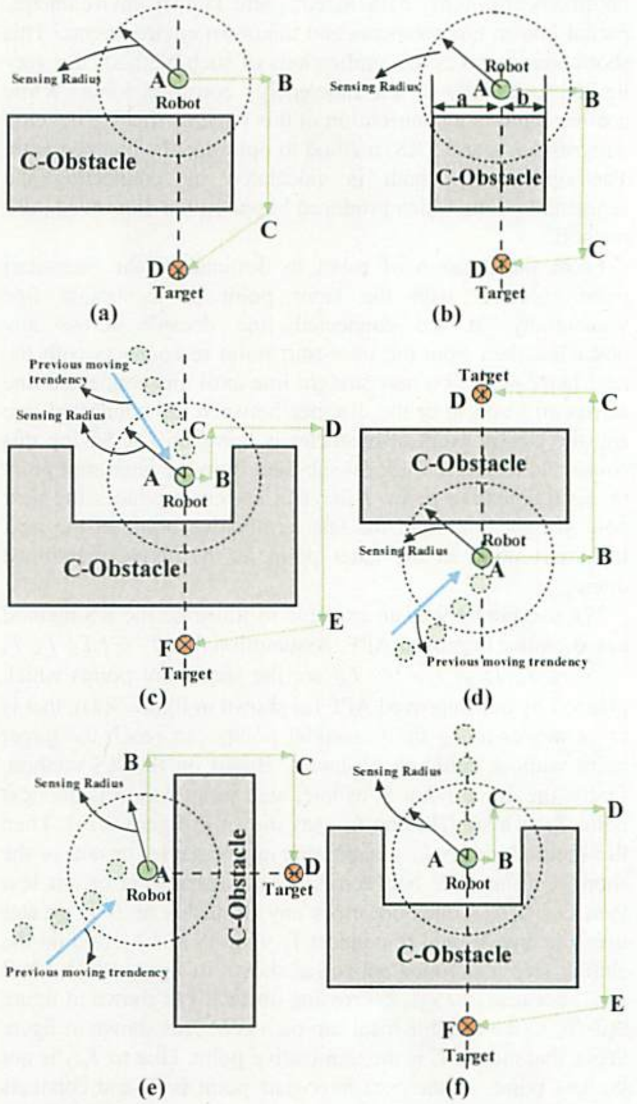
(a) One side of obstacle is in the sensing range of robot. Robot moves toward the visual side and follows the wall of obstacle until escape out of the local minima, as shown in figure 8(a).

(b) Both two sides of obstacle are in the sensing range of robot. Robot compares distance to the two sides, and moves toward closer side and follows the wall of obstacle until escape out of the local minima, as shown in figure 8(b).

(c) Non-side of obstacle is in the sensing range of robot. Robot continues to move toward the previous moving tendency and follows the wall of obstacle until escape out of the local minima, as shown in figure 8(c), (d) and (e).

(d) Non-side of obstacle is in the sensing range of robot, and the previous moving tendency is the perpendicular of obstacle side, then robot randomly selects one side to move along and follows the wall of obstacle until escape out of the local minima, as shown in figure 8(f).

Figure 8 The improved wall-following method, (a) One side in robot's sensing range, (b) Both sides in robot' sensing range, (c) No side in robot's sensing range: example 1, (d) No side in robot's sensing range: example 2, (e) No side in robot's sensing range: example 3, (d) No side in robot's sensing range: example 4



Notes: (a) One side is in the robot's sensing range, robot does not know the distance from its location to another side, then robot selects the visual side to wall-following, e.g. A-B-C-D. (b) Both two sides are in robot's sensing, robot selects the closer side to wall-following, e.g. A-B-C-D. When there is not side in the sensing range of robot, robot continues to move toward the previous moving tendency and follows the wall of obstacle, for examples, (c) The previous of latest five steps moving tendency is lower right, robot follows the A-B-C-D-E-F to move out of local minima. (d) The previous of latest five steps moving tendency is upper right, robot follows the A-B-C-D to move out of local minima. (e) The previous of latest five steps moving tendency is upper right, robot follows the A-B-C-D-E-F to move out of local minima. (f)

The latest five previous moving tendency is vertical the side of obstacle, then robot randomly selects one side to wall-following.

C. Regression Search Based Method (RS Method)

Although our Improved APF method which could resolve the local minima, oscillations and non-reachable problem successfully, but the key problem is that apply all artificial potential field methods including our method could not plan an optimal/near-optimal path in complete known environments, partial known environments and unknown environments. This shortcoming makes the applications of such methods are very limited, especially for the time/energy constrain robot. While another important contribution of this paper is that we develop a regression search (RS) method to optimize the planned path. The optimization path is calculated by connecting the sequential points which produced based on our Improved APF method.

From the location of robot to destination, the inter-start point connects with the latter point as a straight line sequentially. If the connected line doesn't across any obstacles, then from the inter-start point re-connects with the next latter point as a new straight line until this connected line across an obstacle or the distance between the connected line and the closest point of obstacles is less than D_0. Saving this connected line as robot local sub-path from the inter-start point to the terminative point. After that system produces the next new straight line from the last terminative point as the next inter-start point to the latter point as the above mentioned does.

We use Figure 9 as an example to illustrate the RS method based on our Improved APF. Assumption that $T_i \in \{T_1, T_2, T_3 \cdot\cdot\cdot, T_i, T_{i-1}, \cdot\cdot\cdot, T_n\}$ are the sequential points which planned by our Improved APF (as shown in figure 9(a)), that is robot moves along the sequential points can reach the target point without colliding obstacles. Based on the RS method, firstly, the initial point T_1 as inter-start point connects the next point T_2 as a straight line $L_{1,2}$ (as shown in figure 9(b)). Then this method judges $L_{1,2}$ is crossing any obstacles or not, or the shortest distance D between $L_{1,2}$ and obstacle is or not less than D_0. If $L_{1,2}$ does not cross any obstacles or D is greater than D_0, then system re-connect T_1 with T_3 as $L_{1,3}$, and do the similar step mentioned above (as shown in figure 9(c)). Until $L_{1,i+1}$ because of $L_{1,i+1}$ is crossing obstacle (as shown in figure 9(d-f)), so the feasible local sub-path is $L_{1,i}$ (as shown in figure 9(g)), that means T_i is the terminative point. Due to T_{i+1} is not the last point, so the next inter-start point is T_i and connects with the next point T_{i+1} similarly (as shown in figure 9(h)). Therefore, the optimal path of this example is the line $L_{1,i}$ and $L_{i,n}$ (as shown in figure 9(j-m)). In other words, robot move along $L_{1,i}$ and $L_{i,n}$ will consume the least energy, the distance of $L_{1,i}$ and $L_{i,n}$ is the shortest (as shown in figure 9(n)).

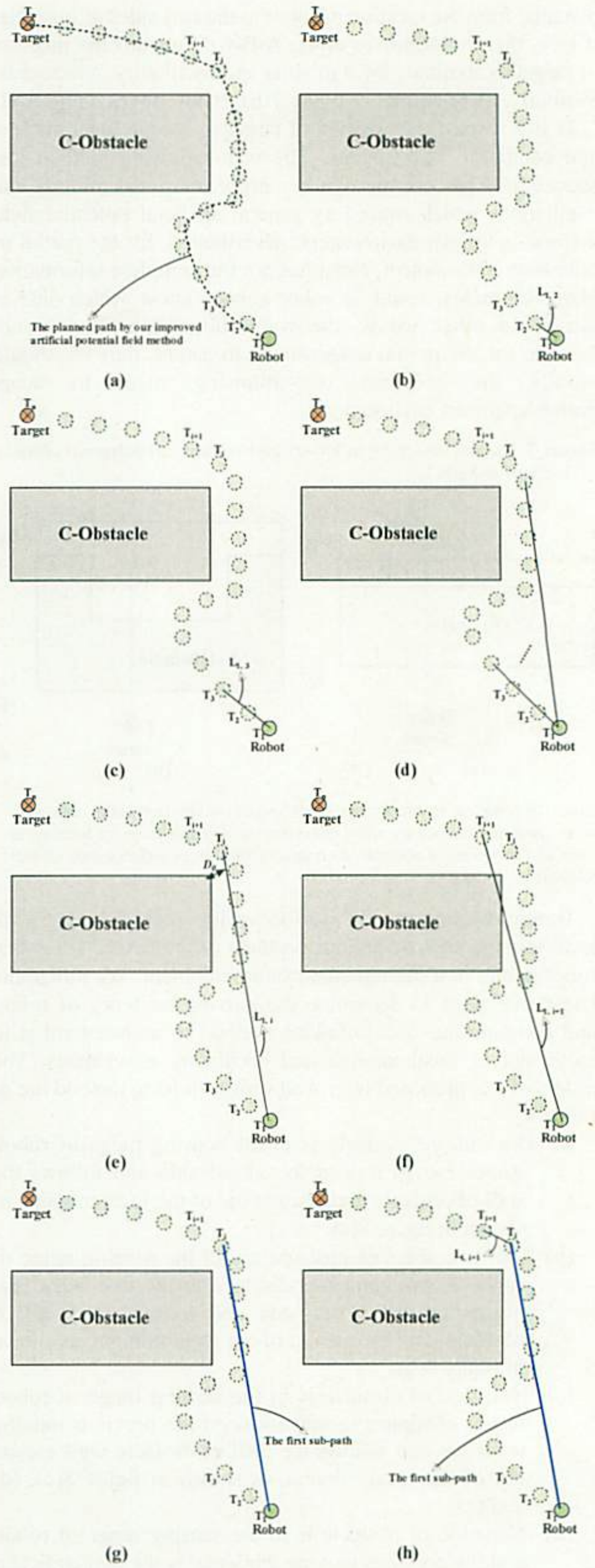
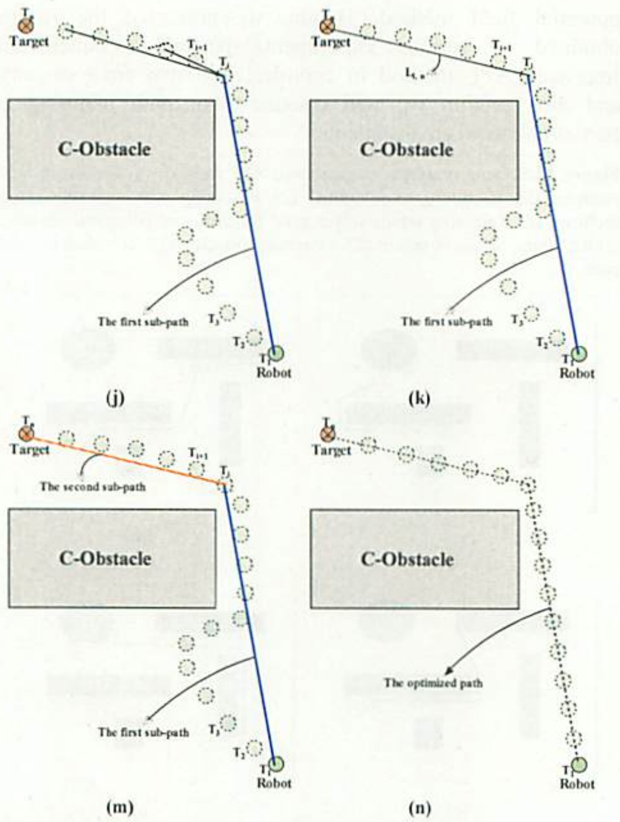


Figure 9 Regression search method (RS method), (a) Planned path by Improved APF, (b) Step *1* of RS method, (c) Step *2* of RS method, (d) Step *i-1* of RS method, (e) Step *i* of RS method, (f) Step *i+1* of RS method, (g) Step *i+2* of RS method, (h) Step *i+3* of RS method, (j) Step *n-1* of RS method, (k) Step *n* of RS method, (m) Step *n+1* of RS method, (n) Obtain optimal path



Notes: (a) From location of robot to the position of target, using Improved APF to produce a sequential point set. According to the sequential point set, we use RS method to optimize the planned path by connecting two point as a straight line and judging the connected line is crossing any obstacle or not, the shortest distance between this connected line and obstacle is less than we set threshold or not. (b) The location of robot T_1 as the first inter-start point connects with the next point T_2, due to $L_{1,2}$ is a feasible line, and then continues to (c). (c) Connect T_1 and T_3, and judge whether $L_{1,3}$ is a feasible line. If it is, then continue to (d-e). (f) Because of $L_{1,i+1}$ is crossing an obstacle, that means $L_{1,i+1}$ is not a feasible line. Therefore, the first sub optimal path is $L_{1,i}$ as (g) shown. (h) Then point Ti as the next inter-start point and connects with its next point T_{i+1}, and does the similarly judgment as mentioned above. Through (j) and (k), we can obtain the second sub optimal path is $L_{i,n}$ in (m). (n) Finally, the optimal path is planned by our Improved APF-based RS method. The distance of optimized path is much shorter than only using Improved APF.

The entire algorithm of our proposed effective Improved APF-based RS method is as follows, the illustration of our proposed method shown in figure 10.

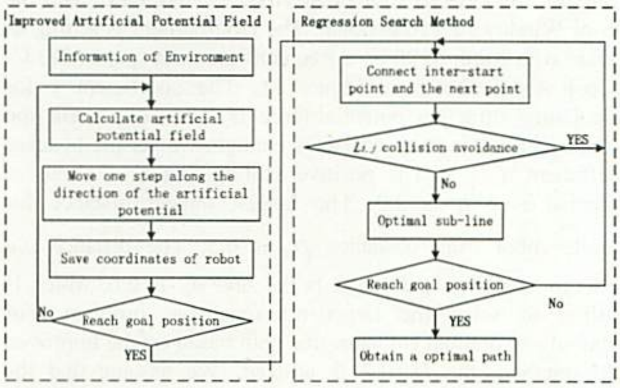
*** Improved APF Method ***

1. *Compute the artificial force $F(q)$ at current configuration under our proposed improved artificial potential field.*
2. *Take a small step in the direction indicated by artificial force.*
3. *Save the coordinate as T_i.*
4. *Repeat until reach goal configuration.*
5. *The sequential points $T_i \in \{T_1, T_2, \cdots, T_n\}$ are the planned path by improved artificial potential field method.*

*** Regression Research (RS) Method ***

6. *The location of robot T_1 as the start point connects with the next points.*
7. *From $T_j \in \{T_2, T_3, \cdots, T_n\}$:*
8. *If the connected line $L_{1,j}$ does not cross any obstacle, then $j=j+1$. Otherwise, turn to step 12.*
9. *If the distance from the connected line $L_{1,j}$ toward any obstacle is greater than D_0, then $j=j+1$. Otherwise, turn to step 12.*
10. *If j is not the last point of T_i. Otherwise, turn to step 19.*
11. *Return to step 7.*
12. *T_j as the next start point, e.g. inter-start point, and connects with the next point.*
13. *From $T_k \in \{T_{j+1}, T_{j+2}, \cdots, \cdots, T_n\}$:*
14. *If the connected line $L_{j,k}$ does not cross any obstacle, then $k=k+1$. Otherwise, turn to step 18.*
15. *If the distance from the connected line $L_{j,k}$ toward any obstacle is greater than D_0, then $k=k+1$. Otherwise, turn to step 18.*
16. *If k is not the last point of T_i. Otherwise, turn to step 19.*
17. *Return to step 13.*
18. *$j=k$, and return to step 12.*
19. *Until the final point.*
20. *Obtain the optimal path.*
21. *Robot moves along the optimal path.*

Figure 10 Illustration of our proposed method



Notes: In the Improved APF-based RS method, firstly, using Improved APF to calculate a valid path, and then utilize RS method to shorten the distance of planned path.

IV. Experiments and Results

This section describes the results obtained in various experiments performed under our proposed Improved APF-based RS method to resolve the key problems of artificial potential field method: local minima, oscillatory movements and non-reachable target, and shorten the planned path. These experiments confirmed the truth that the Improved APF method solved all important problems by using very simple orders, such as: redefined attractive and repulsive potential function, redefined the artificial potential field of nearby vertexes of polygonal obstacles, change the direction of repulsive potential field for circular obstacles and improved the previous wall-following method to extend this method to be applicable for partial /unknown environments, in spite of the wall-following method is very good at deal with local minima and oscillations in the known environments.

Although our Improved APF method can calculates a valid path for robot, as many conventional artificial potential field methods, the planned path is not optimal/sub-optimal compared with almost other classic methods and most heuristic approaches. This is the vital restrain that such method applies to robot systems, especially for the real robot system when we consider the common path planning problem criteria: distance of planned path, computational time and robot travelled energy. Thus, we proposed a regression search method to reduce the distance of planned path by our Improved APF method. The experiments results also proof that the final obtained path under our proposed method is optimal or approximative optimal path. That is we utilize the simplest method to solve the one of the most difficult domains for intelligent robot systems. We believe this method is very useful for autonomous distributed multiple robots systems, due to the computational time and complexity are the most two important problems for such systems.

A. Simulation Environment Settling

Numbers of simulation experiments are carried out for proving the validity and feasibility of our proposed algorithm using VC++, intel(R) CORE(TM) i5-2.52GHz CPU with the OS of Windows 7 Professional. The environment is setting as square with width of 20 m, a free configuration space (free C-space) which shown in Figure 11. The coefficient k for calculating attractive potential/force is 0.3. To prevent the planed path is far away obstacles enough, we set the positive coefficient d is 3. The positive scaling factor of repulsive potential/force η is 2.0. The largest impact distance for mobile robot from obstacles ρ_0 is 0.5. The distance d_{Ob} between obstacles and target is 0.4 and d_{gr} is 0.6, which is settling to solve the target non-reachable problem. For obtaining an optimal collision-free path based on the Improved APF method, the D_0=0.2 is utilized. We assume that the moving step of robot is 0.1. Table I presented the detail parameters. And robot is omni-directional.

Figure 11 Simulation environment

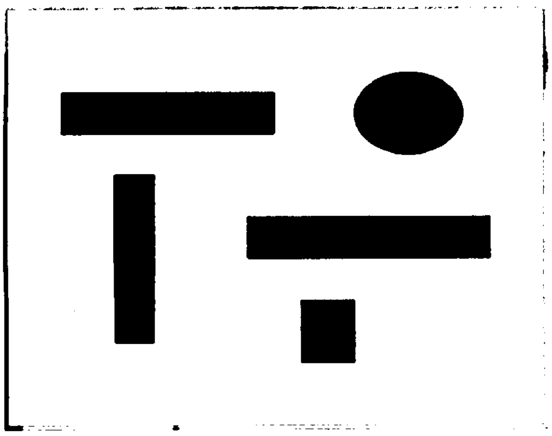


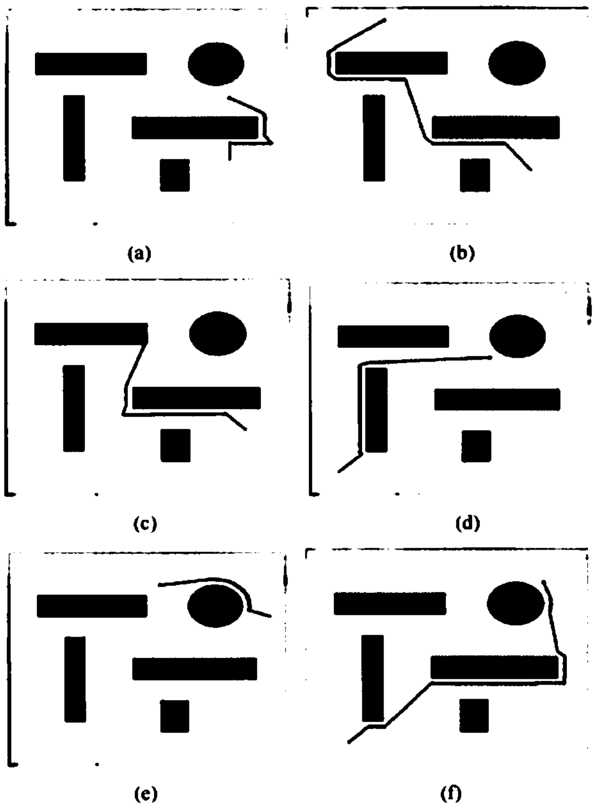
Table I Parameters of our algorithm

Free Configuration space (C-Space)	k	d	η	ρ_0	d_{Ob}	d_{gr}	D_0	ΔS
20×20m	0.3	3.0	2.0	0.5	0.4	0.6	0.2	0.1

B. Improved APF Method

Local minima, oscillations and non-reachable target problem are the three fatal problems for conventional artificial potential field method. Herein, we presented the results obtained in various experiments performed under our Improved APF method in completely known environments, and next section we will discuss robot path planning in partial/unknown environments.

Figure 12 Solving problems by Improved APF method, (a) Resolving local minima, (b) Resolving oscillations, (c) Resolving non-reachable target problem, (d) Resolving repulsive potential for vertex of polygonal obstacle, (e) Resolving repulsive potential for circular obstacle, (f) A complete planned path



Notes: (a) We utilize improved wall-following method to deal with local minima, the distance from robot to right side is shorter than left side, and thus, robot follows the right side wall of obstacle. (b) When both sides of obstacle is out of robot's sensing range, robot determines the previous moving tendency according to the latest five steps. Therefore, robot follows the left side wall to escape oscillations. (c) Because of target is very close with obstacle, once the requirements are satisfied, robot moves along only attractive potential. (d) We redefined the repulsive potential for vertex of polygonal obstacle. (e) We changed the direction of repulsive potential for circular obstacle. (f) Robot can plan a path without any problems by our Improved APF method.

As Figure 12 shown, when the attractive potential and the repulsive potential is collinear reverse (Figure 12(a)), robot will fall into local minima using conventional methods. This is a kind of undesirable solution for autonomous mobile robot. However, the proposed Improved APF method is very good at handling such local minimum problem by using improved wall-following method. Additionally, when artificial attractive potential and repulsive potential satisfied the Eq. (13) or (14), robot will suffer from the oscillations and local minima problem that result in robot never arrives at desired goal position. As illustrated in figure 12(b), the improved wall-following method could assistant robot to move out of these problems once the difference between attractive potential/force and repulsive potential/force is less than ε.

According to the traditional defined artificial potential functions, along with the increase of distance from robot to target and the value of attractive potential/force is increased, on the other hands, the more robot close to target, the smaller attractive potential/force is, in the desired position of target, the value is zero. By contrast, the repulsive potential/force is inversely proportional to the distance between robot and obstacles. The value of repulsive potential/force exponentially increases along with the distance reducing. That cause when target close enough to obstacles, robot never approaches to target, e.g. non-reachable target problem. Figure 12(c) indicates that our method can plan a collision-free and safely path to target even the target is close enough to obstacles.

We mentioned above that conventional methods did not discuss the repulsive field about vertex of polygonal obstacles which is one of the normal reasons lead robot to local minima and oscillations. In this paper, we implement tangent of semicircle for changing the direction of repulsive potential to eliminate it as shown in Figure 12 (d) and change the direction of repulsive potential for circular obstacle which indicated in Figure 12 (e). Figure 12(f) indicated a completely path without local minima, oscillations, non-reachable target and any other problems by using our proposed Improved APF method.

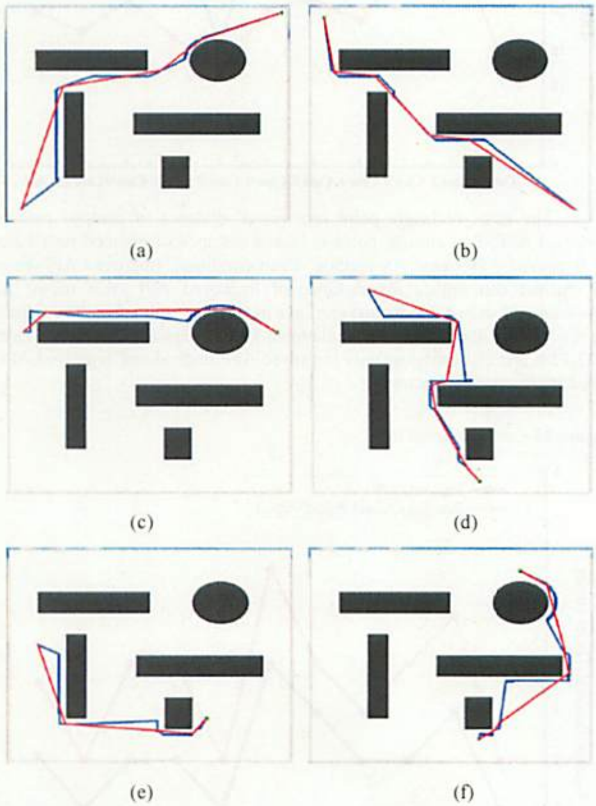
C. *Optimization of the planed path for static target*

As we know that the most three important evaluations of path planning method are distance of planned path, computational time and robot travelled energy. To reduce the distance of planned path, many kinds of classic and heuristic path planning methods are proposed, but the costs of these methods are greatly time computation and complex structure. On the contrary, artificial potential field methods are less computational time and simplest mechanism, while the computed path of artificial potential field methods is not optimal/near-optimal which limits these methods to apply to time/energy constraint robot. In this paper, we proposed a regression search method under Improved APF method to optimal the planed path. The results are shown in Figure 13, Figure 14 and Figure 15.

In Figure 13, blue line is the path which planned by our Improved APF method, while red line is the optimal path utilizing RS method. In Figure 13(a)-(d) are the path planning problem in known environments, the completely information of obstacles and environment are known for robot. When robot encounters local minima and oscillations, robot can select the shorter distance side to wall-following, ultimately, robot computer a valid and safety path. Figure 13(e) and (f) is robot working in partial/unknown environments. Robot only knows the position of itself and target, while the information about obstacles is unknown for robot. Once robot senses obstacles and judge whether it is tramping in local and oscillatory movements, if it is, then implements our improved wall-following method to guide robot escapes these problems. As Figure 13(e) and (f) shown, robot moves along the tendency of the latest five steps and then follows the wall of obstacle.

In the figures, the red paths are obviously shorter than the blue paths in various kinds of conditions. Moreover, the optimal paths have non-oscillations which could save robot travelled energy. The experiment results indicated that our Improved APF-based RS method conforms to the criteria: distance of planned path and robot travelled energy.

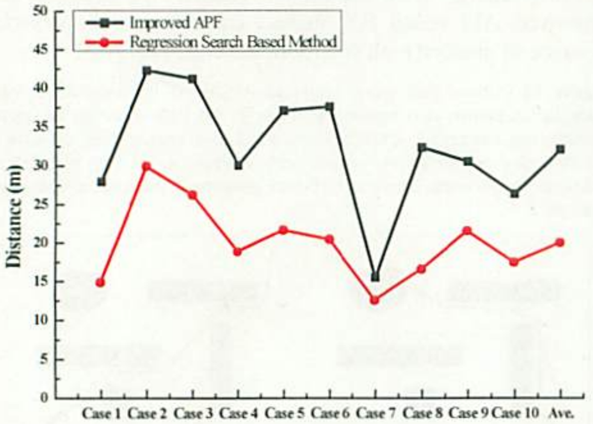
Figure 13 Planned path using Improved APF-based RS method, (a) Path planning in known environment, example *1*, (b) Path planning in known environment, example *2*, (c) Path planning in known environment, example *3*, (d) Path planning in known environment, example *4*, (e) Path planning in unknown environment, example *1*, (f) Path planning in unknown environment, example *2*



Notes: Blue line is the path which planned by our Improved APF method, while red line is the optimal path utilizing RS method. (a)-(d) Path planning in known environments. (e)-(f) Path planning in partial/unknown environment. The distance of red path based on Improved APF-based RS method is obviously shorter than blue path under only Improved APF in each condition.

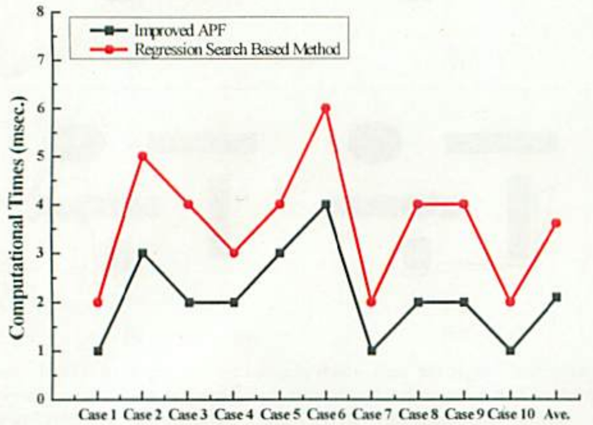
Figure 14 shows the distance of planned path by only Improved APF method and Improved APF-based RS method, the black rectangle point indicated the distance of planned path by Improved APF method, while the red circle point is the distance of optimal path based on Improved APF-based RS method. From the figure we can see that each case our proposed algorithm greatly reduces the distance of planned path from the location of robot to the position of target, the average distance of this ten cases is *32.12 m* and *20.06 m* using only Improved APF method and Improved APF-based RS method, respectively. Therefore, the results demonstration that the regression search method is very efficiency to optimize the planned path by general artificial potential field method.

Figure 14 Distance of planned path



Notes: The black rectangle point represented distance of planned path by Improved APF, Red circular point indicated distance of planned path based on Improved APF-based RS method. Each condition, Improved APF-based RS method can reduce the distance of Improved APF, that means the Improved APF-based RS method can save more energy for robot. The rightest are the average distance of 10 simulations. The average distance of ten cases is 32.12m and 20.06m using only Improved APF method and Improved APF-based RS method, respectively.

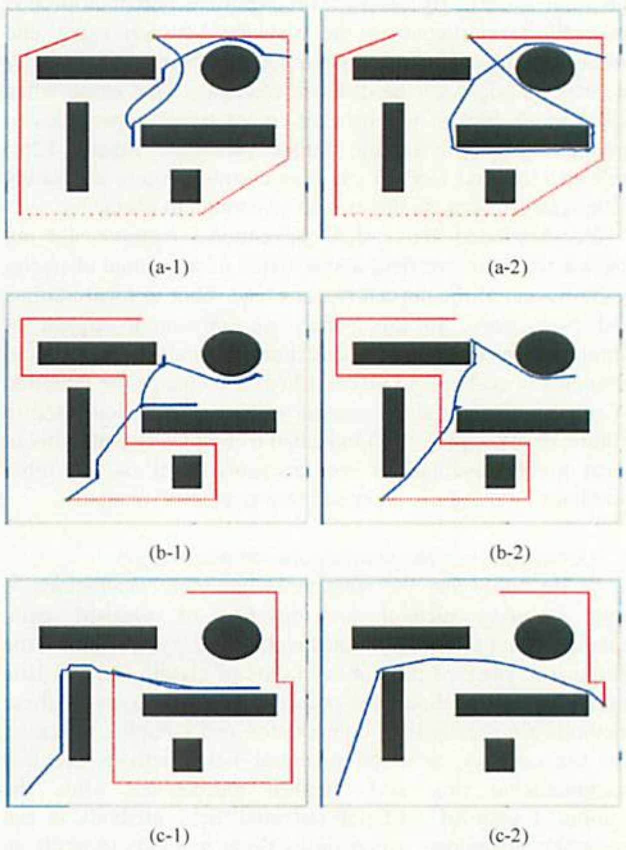
Figure 15 Computational time



Notes: The black rectangle point represented computational time of planned path by Improved APF, Red circular point indicated computational time of planned path based on Improved APF-based RS method. Each condition, Improved APF-based RS method need a little more computational time than Improved APF. The rightest are the average distance of 10 simulations. The average computational time of ten cases is 2.1 milliseconds and 3.6 milliseconds using only Improved APF method and Improved APF-based RS method, respectively.

Since the structure of Improved APF method is very compactness and the algorithm is not so complex, this method only consumed *2.1* milliseconds in average, while our Improved APF-based RS method consumed *3.6* milliseconds in average, only *1.5* milliseconds more computational times (as Figure 15 shown) compare with Improved APF method. The little computational time fulfil also satisfy the common path planning problem criteria: computational time. This is very important for large scale distributed multi-robot systems.

Figure 16 Path planning for dynamic target, (*-1) Path planning based on Improved APF method, (*-2) Path planning using Improved APF-based RS method, (a), (b) and (c) are the different trajectory of moving target and initial position of robot



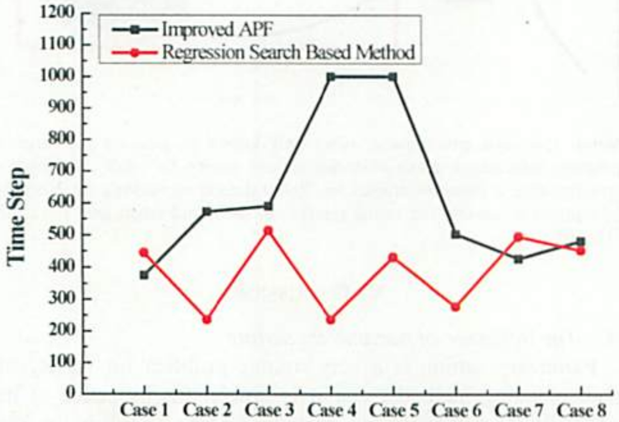
(1) Using Improved APF (2) Using Improved APF-based RS method

Notes: Red is represented the trajectory of moving target, while blue is represented the trajectory of robot. We used Improved APF method and Improved APF-based RS method to plan path for dynamic target at the same conditions. (a) The initial position of robot and target are (19, 16) and (5, 19). (b) The initial position of robot and target are (17, 13) and (10, 19). (c) The initial position of robot and target are (1, 1) and (10, 19.5).

D. Dynamic target in known environments

The little computational time of Improved APF and Improved APF-based RS method make them very suitable to plan path for dynamic target in known environment. Every step, target changes its position and robot should re-plan path to target, if the computational time is very long, such as almost classic path planning algorithms and most heuristic methods, these methods cannot real-time path planning for robot. Figure 16 (*-1) are the trajectory that robot approaches toward moving target by Improved APF method, while Figure 16(*-2) are the trajectory that robot approaches toward moving target utilized our Improved APF-based RS method in the same condition. We simulated 8 different cases and compared the consumed time steps using the two methods. The results are presented in Figure 17. The figure clear that even though for dynamic target in known environments path planning problem, our proposed Improved APF-based RS method distinctly reduced the consumed time steps which robot approach the position of target compare to only using Improved APF method.

Figure 17 Consumed time steps



Notes: The black rectangle point represented consumed time steps by Improved APF, Red circular point indicated consumed time steps based on Improved APF-based RS method. Most conditions, Improved APF-based RS method consumed less time steps to approach moving target than Improved APF, that means the Improved APF-based RS method can save more energy for robot.

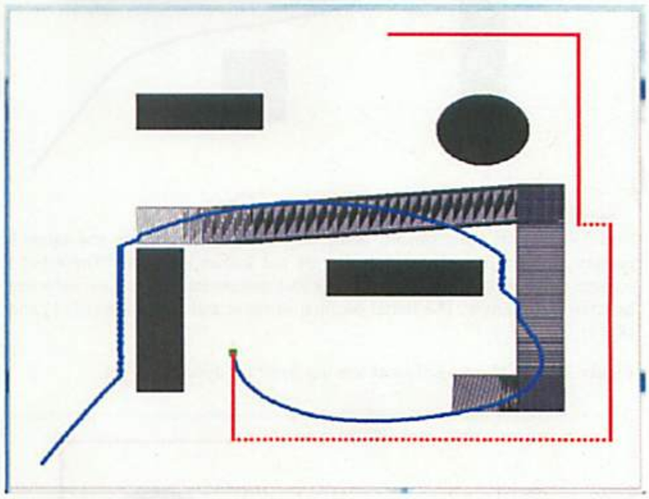
E. Dynamic target and moving obstacle in partial known environments

All conventional artificial potential field methods and its variational methods are not fit with partial known environments. Fortunately, the proposed method can solve any condition in partial known environments by our improved wall-following method. As section III B.3 described, we employ the latest five steps moving tendency to assistant robot approaches to the location of target. Figure 18 indicated the results in simulation based on our Improved APF method and Improved APF-based RS method, which the information about static obstacles, position of robot and target are known for robot, while the information of moving obstacle is unknown. The sensing range of robot is omni-directional $3m$.

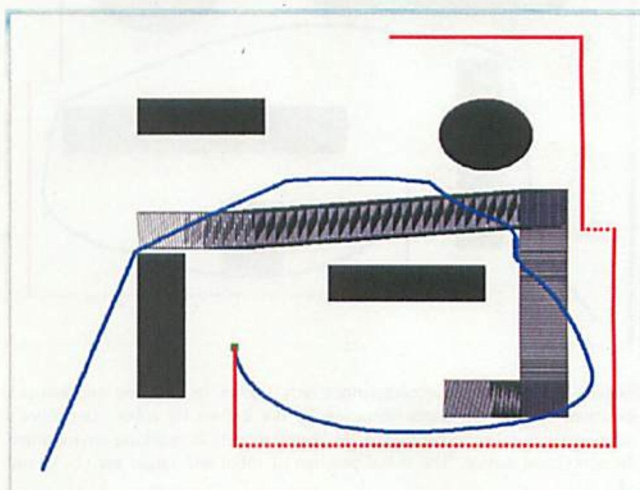
F. Local sensing range, dynamic target and moving obstacle in unknown environments

To demonstration the more applications of our proposed method, we simulated path planning for local sensing range of robot, dynamic target and moving obstacle in unknown environments, respectively. Path planning in unknown environments is impossible for classic path planning algorithms, and very difficult for heuristic path planning algorithms. We assumed that the only locations of robot and target are known for robot, and the sensing range of robot is omni-directional $3m$. Figure 19, 20 and 21 shown local sensing range robot path planning for static target, dynamical target and dynamic target and moving obstacle, respectively.

Figure 18 Path planning for dynamic target and moving obstacle, (a) Improved APF method, (b) Improved APF-based RS method



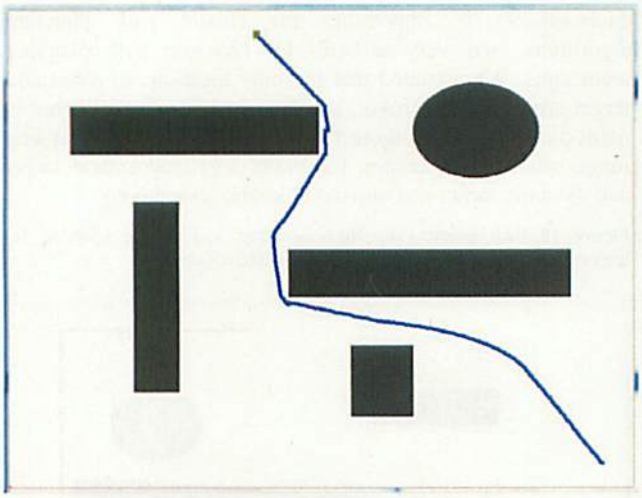
(a) Our Improved APF method



(b) Our Improved APF-based RS method

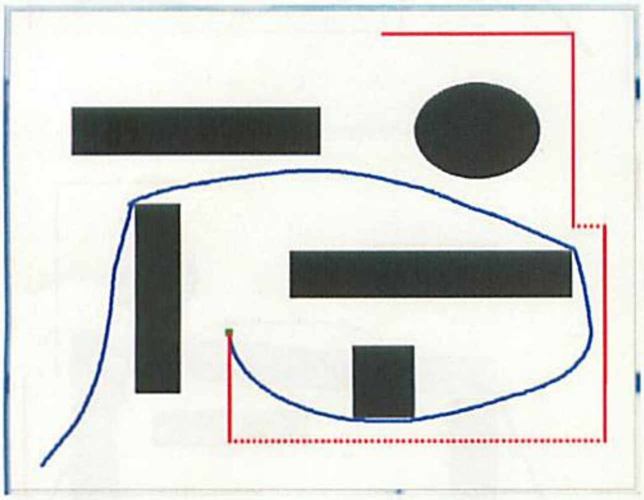
Notes: Partial known environment means the information about static obstacles, coordinates of target and robot are known for robot, but robot does not know the information of moving obstacles. Red is represented the trajectory of moving target, while blue is represented the trajectory of robot. The initial position of robot and target are (1, 1) and (12, 19). We used Improved APF method and Improved APF-based RS method to plan path for dynamic target at the same conditions.

Figure 19 Path planning of local sensing range for static target



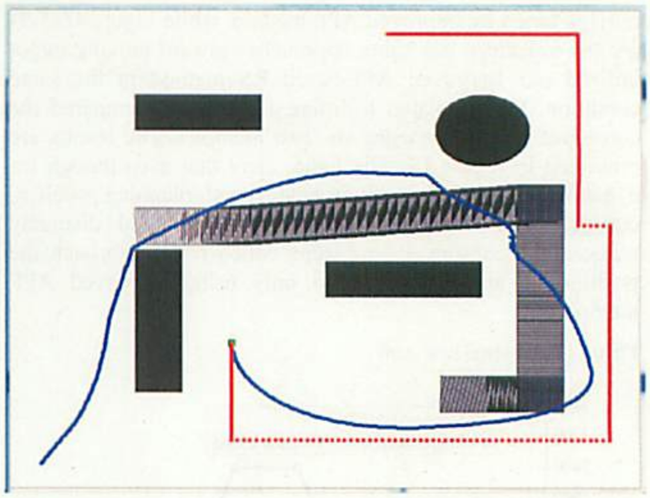
Notes: Unknown environment, robot only knows its position and target's position, information about obstacles are not known for robot. The robot's sensing range is omni-directional $3m$. Robot detects its working environment by equipment sensor. The initial position of robot and target are (19, 1) and (8, 19).

Figure 20 Path planning of local sensing range for dynamic target



Notes: Unknown environment, robot only knows its position and target's position, information about obstacles are not known for robot. The robot's sensing range is omni-directional $3m$. Robot detects its working environment by equipment sensor. The initial position of robot and target are (1, 1) and (12, 19).

Figure 21 Path planning of local sensing range for dynamic target and moving obstacle



Notes: Unknown environment, robot only knows its position and target's position, information about obstacles are not known for robot. The robot's sensing range is omni-directional $3m$. Robot detects its working environment by equipment sensor. The initial position of robot and target are (1, 1) and (12, 19).

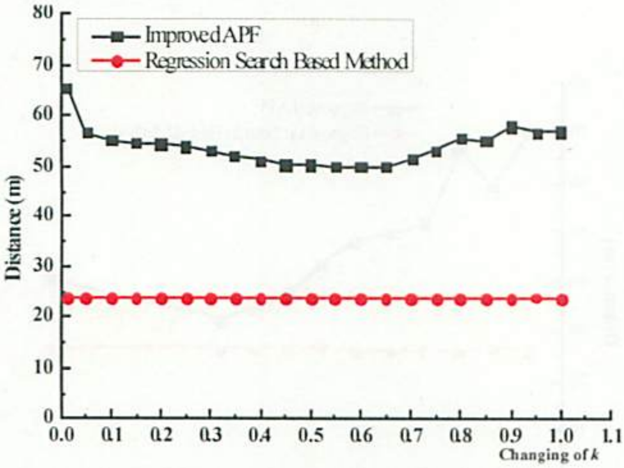
V. Discussion

A. The influence of parameters setting

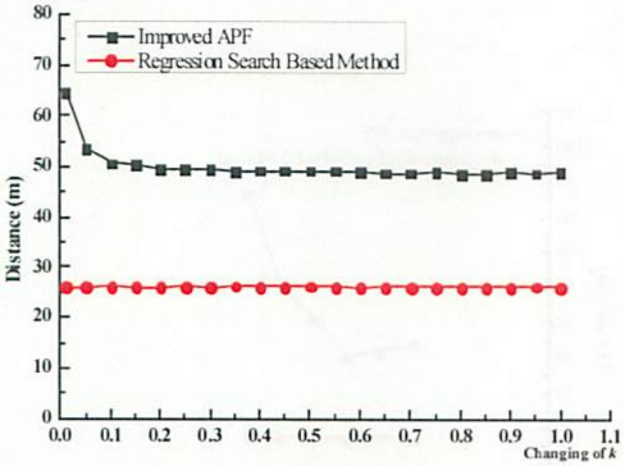
Parameter setting is a very trouble problem for variety of path planning methods, and it is crucial for influence of its capability and applications, such as the size of cell is the key parameter setting for A* algorithm and D* algorithm. When the size of cell is large, the computational time will become very quickly, while the distance of planned path and robot travelled energy are not exactly. On the other hand, it will take an unacceptable long computational time to obtain an optimal path. Similarly, genetic algorithm, colony optimization algorithm, neural network, particle swarm optimization and many others, the parameters setting is the most difficult problem and very impact of these methods' performance and practicality. To reduce the computational time and obtain optimal planned path, some methods need using learning method to determine the value of parameters before path planning.

As others path planning methods, we should in advance set several parameters for our Improved APF-based RS method. The main parameters which affect the performance of our method are k for attractive potential, η and ρ_0 for repulsive potential. Other parameters are set to guarantee robot avoids obstacles and approaches to target, the changing of these parameters are not affect the performances: distance of planned path, computational time and robot travelled energy. Due to the very simple characteristic of such method, the changing of parameters are almost not affect the computational time, only change the distance of planned path and robot travelled energy. As a result of we assumed robot in simulation experiment is an omni-directional robot, we consider the robot travelled energy is the same as distance of planned path. Thus, we analysed the changing of k, η and ρ_0 affect the distance based on our Improved APF method and Improved APF-based RS method, which are presented in figure 22, 23 and 24. From the results we can concluded that the changing of such three parameters a little affect the distance of Improved APF method, but there is almost no influence of Improved APF-based RS method. The figures indicate that although we should carefully choose parameters for Improved APF method to acquire a better path, we need not excessively consider how to select suitable parameters for our Improved APF-based RS method. The facts further demonstrate the simplicity and practicality of our proposed method, and it is very easy to extend our method to many other kinds of path planning problems.

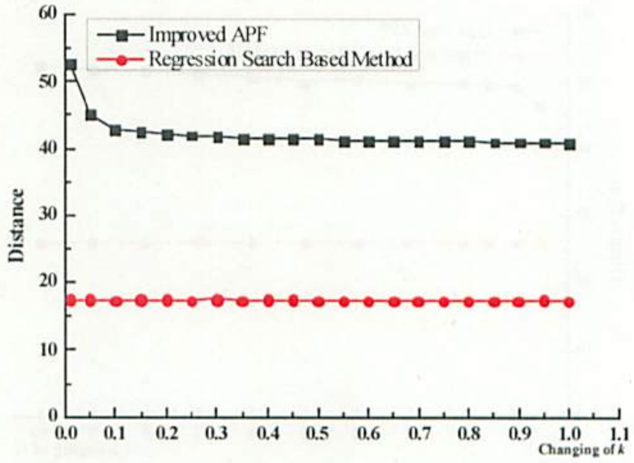
Figure 22 The influence of *k*, (a) Case *1*, (b) Case *2*, (c) Case *3*



(a)



(b)



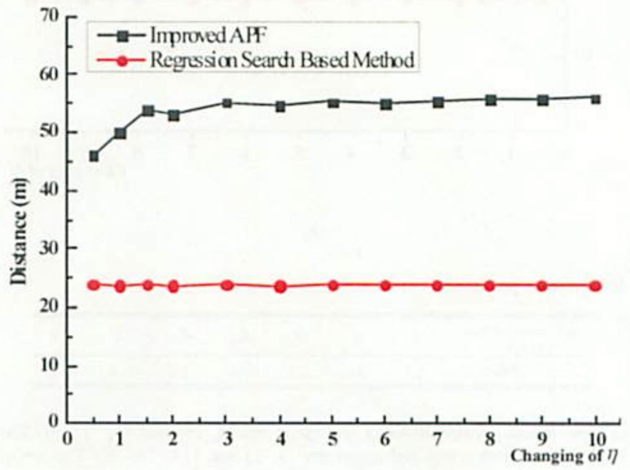
(c)

Notes: Other parameters are set as follows:

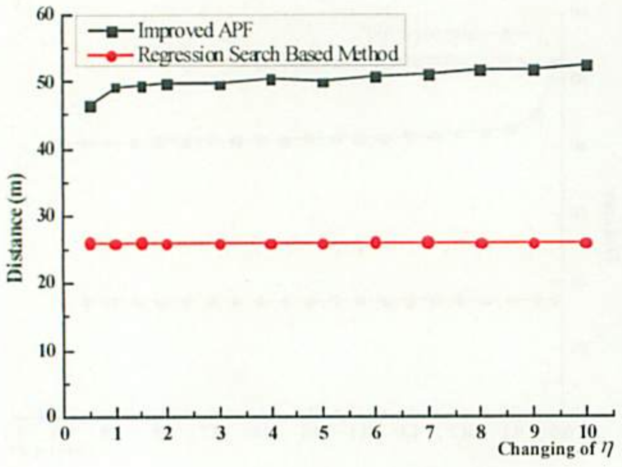
Free Configuration space (C-Space)	d	η	ρ_0	d_{ob}	d_{gr}	D_0	ΔS
$20\times 20m$	3.0	2.0	0.5	0.4	0.6	0.2	0.1

(a) The initial position of robot and target are (4, 19) and (12, 1). (b) The initial position of robot and target are (3, 2) and (17, 17). (c) The initial position of robot and target are (2, 10) and (13.2, 4).

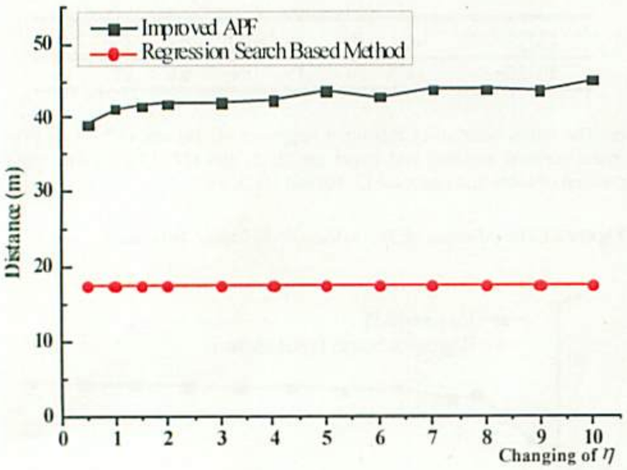
Figure 23 The influence of η, (a) Case *1*, (b) Case *2*, (c) Case *3*



(a)



(b)



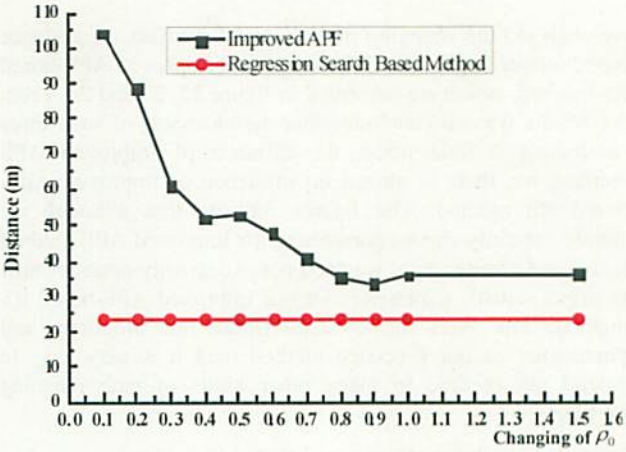
(c)

Notes: Other parameters are set as follows:

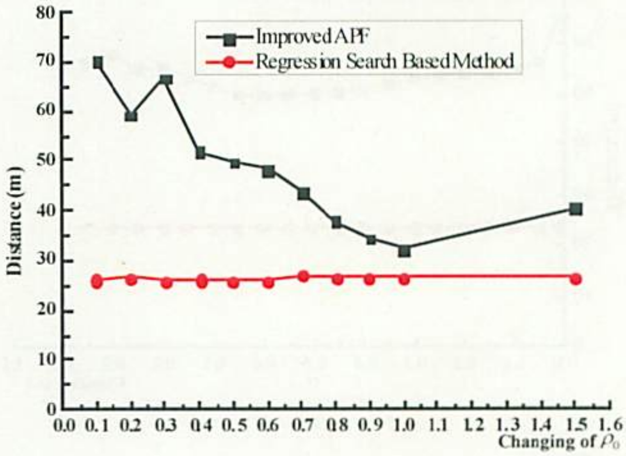
Free Configuration space (C-Space)	k	d	ρ_0	d_{cm}	d_{gr}	D_0	ΔS
$20\times20m$	0.3	3.0	0.5	0.4	0.6	0.2	0.1

(a) The initial position of robot and target are (4, 19) and (12, 1). (b) The initial position of robot and target are (3, 2) and (17, 17). (c) The initial position of robot and target are (2, 10) and (13.2, 4).

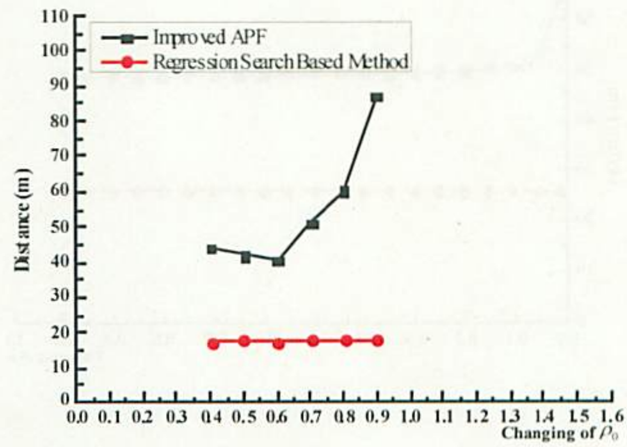
Figure 24 The influence of ρ_0, (a) Case *1*, (b) Case *2*, (c) Case *3*



(a)



(b)



(c)

Notes: Other parameters are set as follows:

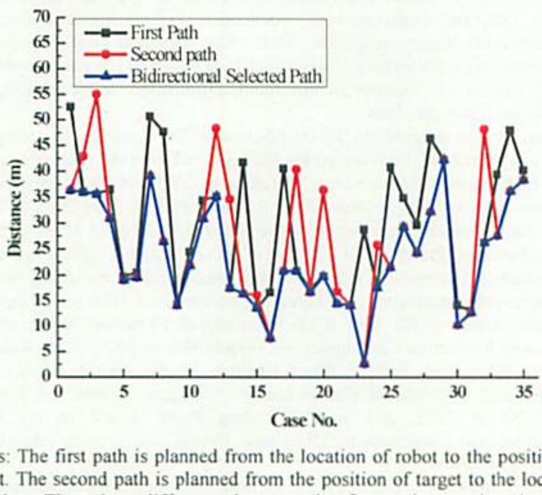
Free Configuration space (C-Space)	k	d	η	d_{om}	d_{gr}	D_0	ΔS
$20\times20m$	0.3	3.0	2.0	0.4	0.6	0.2	0.1

(a) The initial position of robot and target are (4, 19) and (12, 1). (b) The initial position of robot and target are (3, 2) and (17, 17). (c) The initial position of robot and target are (2, 10) and (13.2, 4).

B. *Bidirectional Improved APF*

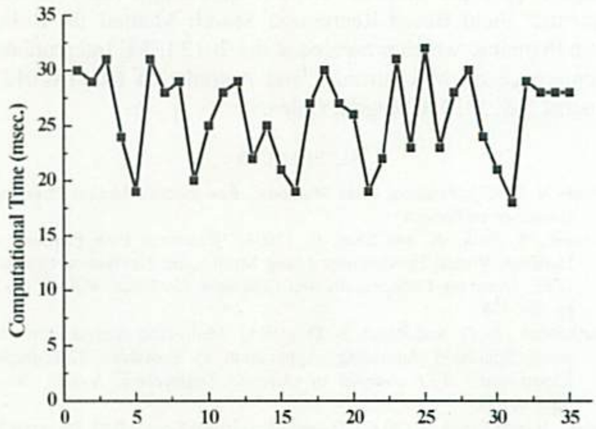
Researchers (paper (Zhang et al., 200) and (Uyanik, 2010)) have proposed a bidirectional artificial potential field method for robot path planning. The bidirectional artificial potential field method has three steps: Firstly, plan a path from the location of robot to the position of target. Secondly, plan anther path from the position of target to the location of robot. Finally, compare the distance of the two paths, and then selects the shorter one as the planned path. They have demonstrated that this method can always selects a shorten distance path. Therefore, in this paper, we utilize the bidirectional path planning method based on our Improved APF method to discuss the performance. Figure 25 and figure 26 are the simulation results, from the figures we can see that the bidirectional Improved APF method can select the shorter distance path every condition as (Zhang et al., 200) and (Uyanik, 2010) mentioned, while the computational time is too long to obtain a better path. As the former described (Figure 15), our proposed Improved APF method only consumes a few milliseconds to computer a valid path. In contrast, the bidirectional Improved APF method spends 10 times computational time to calculate a better path compare to Improved APF method. This is a acceptable computational time for small scale multiple robots systems, but for the real-time middle/large scale distributed multi-robot systems, too long computational time is a undesired according to common path planning problem criteria.

Figure 25 Bidirectional Improved APF method



Notes: The first path is planned from the location of robot to the position of target. The second path is planned from the position of target to the location of robot. There is a difference between the first and second path in all conditions. Bidirectional Improved APF method can always select the shorter path.

Figure 26 Computational time of bidirectional Improved APF method



Notes: As mentioned above, Improved APF spends only a few milliseconds to plan a valid path, while bidirectional Improved APF need 10 times of Improved APF to computer a better path. This is a acceptable computational time for small scale multiple robots systems, but for the real-time middle/large scale distributed multi-robot systems, too long computational time is a undesired according to common path planning problem criteria.

VI. Conclusion

Path planning problem is one of the most important robotic problems for autonomous mobile robot to accomplish given tasks. An effective Improved APF-based RS method was proposed to obtain a global sub-optimal/optimal path without local minima, oscillations and non-reachable target problem in variety of environments contain: completely known, partial known, unknown, static and dynamic environments. Redefined potential functions and improved wall-following method utilized to eliminate problems which are the fatal three problems for artificial potential filed. Due to the computed path by Improved APF method is not the shortest distance, we developed a regression search (RS) method to optimize the planned path, and proved that a safely, optimal and collision-free path for autonomous mobile robot could be produced by amount of simulation experiments. The results demonstrated that our Improved APF-based RS method is very feasibility and efficiency to solve mobile robot path planning problem. Moreover, we verified that our method can apply for real-time path planning: dynamic target, moving obstacle and local sensing range of robot.

In the future works, we attend to smooth the planned path, improve our method for more complex environment and make it suitable for large scale distributed multi-robot coordination systems. And reduce the consumed computational time of bidirectional Improved APF method.

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Biographical notes: Guanghui Li is currently a PhD student of the Department of Precision Engineering at the School of Engineering, The University of Tokyo. He received his Bachelor's degree in Traffic and Transportation from the Faculty of Transportation Engineering, Kunming University of Science and Technology, China, in 2005, and received his MS from the Department of Automobile Engineering at College of Mechanical Engineering, the State Key Laboratory of Mechanical Transmission, Chongqing University, China, in 2008. His current research interests include multiple mobile robot coordination, service robots, and optimization algorithms.

Yusuke Tamura received his BE from School of Engineering, The University of Tokyo in 2003. He received his ME and PhD from the Graduate School of Engineering, The University of Tokyo, in 2005 and 2008, respectively. From 2006 to 2008, he was a JSPS Research Fellow. From 2008 to 2012, he was a Project Researcher with The University of Tokyo. He is currently an Assistant Professor of Faculty of Science and Engineering, Chuo University. His research interests include mobile robots coexisting humans, human-robot interaction, and human motion analysis. He received the Best Paper Award at the 13th IEEE International Workshop on Robot and Human Interactive Communication (RO-MAN) in 2004, IEEE Robotics and Automation Society Japan Chapter Young Award at the 2005 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) in 2005, and an Outstanding Paper Award of the Sixth International Conference on Ubiquitous Robots and Ambient Intelligence (URAI) in 2009.

Atsushi Yamashita received B.E., M.E., and Ph.D. degrees from the Faculty of Engineering, The University of Tokyo in 1996, 1998, and 2001, respectively. From 2001 to 2008, he was an Assistant Professor of

Shizuoka University. From 2006 to 2007, he was a Visiting Associate at the California Institute of Technology. From 2008 to 2011, he was an Associate Professor of Shizuoka University. From 2011, he has been an Associate Professor of The University of Tokyo. His research interests are robot vision, image processing, multiple mobile robot system, and motion planning. He is a member of ACM, IEEE, JSPE, RSJ, IEICE, JSME, IEEJ, IPSJ, ITE, and SICE.

Hajime Asama received his B. S., M. S., and Dr. Eng in Engineering from the University of Tokyo, in 1982, 1984 and 1989, respectively. He was Research Associate, Research Scientist, and Senior Research Scientist in RIKEN (The Institute of Physical and Chemical Research, Japan) from 1986 to 2002. He became a professor of RACE (Research into Artifacts, Center for Engineering), the University of Tokyo in 2002, and a professor of School of Engineering, the University of Tokyo in 2009. He received JSME (Japan Society of Mechanical Engineers) Robotics and Mechatronics Division Academic Achievement Award in 2001, RSJ (Robotics Society of Japan) Best paper Award, JSME Robotics and Mechatronics Award in 2009, etc. He is the vice-president of Robotics Society of Japan since 2011. He was an AdCom member of IEEE Robotics and Automation Society from 2007 to 2009, an editor of Journal of International Journal of Intelligent Service Robotics, Journal of Field Robotics, Journal of Robotics and Autonomous Systems. He played the director of the Mobiligence (Emergence of adaptive motor function through the body, brain and environment) program in the MEXT Grant-in-Aid for Scientific Research on Priority Areas from 2005 to 2009. He is a Fellow of JSME since 2004 and RSJ since 2008. His main research interests are distributed autonomous robotic systems, ambient intelligence, service engineering, and Mobiligence, and service robotics.