Effective improved artificial potential field-based regression search method for autonomous mobile robot path planning

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Abstract: This paper presents an effective improved artificial potential field-based regression search (improved APF-based RS) method that can obtain a better and shorter path efficiently without local minima and oscillations in an environment including known, partially known or unknown, static, and dynamic environments. We redefine potential functions to eliminate oscillations and local minima problems, and use improved wall-following methods for the robots to escape non-reachable target problems. Meanwhile, we develop a regression search method to optimise the planned path. The optimisation path is calculated by connecting the sequential points produced by improved APF. The simulations demonstrate that the improved APF method easily escapes from local minima, oscillations, and non-reachable target problems. Moreover, the simulation results confirm that our proposed path planning approach can calculate a shorter or more nearly optimal than the general APF can. Results prove our improved APF-based RS method's feasibility and efficiency for solving path planning.

Keywords: autonomous mobile robot; path planning; navigation; artificial potential field; APF; bidirectional artificial potential field; regression search method; RS method.

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1 Introduction

During the last few decades, mechatronics and automation have become rapidly growing fields affecting almost all aspects of daily life. Especially, robotics has become a major part of this trend because robotic scientists have investigated service mobile robots that can operate within human-robot coexistent environments to execute different complex tasks, transportation of heavy objects, surveillance, rescue, and guidance of people at exhibitions and in museums. Autonomous mobile robot path planning and navigation, which are important applications for intelligent robot control systems, have attracted remarkable attention from many researchers. Path planning is aimed at enabling robots to have capabilities of automatically ascertaining and executing a sequence of collision-free and safe motions to achieve certain tasks in a given environment. Therefore, the basic function of the path planning problem is to compute a valid and feasible solution. Nowadays, path planning problems have been transformed into optimisation problems with the development of computer technology and modern control methodology. A robot searches for an optimal or approximately optimal path with respect to the problem objectives. As described in many interesting reports, two important 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 related to obstacles and targets is known a priori. The robot motion is subsequently designed based on that given information. Examples of algorithms for path planning in such environments include sub-goal network, cell decomposition, A* and D* algorithm, traditional artificial potential field (APF), and many others. Usually, a robot under a known environment can calculate an optimal or sub-optimal path. However, in unknown environments, a robot has no previous knowledge or only partial information about the environment. Alternatively, only partial information is available in relation to obstacles and targets. Therefore, a robot must plan a path based on available information or on information that is sensed within the range of available sensors. In other words, the robot cannot plan a global optimal path in a single attempt. In recent years, many researchers have achieved important investigation results in such environments using, for example, fuzzy logic, neural networks, rapidly exploring random tree algorithms, and ant colony optimisation.

As described above, autonomous intelligent mobile robot path planning in a known environment is regarded as static. In contrast, the following conditions make environments dynamic: environments where the target moves continuously during a robot approach, moving obstacles, and dynamic obstacles appearing randomly. This paper presents a new approach for autonomous mobile robot path planning and navigation in an environment including known, partially known or unknown, static, and dynamic environments. Herein, we propose an improved artificial potential field-based regression search methodology (improved APF-based RS method) intended for use with autonomous mobile robot path planning. It can programme a valid, feasible and shorter solution from the robot location to the target position. We first modify the potential functions of traditional APFs and improve the wall-following method to resolve the intrinsic fatal problems of previous methods. Then we use the proposed regression search algorithm to shorten the planned path. At the end of this paper, the validity and efficiency of our proposed methodology are demonstrated with simulation experiments.

The remainder of this paper is organised as follows. The next section presents a discussion of related works, classic, and heuristic approaches for autonomous mobile robot path planning. We specifically present discussion and analysis of the problems of traditional and variable APF methods. In Section 3, we briefly introduce the conventional APF method; then we present our improved artificial potential field (improved APF) to address local minima and oscillation problems by modifying potential functions and by applying improved wall-following methods in unknown and partially known environments. Finally, we use regression search method (RS method) to shorten the path that is planned using our improved APF method. To demonstrate our proposed method, some simulations are conducted in Section 4, where we prove that the proposed improved APF method can resolve the problems of previous conventional methods completely. 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 the robot. In Section 5, the influence of parameter setting under our method is discussed. Furthermore, we analyse the necessity by implementing the bidirectional improved APF method to address autonomous mobile robot path planning problems. Finally, Section 6 presents conclusions and sketches promising avenues along which to pursue future work.

2 Related works

A large part of autonomous mobile robot path planning pertains to scheduling and routing. It is well known to be an NP-hard (NP-complete) problem. Path-planning algorithms are classified as classic and heuristic approaches (Masehian and Sedighizadeh, 2007). Classic algorithms are designed to calculate an optimal solution if one exists, or to prove that no feasible path exists. In contrast, heuristic algorithms are intended to search for a good quality solution in a short time. Classic algorithms are usually computationally expensive. However heuristic algorithms can fail to find a good solution for a difficult problem. We introduce works related to classic and heuristic algorithms.

2.1 Classic algorithms

Currently, the classic methods that have been developed are variations of a few general approaches such as roadmap, cell decomposition, APFs, and mathematical programming. Most autonomous mobile robot path planning problems are solvable using classic algorithms. These approaches are not necessarily mutually exclusive, but their combination is often used in developing more reliable paths. In the roadmap approach (Oh et al., 2004), feasible paths are mapped onto a network of one-dimensional lines; then a search for a desired path is conducted in such a network. However, the searched path is limited to the network, and path planning becomes a graph-searching problem. Well-known roadmaps include the visibility graph, Voronoi diagram, and sub-goal networks. The visibility graph algorithm (Tarjan, 1981) can compute the shortest distance or optimal path. This approach does not consider the mobile robot size or that a lead robot is too close to the vertex of an obstacle, even colliding 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 improved methods of the visibility graph. Additionally, several researchers have demonstrated that cell decomposition (Cai and Ferrai, 2009) is the simplest method for mobile robot path planning, but they are inefficient for computational memory and planning time according to the cell size.

However, most classic approaches, roadmaps, and cell decomposition are based on the free configuration space (C-space) concept. In addition to their lack of adaptation and robustness, conventional approaches are unsuitable for dynamic environments because they use a sequential search algorithm to generate a single solution that might become infeasible when a change in the environment dictates that a new solution must be generated from scratch. Moreover, the greater the dimensions of free C-space, the more complex the path planning problem will be.

2.2 Heuristic algorithms

A* algorithm calculates a shortest path (with minimum cost) in a given map by keeping track of an open list and a closed list (Nilsson, 2000). A* algorithm is a classical heuristic search algorithm. Although the applied A* algorithm for the robot path planning in the free C-space uses search space that is too large, the search efficiency of the A* algorithm is low, and the planned path is optimal relative to the cell decomposition. The D* algorithm (Stentz, 1995) is almost identical to the A* algorithm, but it has no heuristic, so its searches expand equally in all directions; the method might search a huge area before reaching a goal. For that reason, D* is slower than A*, but it performs better with an unknown goal.

Genetic algorithms can obtain the best feasible path for mobile robot path planning in an uncertain environment after many iterations. Because the genetic algorithm structure is very complex, it requires a long time to process and affect the real-time performance of the robot during path planning (Sedighi et al., 2004). When dealing with a dynamic environment most genetic algorithms do not control the population diversity because of premature convergence. It is very easy to fall into local optimisation. Some researchers suggest that combining genetic algorithms with simulated annealing (Blackowiak and Rajan, 1995) can resolve these problems. In one paper (Elshamli et al., 2004), a genetic algorithm is developed for dynamic path planning method which incorporates path safety and smoothness.

In addition, some scholars have investigated robot navigation algorithms based on ant colony optimisation algorithms (Garcia et al., 2009) and improved ant colony optimisation (Dorigo and Gambardella, 1997) algorithms. The convergence speed of both algorithms is far from satisfying when intended for use for real-time global dynamic planning. One study (Zhua et al., 2011) developed 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 the algorithm has good effect and high real-time performance. The results also indicate that it is suitable for real-time navigation in complex and dynamic environments.

Many other heuristic path planning methods, neural networks, particle swarm optimisation, fuzzy logic, and Tabu search algorithms are implemented. However, the time complexity of all heuristic algorithms will increase greatly when a larger and more complex environment is considered. For example, the path planning algorithm based on the genetic algorithm might produce numerous invalid paths and might fail when the obstacle number increases. Furthermore, deadlock and oscillation occur easily in the rolling window method, and stagnation is a general problem related to the ant colony optimisation algorithm.

2.3 *Artificial potential field*

The APF was first introduced by Khatib (1986). The potential function is definable over free C-space as the sum of attractive potential pulling a robot toward the goal configuration, and a repulsive potential pushing a robot away from obstacles. An APF is an important classic method for autonomous mobile robots. Many researchers are studying it continually all over the world. An APF has often represented a good quality method to achieve a fast and reactive response to a dynamic environment. However, this method has been widely demonstrated as suffering from unavoidable drawbacks which make it very likely that a robot will become trapped in a local minimum and oscillations. One paper (Sgorbissa and Zaccaria, 2012) describes a hybrid approach that integrates a priori knowledge of an environment with local perceptions to execute the assigned tasks efficiently and safely. The results indicate that this method guarantees that 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 includes a typical shortcoming: the system relies on local perceptions and navigation strategies. Another improved APF has been proposed (Zhang et al., 2011) using quantum particle swarm optimisation for rapid global searching and realising optimal path planning. They employ quantum particle swarm optimisation to modify the parameters of the APF to adapt to a different environment and dynamic obstacles. To address the local minima problem in the traditional APF, a method including robot regression and a potential field filling has been proposed (Qi et al., 2008; Shi et al., 2010). Similar methods have been proposed in other papers (Zhang et al., 2006a; 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 optimise the planned solution. Improved APFs of other kinds have been investigated (He et al., 2011). They introduce the relative distance between a robot and target into a repulsive force function and modify the repulsion direction to ensure that the global minimum is at the target position. Donnart and Meyer (1996) researched the learning reactive and planning rules into mobile robot path planning. The main thrust of some reports (Sheng et al., 2010; Yang et al., 2011) is that application of a virtual local target to a guide robot escapes the local minimum.

The approaches described above, including the APF and its improved methods, still suffer from many shortcomings such as high time complexity in high dimensions that prevent these methods from addressing real-time path planning, some methods do not completely solve local minima, oscillations and non-reachable target problems, which renders them inefficient in practice. Moreover, the path under previous methods is not optimal or near-optimal, but only feasible for an autonomous mobile robot to adapt to the given environment. In other words, robots moving along the planned path will consume more energy and entail higher costs. As described in one report (Elshamli et al., 2004), the common path planning problem criteria might include the distance of the planned path, computational time, and the robot travel energy. All these methods are therefore incapable of handling common criteria well. Herein, we present an effective improved APF-based RS method that can obtain a shorter planned path without local minima, oscillatory movements, and the non-reachable target problem. We use the simplest path planning algorithm to plan an effective and shorter distance path for autonomous mobile robot very rapidly.

3 Proposed path planning method

3.1 *Traditional APF*

The basic idea underlying the APF method is the assumption that a robot, as a point, moves in an abstract artificial force field. The APF in the environment comprises the attractive potential of target and the repulsive potential of obstacles. The attractive potential is produced by a target and increases in a direction to a target point. The repulsive potential is that of different obstacles. The direction of the synthesised repulsive potential is repellent from obstacles. Therefore, the potential function (1) is the APF of a robot, defined as a resultant of attractive potential and repulsive potential. A robot controls its movement toward the target point along the direction of APF. Under the method of the APF, a robot can find a collision-free path by seeking a route along the direction of the declining potential function.

The robot coordinate is $q = (x, y)^T$; thereby the APF is defined as shown below.

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

In that equation, $U(q)$ stands for the APF. $U_{att}(q)$ represents the attractive potential. Also, $U_{rep}(q)$ denotes the repulsive potential.

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

Consequently, the artificial force of robot is the following.

$$\begin{aligned} F(q) &= -\nabla U(q) \\ &= -\nabla U_{att}(q) - \nabla U_{rep}(q) \\ &= F_{att}(q) + F_{rep}(q) \end{aligned} \tag{2}$$

In that equation, $F(q)$ is the artificial force. $F_{att}(q)$ denotes the attractive force, and $F_{rep}(q)$ is the repulsive force.

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

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

In that equation, k is a positive coefficient for the APF, and $q_g = (x_g, y_g)^T$ is the location vector of target. $\rho_{goal}(q) = \|q - q_g\|$ is the Euclidean distance from the robot location to the target position.

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

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

Therein, $F_{att}(q)$ is a vector directed toward q_g with magnitude that is 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 presented below.

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

Therein, F_{att-x} is the attractive force in the x direction. F_{att-y} is the attractive force in the y direction.

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

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

In that equation, η is a positive scaling factor. Letting $q_c = (x_c, y_c)$ be a unique configuration in an obstacle closest to q, then $\rho(q) = \|q - q_c\|$ is the shortest distance between the robot and obstacle. ρ_0 is the greatest impact distance of a single obstacle. No impact occurs for the robot when the distance between a robot and obstacle is greater than ρ_0. Similarly, the repulsive force is the negative gradient of the repulsive potential function, as follows.

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

or

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

F_{rep-x} and F_{rep-y} stand for the Cartesian components of the repulsive force F_{rep}. When the repulsive potential acting on the robot takes effect, the components are expressed as the following.

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

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

The environment has many obstacles, so the total repulsive potential field is the sum of all obstacles' repulsive potential field. The total APF is

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

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

The total artificial force field is the following.

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

Although the traditional APF method can plan a smooth path effectively, it has fatal problems. The traditional APF method used in the path planning might suffer from the local minimum and oscillations problem instead of the desired global minimum. We define the local minima and oscillations problem as

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

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

Equation (13) means that for any small ε greater than zero, the resultant attractive potential and repulsive potential at point q are smaller than ε. Similarly, equation (14) means that, for any small ε greater than zero, the resultant of the attractive force and the repulsive force at point q is smaller than ε. The robot is regarded as trapped in local minima and oscillations if the APF or artificial force field satisfies equations (13) or (14): when the attractive potential or force and repulsive potential or force is equivalent or almost equivalent and collinear reverse or almost collinear reverse, then the artificial potential or force field of a robot is almost zero. It will cause a robot to be trapped in local minima and oscillations [Figures 1(a) and 1(b)]. Furthermore, when the target position is very close to obstacles, a robot can not reach the target [Figure 1(c)].

3.2 Improved APF

3.2.1 Redefined attractive potential function

As equations (3) and (4) presented, the attractive potential or force is directly related to distance $\rho_{goal}(q)$ [Figure 2(a)]. The value of attractive potential or force is determined according to the distance between a robot and target, as proposed in the traditional attractive potential function. When $\rho_{goal}(q)$ is very great, the attractive potential or force will become very great as well. In other words, when a robot is distant from a target, it easily leads the robot to move too close to an obstacle (Amato, 2004). Therefore, in the real environment presented in Figure 3, the robot confronts the risk of collision with obstacles when we take account of the error of path planning (Li et al., 2012). Consequently, the attractive potential and attractive force are modified as functions (15) and (16).

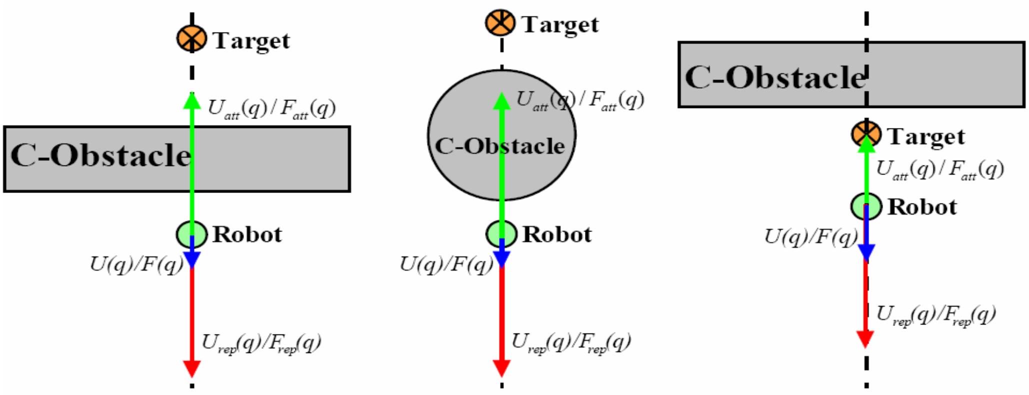
$$U_{att}(q) = \begin{cases} \frac{1}{2} k \rho_{goal}^2(q) & , \rho_{goal}(q) \leq d \\ kd\, \rho_{goal}(q) & , \rho_{goal}(q) \geq d \end{cases} \tag{15}$$

$$F_{att}(q) = \begin{cases} -k\left(q - q_g\right) & , \left\|q - q_g\right\| \leq d \\ -kd \dfrac{\left(q - q_g\right)}{\left\|q - q_g\right\|} & , \left\|q - q_g\right\| \geq d \end{cases} \tag{16}$$

Therein, d is a positive coefficient for attractive potential and force.

When distance $\rho_{goal}(q)$ is less than d, then the redefined attractive potential and force are the same as in the conventional definition. Otherwise, the attractive potential and force are a constant presented in Figure 2(b). We redefined the attractive potential function as equations (15) and (16) to guarantee that a robot avoids collisions with obstacles. When the robot moves near an obstacle, the repulsive potential or force from obstacles is sufficiently greater than kd to push the robot away from obstacles.

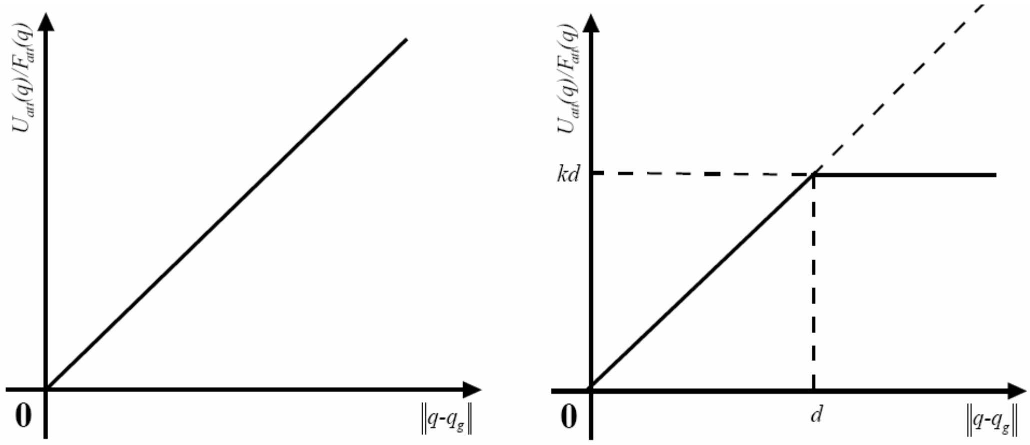
Figure 1 Problems of a traditional APF, (a) and (b) are local minima and oscillations, and (c) is a non-reachable target problem (see online version for colours)



(a) (b) (c)

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

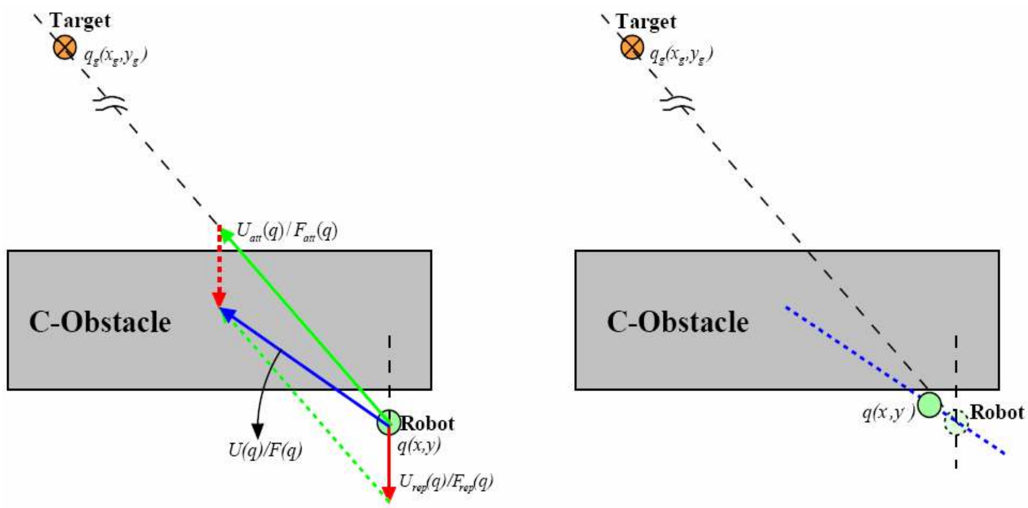
Figure 2 Attractive potential function, (a) traditional attractive potential function (b) improved attractive potential function



(a) (b)

Notes: (a) The traditional APF defines the relation between the attractive potential or force and the distance from the robot to the target. Consequently, the value of the attractive potential or force increases linearly according to the increasing distance. (b) In the improved APF, we assess the risk of collision and real robot path planning error, and modify the attractive potential or force function: set a threshold *d*. If the distance is less than *d*, then the value of attractive potential or force increases linearly according to increasing distance, as in the definition of a traditional APF. Otherwise, the attractive potential or force is a constant.

Figure 3 Attractive potential field, (a) at $T = t$ and (b) at $T = t'$ (see online version for colours)



(a) (b)

Notes: When the target is too distant from a robot, the result in the attractive force is too much greater than that of a repulsive force even though a robot is very close to an obstacle. Then at the next step, the robot moves along the direction of the resultant force to a closer obstacle. In real path planning, the robot confronts the risk of collision with obstacles, especially considering error.

3.2.2 Redefine repulsive potential function

As many papers have described (Khatib, 1986; Zhang et al., 2011), when a target is extremely close to obstacle, the repulsive potential or force is too much greater than the attractive potential or force, as

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

or

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

such that a robot will find it impossible to arrive at the position of a target in such circumstances. This condition, named the non-reachable target problem [shown in Figure 1(c)], is undesirable for the robot path planning problem. Herein, we redefine the potential function and use functions (19) and (20) to resolve the robot non-reachable target problem. We named this redefined potential function the repulsive potential or force instantaneous disappearance if (a) and (b) are satisfied simultaneously.

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

b $\rho_{goal} \le d_{gr}$.

Therein, d_{Ob} and d_{gr} respectively denote positive coefficients.

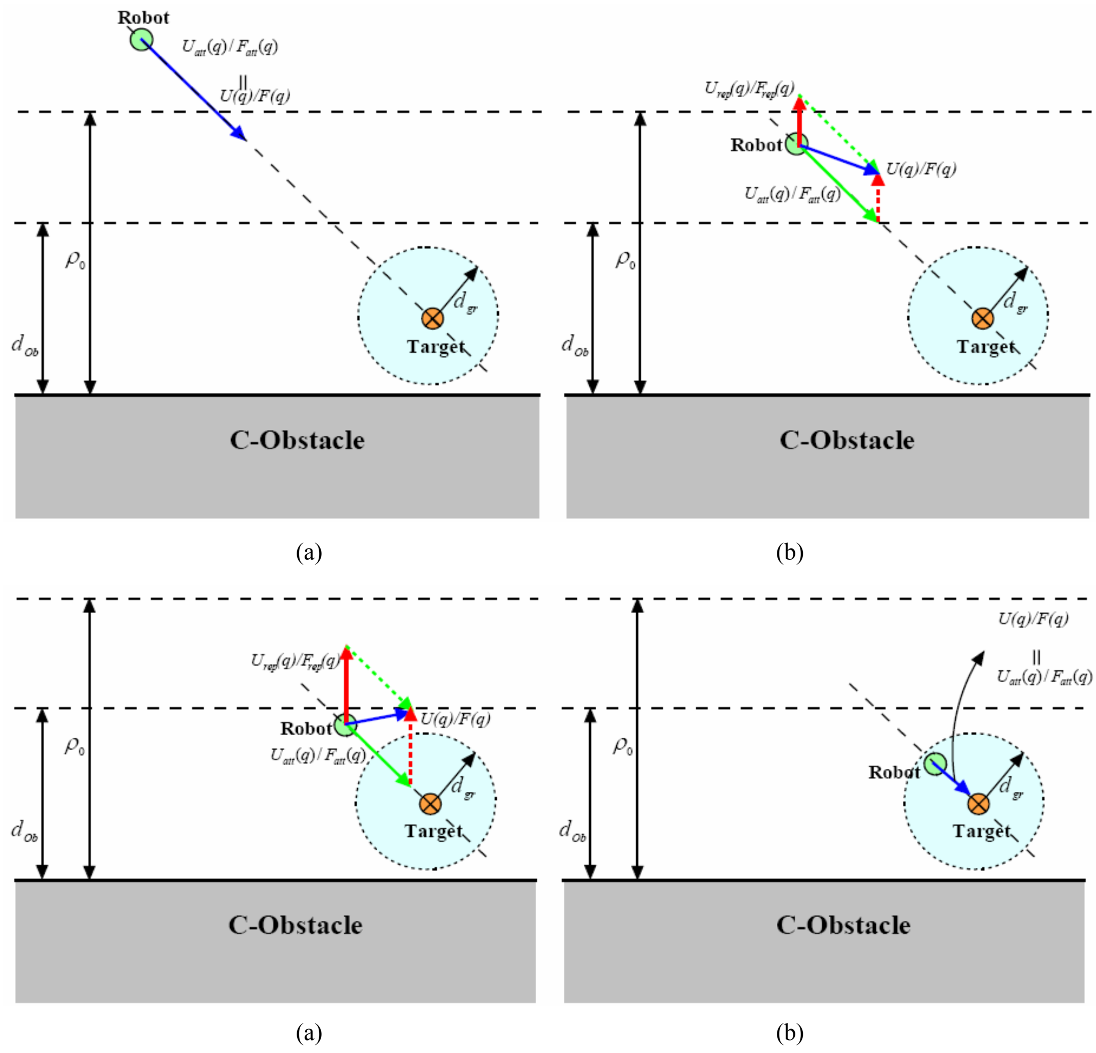
Once the robot detecting the distance between the target and obstacle is less than d_{Ob}, and simultaneously the distance between target and robot is less than d_{gr}, then the robot only moves along the attractive potential or force instead of considering the resultant of attractive potential or force and repulsive potential or force until the robot arrives at the target location (Figure 4). When (a) and (b) are satisfied, no repulsive potential or force remains. The robot is attracted only by the target, as

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

and

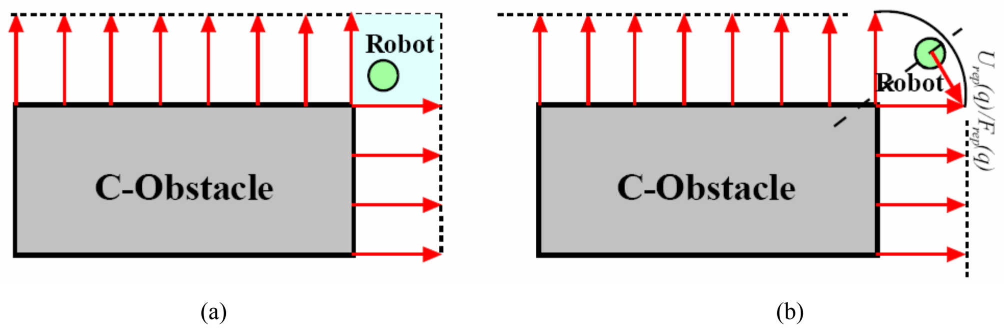
$$U(q)=\begin{cases} F_{att}(q) & ,\rho(q)\le d_{Ob} \text{ and } \rho_{goal} \le d_{gr} \\ F_{att}(q)+F_{rep}(q) & ,\text{Otherwise} \end{cases} \tag{20}$$

Figure 4 Illustration of redefined APFs (a) at $T = t_1$, (b) at $T = t_2$, (c) at $T = t_3$, and (d) at $T = t_4$ (see online version for colours)



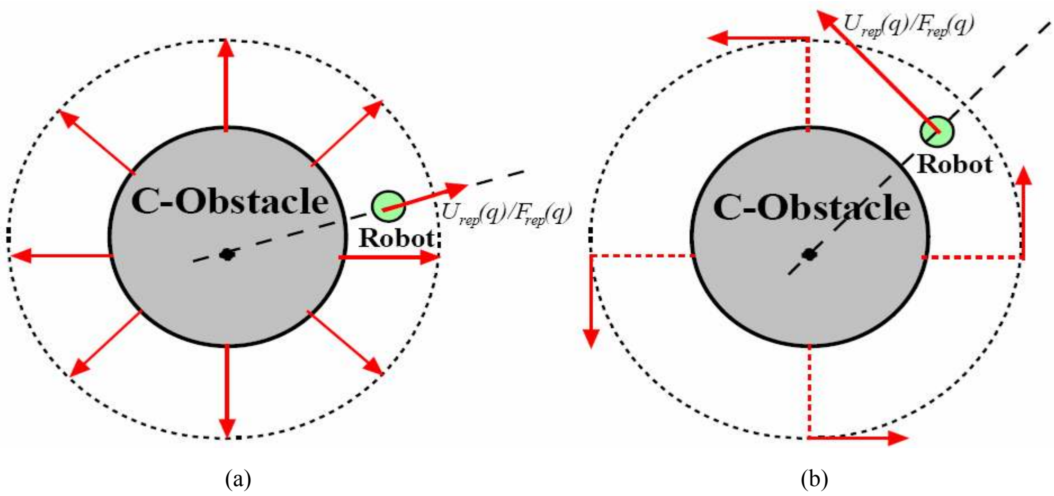
Notes: (a) $\rho(q)$ is greater than ρ_0. The APF of the robot is only attractive potential. The repulsive potential is zero. The robot moves along the direction of the attractive force. (b) $\rho(q)$ is less than ρ_0, the APF of robot is the resultant of the attractive potential and repulsive potential. The robot moves along the direction of resultant force. (c) $\rho(q)$ is less than ρ_0 and d_{Ob}, but is $\rho(q)$ greater than d_{gb}, which does not satisfy requirements of non-reachable target problem. Consequently, the APF of the robot is the resultant of the attractive potential and the repulsive potential. The robot moves along the direction of the resultant force: (d) $\rho(q)$ is less than ρ_0 and d_{Ob}; simultaneously, $\rho(q)$ is less than d_{gb}, the requirements of the non-reachable target problem are satisfied. Therefore, the non-reachable target problem emerges. Consequently, in this condition, the repulsive potential disappears instantaneously, and the APF of the robot is the only attractive potential. The robot moves along the direction of the resultant force to arrive at the target location. This modified APF is extremely effective to address such a non-reachable target problem.

Figure 5 Repulsive potential of polygonal obstacle, (a) repulsive potential defined by a traditional APF (b) repulsive potential defined by our improved APF (see online version for colours)



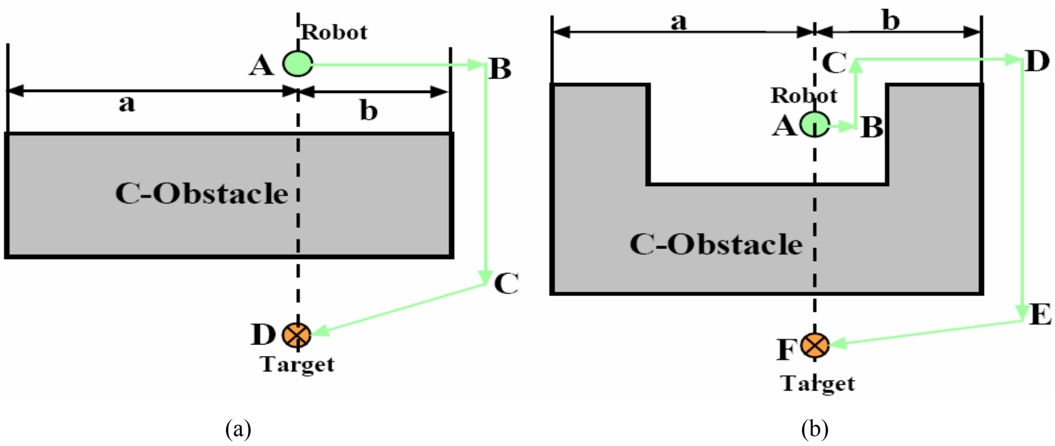
Notes: (a) The traditional APF defines the repulsive potential of polygonal obstacle as the vertical polygonal side and away from the obstacle. Near the vertex, no repulsive potential exists, which is unreasonable. (b) Improved APF, for which we redefine the repulsive potential. Its direction is the tangent of the semicircle.

Figure 6 Repulsive potential of circular obstacle, (a) traditional APF, and (b) our improved APF (see online version for colours)



Notes: (a) The traditional APF defines the direction of the repulsive circular obstacle as vertical and away from the obstacle. Such a defined repulsive potential easily causes local minima and oscillations. (b) For improved APF, we change the direction of the repulsive potential for the circular obstacle, forming the tangent of the circle.

Figure 7 Wall-following in a known environment, (a) polygonal obstacle (b) U-shaped obstacle (see online version for colours)



Notes: In complete environments, the robot knows information related to obstacles. When local minima occur, a robot compares the distance from the location of itself and two sides of the obstacle. Then it selects the shorter distance side for wall-following.

No previously proposed APF or improved APF method explicitly defines the repulsive potential or force related to the vertex of polygonal obstacles. As described by the general APF, the direction of repulsive potential or force for polygonal obstacles is the perpendicular of the polygon side and away from the obstacles, as Figure 5(a) shows, thereby it will be unreasonable because no repulsive potential or force exists near the area of vertex of polygonal obstacles (Zhang et al., 2006b). Therefore, we define the repulsive potential or force around the vertex of polygonal obstacles as in Figure 5(b). The direction is the tangential line of a semicircle (Uyanik, 2010). Similarly, we change the direction of the repulsive potential or force that results from circular obstacles (Figure 6) to resolve problems of a general APF: local minima and oscillatory movements.

3.3 *Improved wall-following*

The APF method used in robot path planning might suffer from the local minima and oscillations problem when equations (13) or (14) is satisfied as described above. During path planning, once local minima and oscillatory movements occur as shown in Figures 1(a) and 1(b) shown, we use the wall-following method presented by Sheng et al. (2010) to guide a robot to escape from local minima. This method can resolve oscillations. However, the previously proposed wall-following method requires detailed information of each obstacle. Moreover, this method can only solve local minima and oscillations in a known environment. The illustration of wall-following method is presented in Figure 7(a). Because the robot has information about obstacles, the robot compares the distance from the robot location to the two sides of obstacles. If $b < a$, then the robot moves along A–B–C–D toward the target position 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 the target to escape local minima and oscillatory movements. The wall-following method can resolve the two key problems: local minima and oscillations caused by general APF method in a known environment. Nevertheless, for the partial or unknown environment, the robot has no complete information related to obstacles. Therefore, the robot cannot know which side is closer. In other words, the wall-following method is unsuitable for use in a partially known or unknown environment. We should therefore modify the previous wall-following method to adapt to partially known and unknown environments.

Herein, we improve the wall-following method to address local minima and oscillation problems of improved APF when a robot moves in a partially or entirely unknown environment. We use the latest five steps to assess the moving tendency of the robot, and combine the wall-following method to an assistant robot to move out of local minima and oscillatory movements. The orders of our proposed improved wall-following method are the following.

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

b Both sides of the obstacle are in the sensing range of the robot. The robot compares the distances to the two sides, moves to the closer side, and follows the wall of the obstacle until it escapes from the local minima, as shown in Figure 8(b).

c No side of the obstacle is in the robot sensing range. The robot continues to move to the previous moving tendency and follows the wall of the obstacle until it escapes from the local minima, as shown in Figures 8(c) to 8(e).

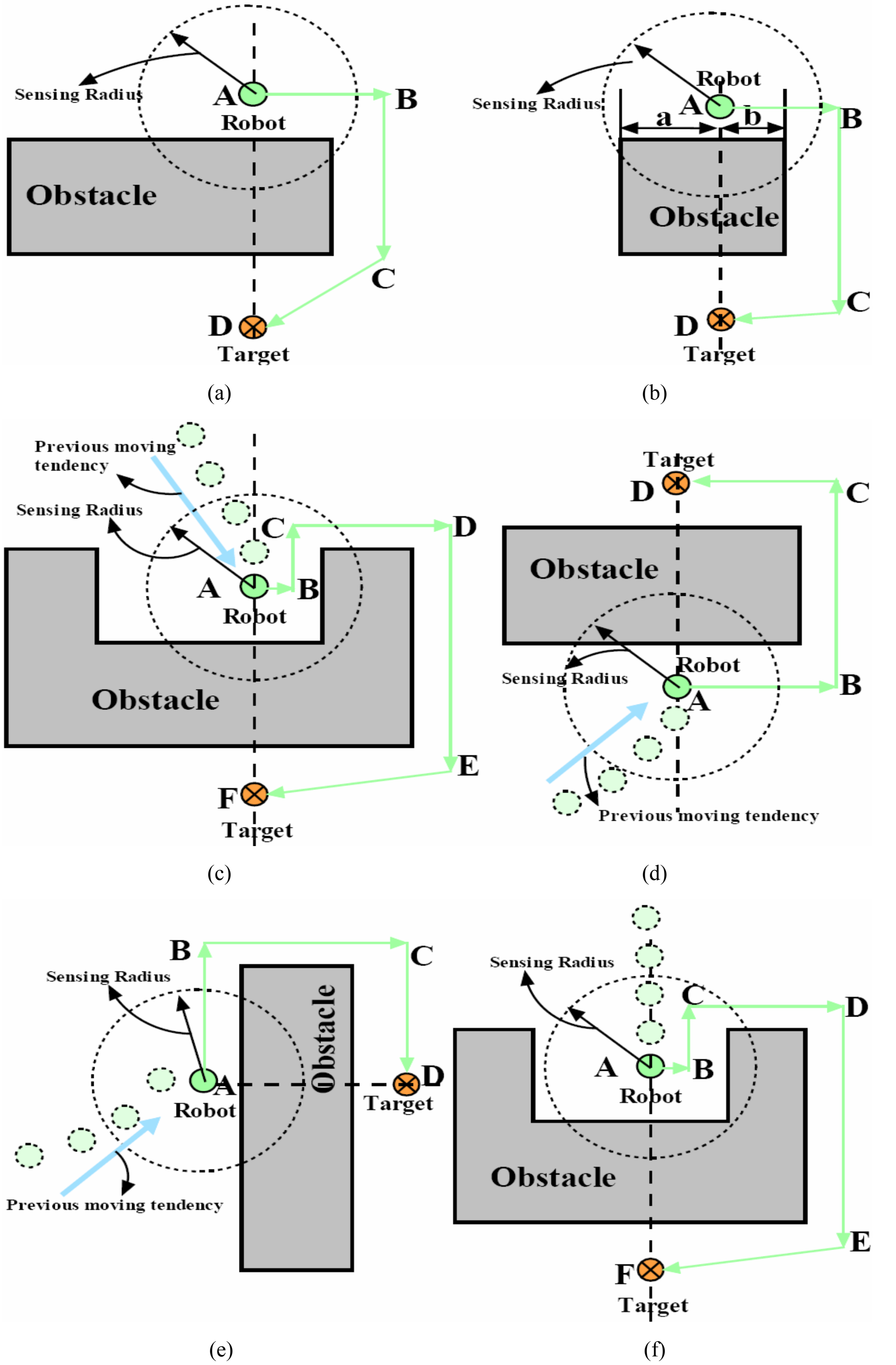
d A non-side of obstacle is in the robot sensing range, and the previous moving tendency is the perpendicular of obstacle side. The robot randomly selects one side to move along and follows the obstacle wall until escaping from the local minima, as shown in Figure 8(f).

3.4 *Regression search-based method*

Although our improved APF method can resolve local minima, oscillations, and non-reachable problems, a key problem remaining is that application of all APF methods including our method can not plan an optimal or near-optimal path in completely known environments, partially known environments, or unknown environments. This shortcoming severely limits the applications of such methods, especially for a time and energy constrained robot. Another important contribution of this paper is that we developed a RS method to optimise the planned path. The optimisation path is calculated by connecting the sequential points that were produced based on our improved APF method.

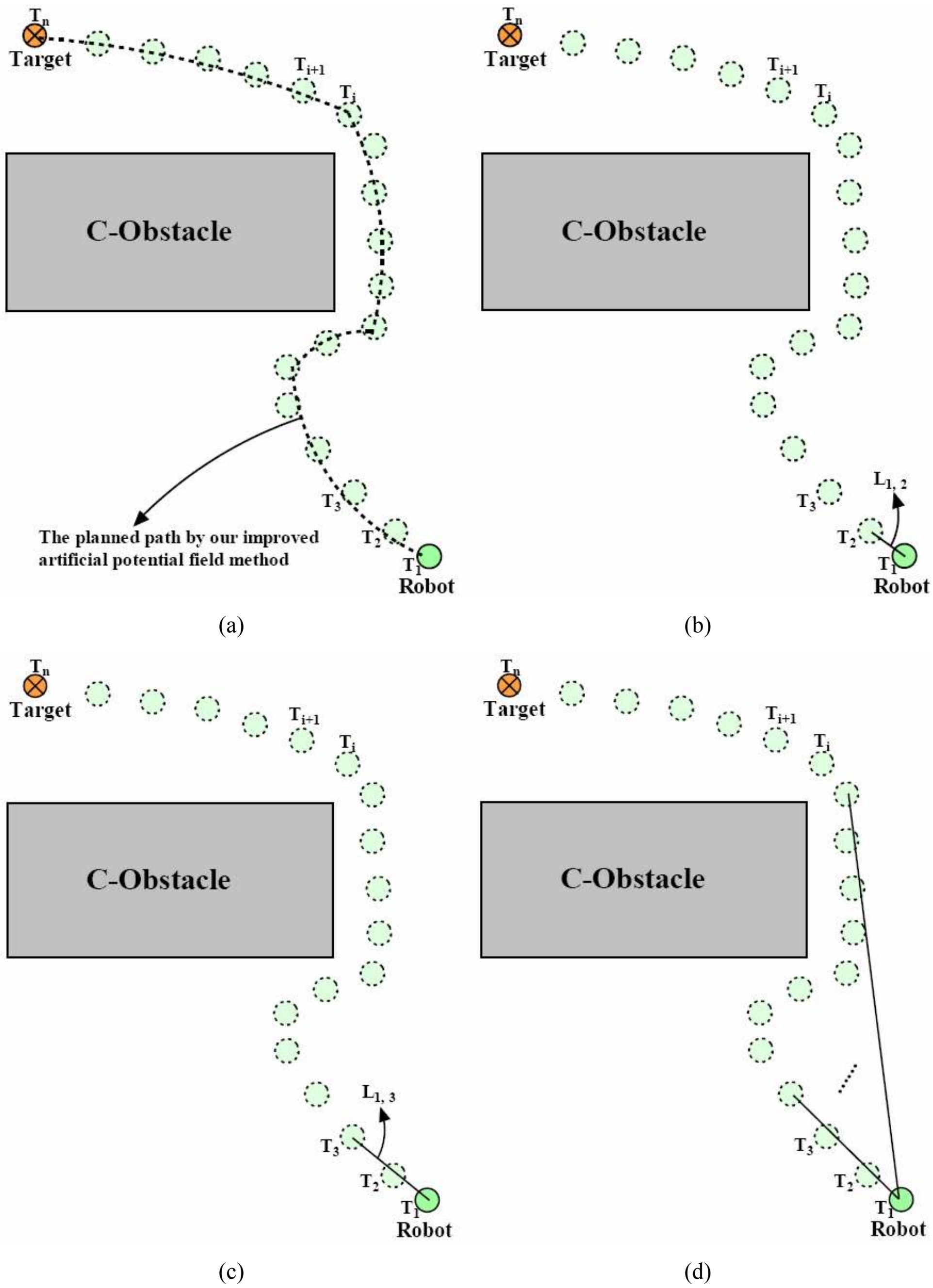
From the robot location to the destination, the inter-start point connects with the latter point sequentially as a straight line. If the connected line does not cross any obstacle, then from the inter-start point re-connects with the next latter point as a new straight line until this connected line crosses an obstacle or the distance between the connected line and the closest point of obstacles becomes less than D_0. This connected line is saved as a robot local sub-path from the inter-start point to the terminative point. Subsequently, the system produces the next new straight line from the last terminative point as the next inter-start point to the latter point as described above.

Figure 8 Improved wall-following method, (a) one side in the robot's sensing range (b) both sides in the robot's sensing range (c) no side in the robot's sensing range, example 1 (d) no side in the robot's sensing range, example 2 (e) no side in the robot's sensing range, example 3 (f) no side in the robot's sensing range, example 4 (see online version for colours)



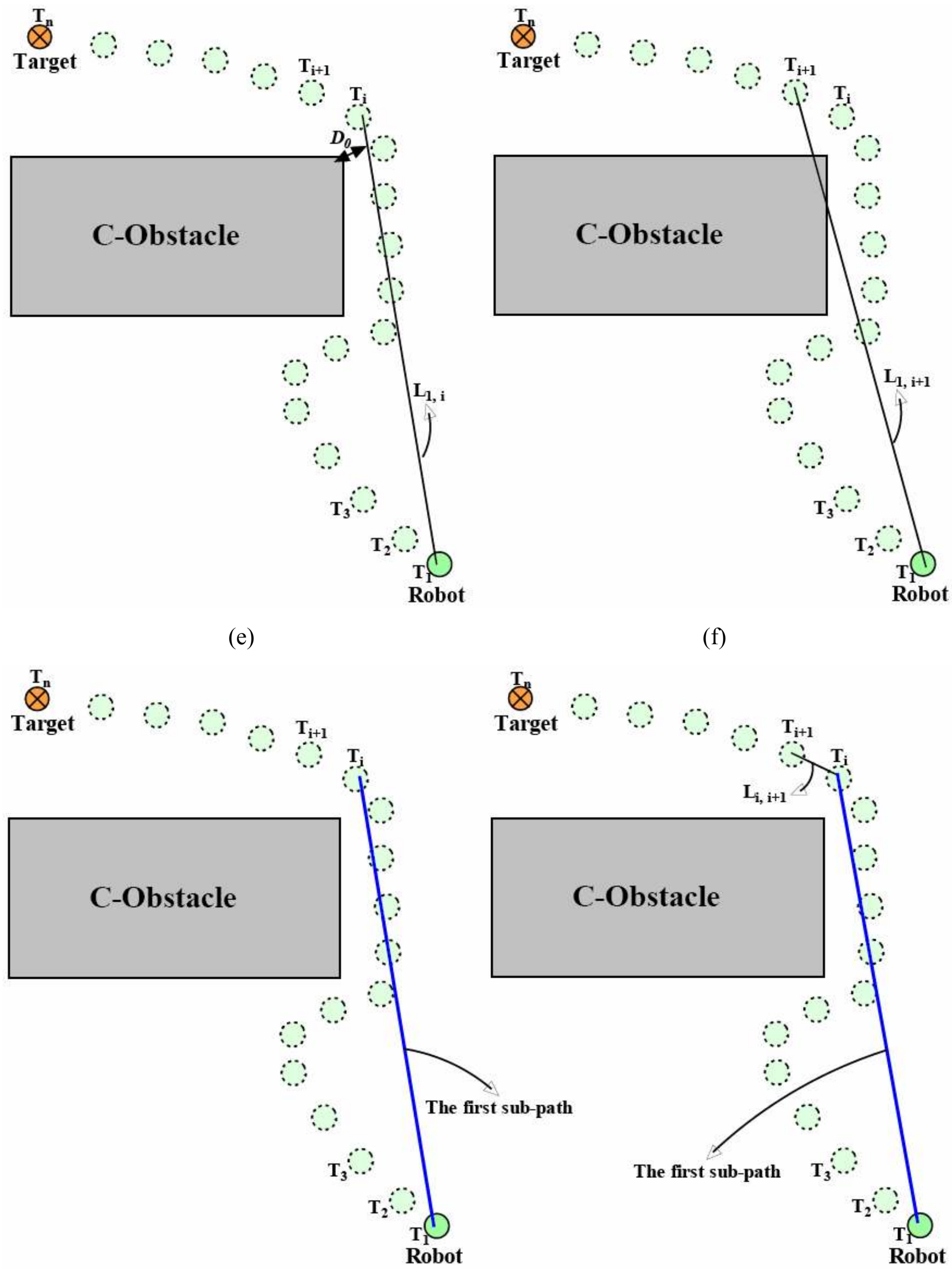
Notes: (a) One side is in the robot's sensing range. The robot does not know the distance from its location to another side. Then the robot selects the visual side to wall-following, i.e., A–B–C–D. (b) Both sides are in the robot's sensing, and the robot selects the closer side for wall-following, i.e., A–B–C–D. when there is no side in the sensing range of the robot, the robot continues to move to the previous moving tendency and follows the wall of the obstacle. (c) Previous of the latest five-step moving tendency is the lower right, where the robot follows A–B–C–D–E–F to move out of local minima. (d) Previous of the latest five-step moving tendency is the upper right, where the robot follows A–B–C–D to move out of local minima. (e) Previous of the latest five-step moving tendency is the upper right, where the robot follows A–B–C–D–E–F to move out of local minima. (f) The latest five previous moving tendencies are vertical to the side of the obstacle. The robot selects one side randomly for wall-following.

Figure 9 RS 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, (i) Step *n*–1 of RS method, (j) Step *n* of RS method, (k) Step *n*+*1* of RS method, and (l) Obtaining the optimal path (see online version for colours)



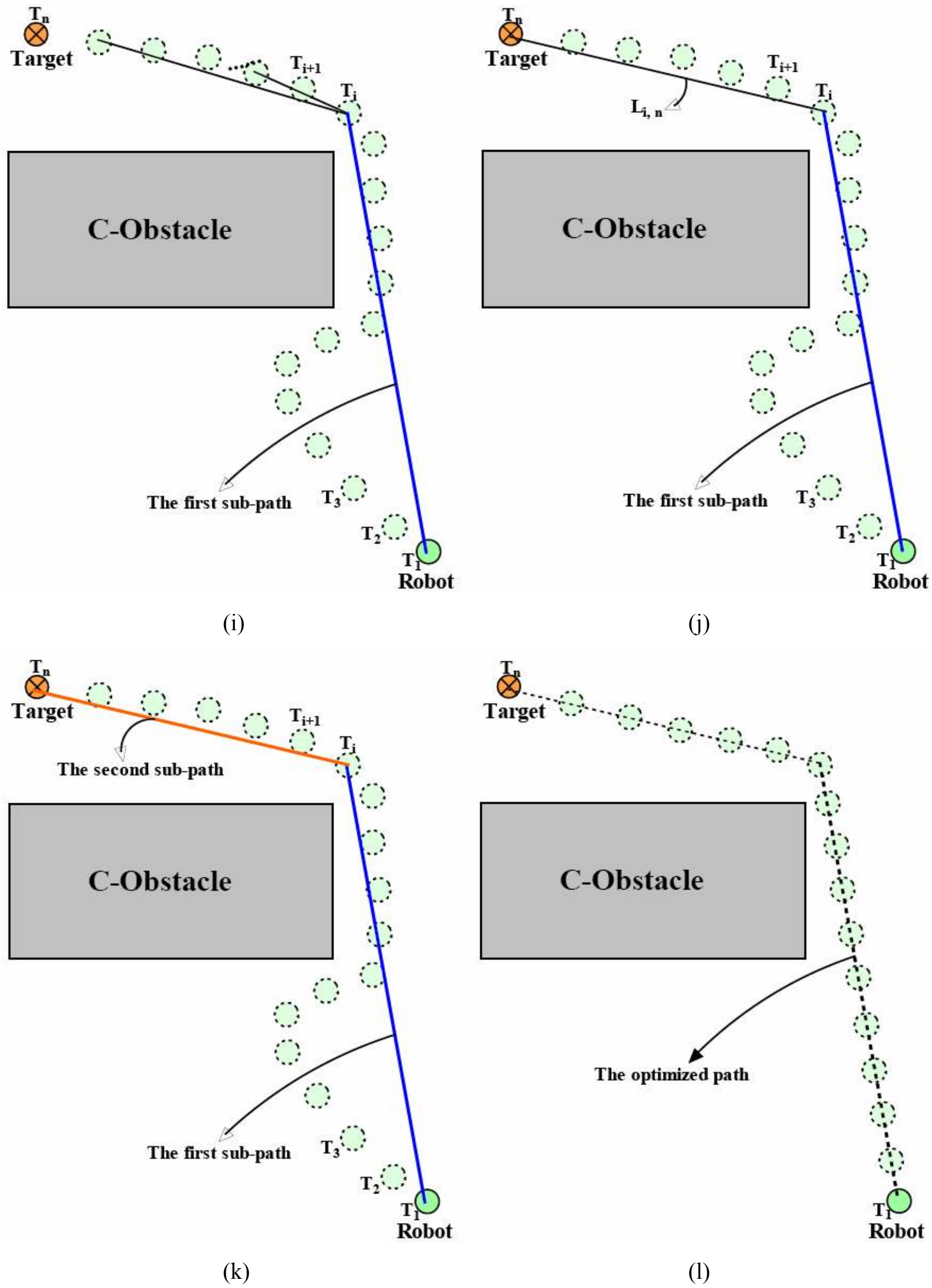
Notes: (a) From the robot location to the target position, using improved APF to produce a sequential point set. According to the sequential point set, we use RS method to optimise the planned path by connecting two points as a straight line and judging the connected line as crossing any obstacle or 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, caused by $L_{1,2}$ is a feasible line; 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 $L_{1,i+1}$ is crossing an obstacle, $L_{1,i+1}$ is not a feasible line. Therefore, the first suboptimal path is $L_{1,i}$ as (g) shown. (h) Then point T_i as the next inter-start point and connect with its next point T_{i+1}, and make a similar judgment as described above. Through (i) and (j), we can obtain the second suboptimal path as $L_{i,n}$ in (k). (l) Finally, the optimal path is planned by our improved APF-based RS method. The distance of the optimised path is much shorter than that using improved APF.

Figure 9 RS 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, (i) Step n–1 of RS method, (j) Step n of RS method, (k) Step $n+1$ of RS method, and (l) Obtaining the optimal path (continued) (see online version for colours)



Notes: (a) From the robot location to the target position, using improved APF to produce a sequential point set. According to the sequential point set, we use RS method to optimise the planned path by connecting two points as a straight line and judging the connected line as 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, caused by $L_{1,2}$ is a feasible line; 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 $L_{1,i+1}$ is crossing an obstacle, $L_{1,i+1}$ is not a feasible line. Therefore, the first suboptimal path is $L_{1,i}$ as (g) shown. (h) Then point T_i as the next inter-start point and connect with its next point T_{i+1}, and make a similar judgment as described above. Through (i) and (j), we can obtain the second suboptimal path as $L_{i,n}$ in (k). (l) Finally, the optimal path is planned by our improved APF-based RS method. The distance of the optimised path is much shorter than that using improved APF.

Figure 9 RS 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, (i) Step *n*–1 of RS method, (j) Step *n* of RS method, (k) Step *n+1* of RS method, and (l) Obtaining the optimal path (continued) (see online version for colours)



Notes: (a) From the robot location to the target position, using improved APF to produce a sequential point set. According to the sequential point set, we use RS method to optimise the planned path by connecting two points as a straight line and judging the connected line as 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, caused by $L_{1,2}$ is a feasible line; 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 $L_{1,i+1}$ is crossing an obstacle, $L_{1,i+1}$ is not a feasible line. Therefore, the first suboptimal path is $L_{1,i}$ as (g) shown. (h) Then point T_i as the next inter-start point and connect with its next point T_{i+1}, and make a similar judgment as described above. Through (i) and (j), we can obtain the second suboptimal path as $L_{i,n}$ in (k). (l) Finally, the optimal path is planned by our improved APF-based RS method. The distance of the optimised path is much shorter than that using improved APF.

We use Figure 9 as an example to illustrate the RS method based on our improved APF. Assuming that $T_i \in \{T_1, T_2, T_3 \cdots, T_i, T_{i+1}, \cdots, T_n\}$ are the sequential points planned by our improved APF [as shown in Figure 9(a)], the robot moves along the sequential points and can reach the target point without colliding with obstacles. Based on the RS method, first, 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 $L_{1,2}$ as 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 obstacle or if D is greater than D_0, then the system re-connects T_1 with T_3 as $L_{1,2}$, and performs a similar step to that described above until line $L_{1,i}$ [as shown in Figures 9(c) and 9(e)]. Because of line $L_{1,i+1}$ is a crossing obstacle [as shown in Figure 9(f)]. Therefore, the feasible local sub-path is $L_{1,i}$ [as shown in Figure 9(g)], which means that T_i is the terminative point. Because T_{i+1} is not the last point, 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 Figures 9(i) to 9(k)]. In other words, the robot movement 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(l)].

The entire algorithm of our proposed effective improved APF-based RS method is the following. An illustration of our proposed method is presented in Figure 10.

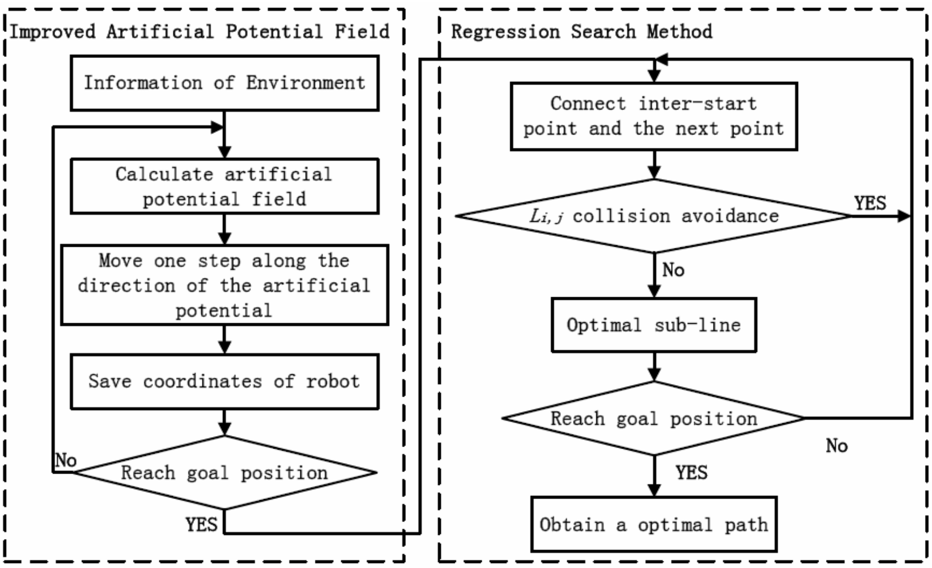
***** Improved APF method *****

1. *Compute the artificial force $F(q)$ at the 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 reaching the 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, go 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, go to step 12.*
10. *If j is not the last point of T_i, then $j = j + 1$. Otherwise, go to step 19.*
11. *Return to step 7.*
12. *T_j is the next start point, i.e., the 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, go 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, go to step 18.*
16. *If k is not the last point of T_i, then $k = k + 1$. Otherwise, go to step 19.*
17. *Return to step 13.*
18. *$j = k$, and return to step 12.*
19. *End*
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, first, improved APF is used to calculate a valid path; then RS method is used to shorten the planned path distance.

4 Experiments and results

This section presents a description of the results obtained in various experiments performed under our proposed improved APF-based RS method to resolve the key problems of APF method: local minima, oscillatory movements and non-reachable target, and shortening of the planned path. These experiments confirmed that the improved APF method solved all important problems using extremely simple orders: redefine attractive and repulsive potential function, redefine the APF of nearby vertexes of polygonal obstacles, change the direction of repulsive potential field for circular obstacles, and improve the previous wall-following method to extend this method to be applicable for partially known or unknown environments. The wall-following method is extremely good at dealing with local minima and oscillations in the known environments.

Although our improved APF method can calculate a valid path for the robot, as with many conventional APF methods, the planned path is not optimal or is sub-optimal compared with almost all classic methods and most heuristic approaches. This is the vital constraint that such a method imposes on robot systems, especially for a real robot system when we consider the common path planning problem criteria: distance of planned path, computational time and robot travelled energy. Therefore, we proposed a RS method to reduce the distance of the planned path by our improved APF method. The experiment results also prove that the final obtained path under our proposed method is a optimal or approximate optimal path. That is, we use the simplest method to solve the most difficult domains for intelligent robot systems. This method is believed to be extremely useful for autonomous distributed multiple robot systems because the computational time and complexity are the two most important problems for such systems.

4.1 Simulation environment settling

Numbers of simulation experiments are conducted for proving the validity and feasibility of our proposed algorithm using VC++, a 2.52 GHz CPU (Core i5; Intel Corp.) with the Windows 7 OS (Professional Microsoft Corp.). The environment is setting as square with 20 m width, a free configuration space (free C-space), shown in Figure 11. The coefficient k for calculating the attractive potential or force is 0.3. To prevent the planned path from being affected by far away obstacles sufficiently, we set the positive coefficient d as 3. The positive scaling factor of the repulsive potential or force η is 2.0. The largest impact distance for a mobile robot from obstacle ρ_0 is 0.5. The distance d_{Ob} between the obstacles and target is 0.4 and d_{gr} is 0.6, which is the setting to solve the target non-reachable problem. For obtaining an optimal collision-free path based on the improved APF method, the D_0 = 2 is used. We assume that the moving step of the robot is 0.1. Table 1 presents detailed parameters. Furthermore, the robot is omni-directional.

Figure 11 Simulation environment

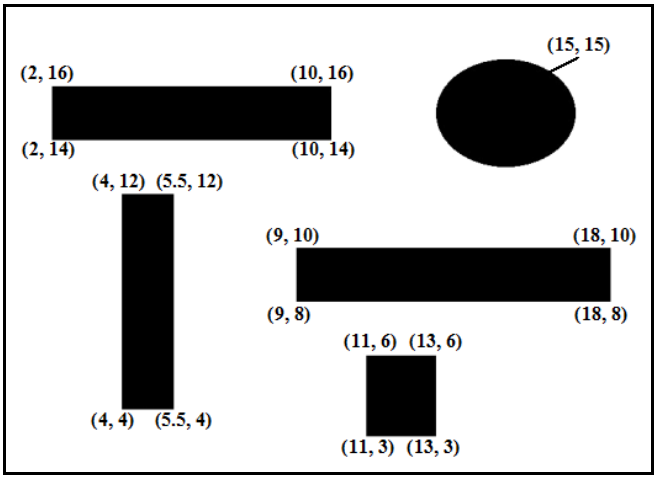


Table 1 Parameters of our algorithm

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

4.2 Improved APF method

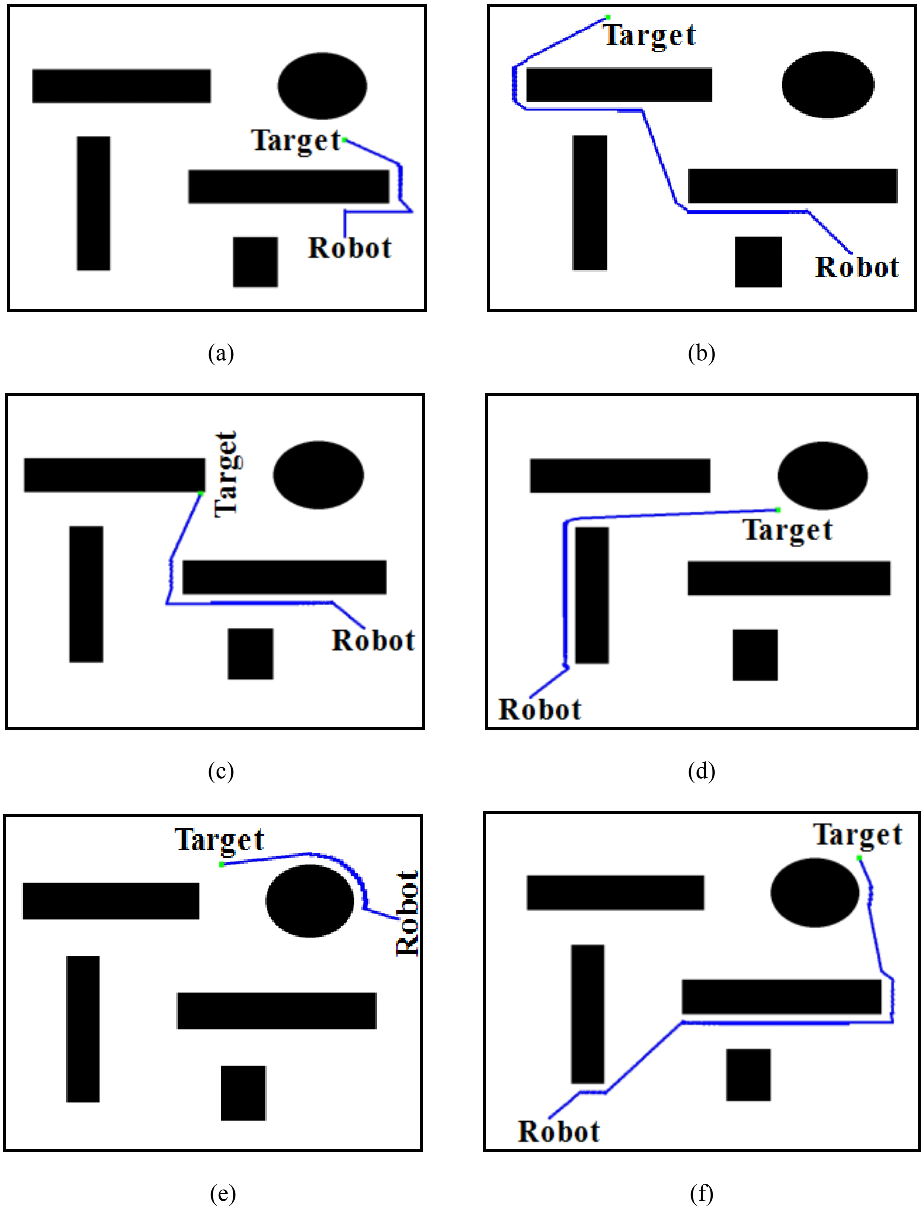
Local minima, oscillations and non-reachable target problem are the three fatal problems for the conventional APF method. Herein, we presented the results obtained in various experiments performed under our improved APF method in completely known environments. In the next section, we discuss robot path planning in partially known or unknown environments.

As Figure 12 shows, when the attractive potential and the repulsive potential are collinear reverse [Figure 12(a)], the robot will fall into local minima when 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 a local minimum problem using the improved wall-following method. Additionally, when the artificial attractive potential and repulsive potential satisfy equations (13) or (14), the robot will suffer from oscillations and a local minima problem that result in the robot never arriving at the desired goal position. As Figure 12(b) shows, the improved wall-following method can assist a robot in moving out of these problems once the difference between attractive potential or force and repulsive potential or 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 increased value of attractive potential or force, the closer a robot is to a target, the smaller the attractive potential or force is, in the desired position of target, the value is zero. By contrast, the repulsive potential or force is inversely proportional to the distance between robot and obstacles. The value of repulsive potential or force exponentially increases along with the distance reduction. That cause when target close sufficient to obstacles, the robot never approaches the target, e.g., a non-reachable target problem. Figure 12(c) shows that our method can plan a safe path to a target even when the target is sufficiently close to obstacles.

We described above that conventional methods did not discuss the repulsive field for the vertex of polygonal obstacles, which is a normal reason leading a robot to local minima and oscillations. In this paper, we implement a 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 indicated in Figure 12(e). Figure 12(f) shows a complete path without local minima, oscillations, non-reachable target, or any other problem using our proposed improved APF method.

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, and (f) complete planned path (see online version for colours)

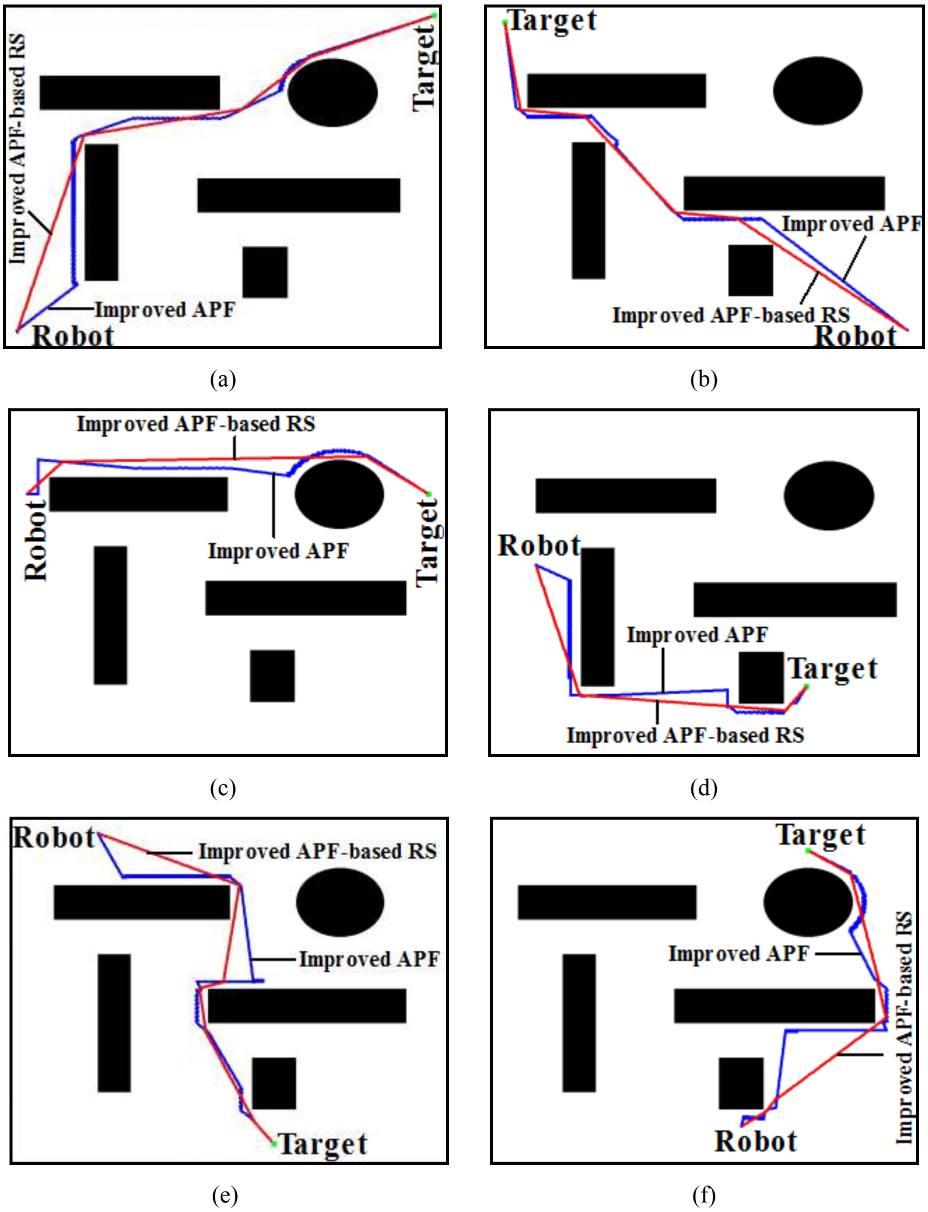


Notes: (a) We use improved wall-following method to address local minima, with the distance from the robot to the right side as shorter than the left side. Therefore, the robot follows the right side wall of the obstacle. (b) When both sides of the obstacle are out of the robot's sensing range, the robot determines the previous moving tendency according to the latest five steps. Therefore, the robot follows the left side wall to escape oscillations. (c) Because the target is close to the obstacle, once the requirements are satisfied, the robot moves along the attractive potential. (d) We redefined the repulsive potential for the vertex of the polygonal obstacle. (e) We changed the direction of repulsive potential for the circular obstacle. (f) The robot can plan a path with no problems using our improved APF method.

4.3 Optimisation of the planned path for a static target

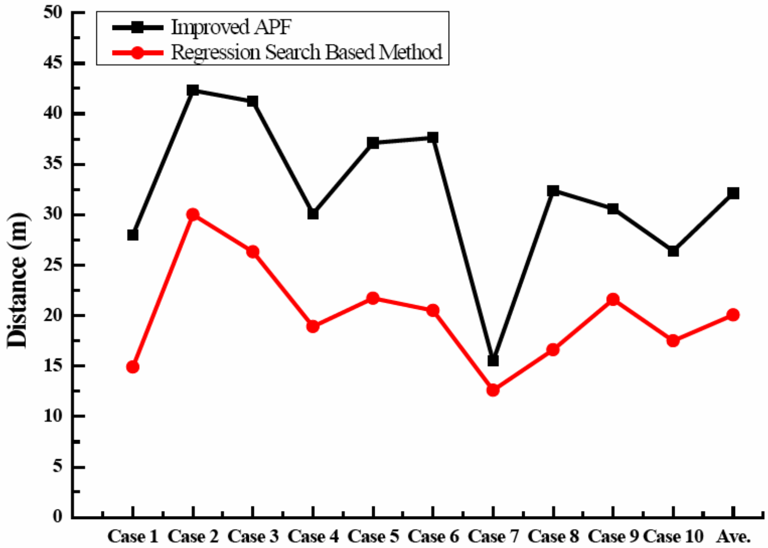
The three most important evaluations of path planning method are the distance of the planned path, computational time and robot travelled energy. To reduce the distance of planned path, many classic and heuristic path planning methods are proposed, but the costs of these methods are a long time necessary for computations and a complex structure. In contrast, APF methods entail less computational time and the simplest mechanism, although the computed path of APF methods is not optimal or near-optimal, which limits these methods to application to time-constrained and energy-constrained robots. We propose a RS method under improved APF method to optimise the planned path. The results are presented in Figures 13 to 15.

Figure 13 Planned path obtained using the improved APF-based RS method, (a) path planning in a known environment, example 1 (b) path planning in a known environment, example 2 (c) path planning in a known environment, example 3 (d) path planning in a known environment, example 4 (e) path planning in an unknown environment, example 1 (f) path planning in an unknown environment, example 2 (see online version for colours)



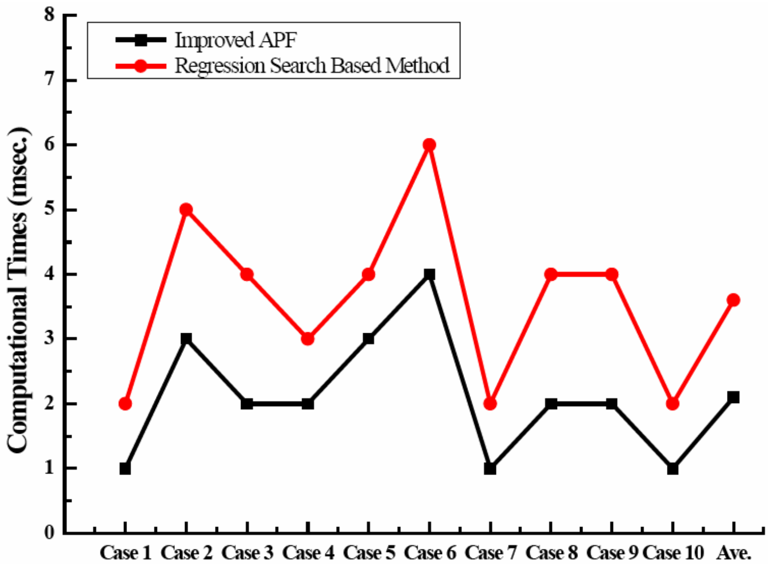
Notes: Blue line is the path planned using our improved APF method, whereas the red line is the optimal path using RS method. (a–d) Path planning in known environments. (e–f) Path planning in partially known or unknown environment. The red path distance is based on the improved APF-based RS method. It is shorter than blue path under only improved APF in each condition.

Figure 14 Distance of planned path (see online version for colours)



Notes: The black rectangle point represents the distance of the planned path by improved APF, with the 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 the improved APF, which means that the improved APF-based RS method can conserve more energy for the robot. The right most are the average distance of ten simulations. The average distances of ten cases are, respectively, 32.12 m and 20.06 m using the improved APF method and the improved APF-based RS method.

Figure 15 Computational time (see online version for colours)



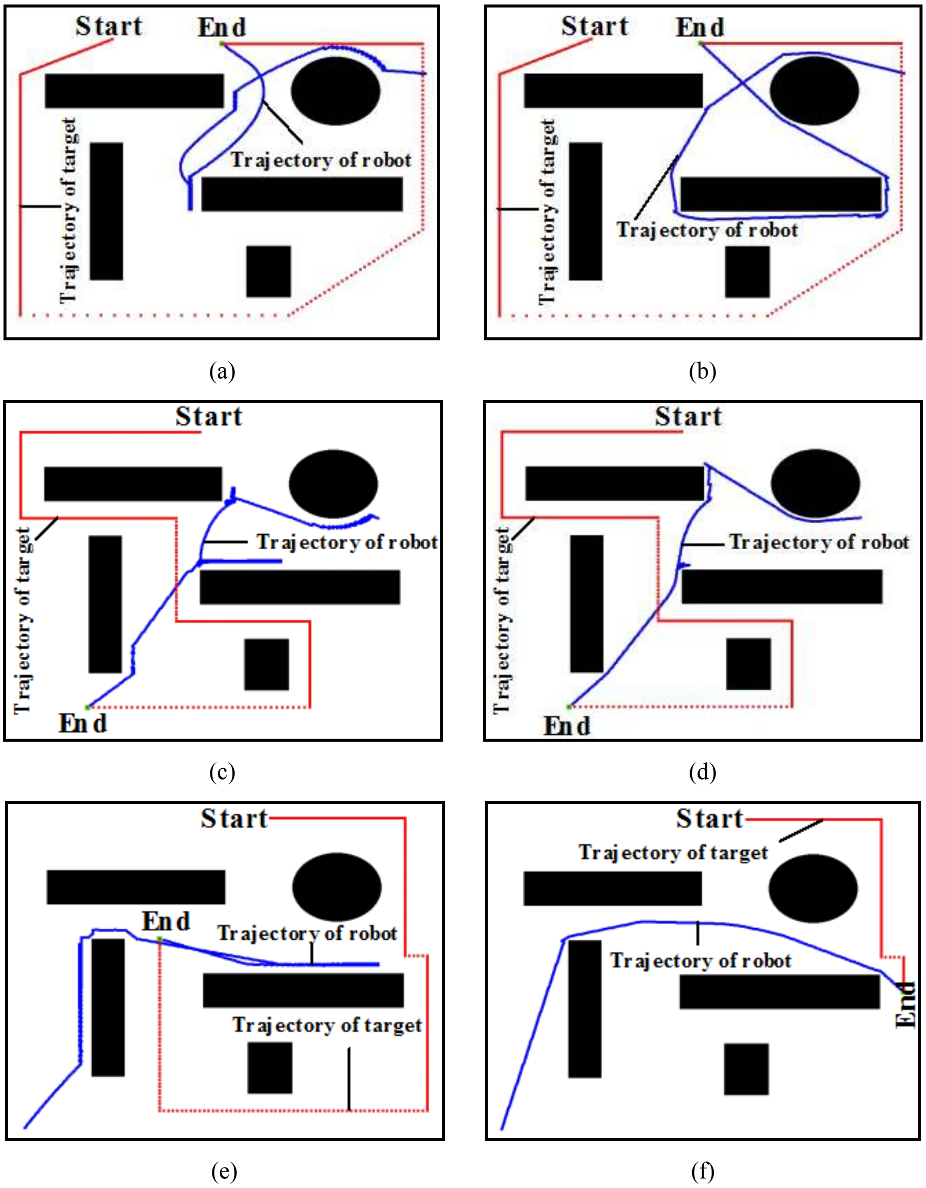
Notes: The black rectangle points show the computational time of the planned path by improved APF. The red circular points show computational times of the planned path based on improved APF-based RS method. For each condition, the improved APF-based RS method needs slightly more computational time than the improved APF. The right most are the average distances of ten simulations. The average computational times of ten cases are, respectively, 2.1 ms and 3.6 ms using the improved APF method and improved APF-based RS method.

In Figure 13, the blue line shows a path planned using our improved APF method, whereas the red line is the optimal path using RS method. Figures 13(a) to 13(d) show the path planning problem in known environments. The complete information of obstacles and environment are known for the robot. When the robot encounters local minima and oscillations, the robot can select the shorter distance side to wall-following. Ultimately, the robot computes a valid and safe path. Figures 13(e) and 13(f) show the robot working in partially known and unknown environments. The robot only knows the positions of itself and the target, whereas the information related to obstacles is unknown for the robot. A robot senses obstacles and judges whether it is in local and oscillatory movements. If it is, then it implements our improved wall-following method to guide robots to escape these problems. As Figures 13(e) and 13(f) show, the robot moves along the tendency of the latest five steps and then follows the wall of the obstacle.

In the figures, the red paths are markedly shorter than the blue paths in conditions of various kinds. Moreover, the optimal paths have non-oscillations which can conserve a robot's travelled energy. The experiment results indicate that our improved APF-based RS method conforms to the important criteria: the planned path distance and the robot travel energy.

Figure 14 shows the distance of the planned path with the improved APF method and improved APF-based RS method, the black rectangle points show the distance of the planned path obtained using the improved APF method, while the red circle points show the distance of optimal path based on the improved APF-based RS method. As the figure shows, it is apparent that in each case, our proposed algorithm greatly reduces the distance of the planned path from the robot location to the target position, the average distances of these ten cases are 32.12 m and 20.06 m, respectively, using only improved APF method and improved APF-based RS method. Therefore, the result demonstrates that the RS method is extremely efficient to optimise the planned path using the general APF method.

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 different trajectories of moving target and the initial robot position (see online version for colours)



Notes: Red represents the trajectory of the moving target, whereas blue represents the robot trajectory. We used the improved APF method and improved APF-based RS method to plan path for dynamic target at the same conditions. (a) Initial robot and target positions are (19, 16) and (5, 19). (b) Initial robot and target positions are (17, 13) and (10, 19). (c) Initial robot and target positions are (1, 1) and (10, 19.5).

Because the structure of the improved APF method is very compact and the algorithm is not so complex, this method only consumes 2.1 ms on average, although our improved APF-based RS method required 3.6 ms on average, only 1.5 ms more computational times (as Figure 15 shown) compared to the improved APF method. The short computational time also satisfies the common path planning problem criterion: computational time, which is extremely important for large-scale distributed multi-robot systems.

4.4 Dynamic target in known environments

The short computational time of improved APF and improved APF-based RS method makes them very suitable to plan paths for dynamic targets in a known environment. At every step, the target changes its position and the robot should re-plan the path to the target. If the computational time is very long, almost all classic path planning algorithms and most heuristic methods cannot perform real-time path planning for the robot. Figure 16 (*–1) shows the trajectory that a robot approaches toward moving target using the improved APF method, while Figure 16 (*–2) shows the trajectory by which a robot approaches a moving target using our improved APF-based RS method in the same condition. We simulated eight different cases and compared the consumed time steps using the two methods. The results are presented in Figure 17. The figure clarifies that even for a path planning problem for a dynamic target in a known environment, our proposed improved APF-based RS method distinctly reduced the consumed time steps by which the robot approaches the target position compared to improved APF method.

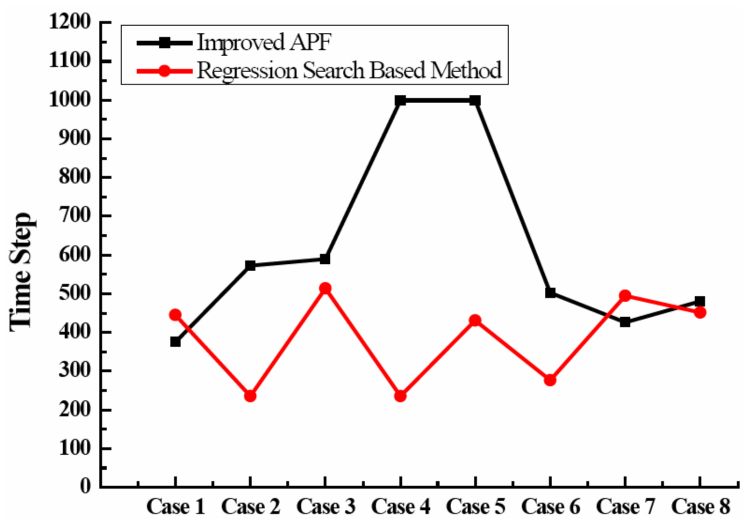
4.5 Dynamic target and moving obstacle in partial known environments

All conventional APF methods and variational methods do not fit with partial known environments. Fortunately, the proposed method can solve any condition in partial known environments using our improved wall-following method. As section 3.2.3 shows, we use the latest five steps moving tendencies to assist robot approaches to the target location. Figure 18 presents results in simulation based on our improved APF method and improved APF-based RS method, by which information about static obstacles, robot and target positions are known for the robot, while the information of moving obstacles is unknown. The sensing range of robot is 3 m, omni-directional.

4.6 Local sensing range, dynamic target and moving obstacles in unknown environments

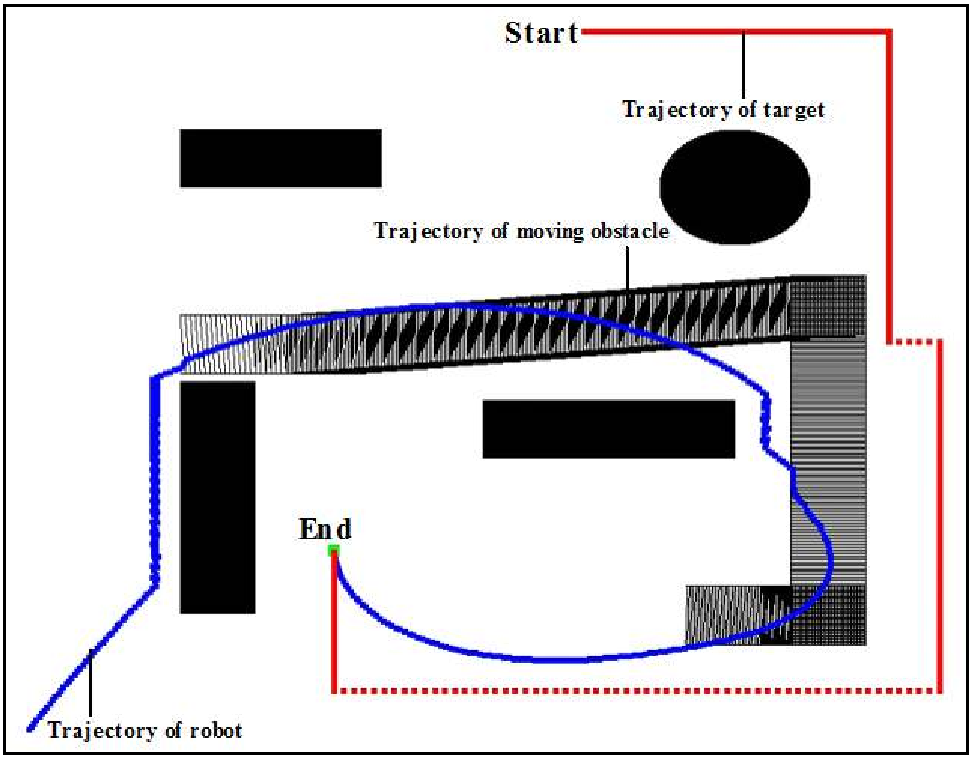
To demonstrate more applications of our proposed method, we simulated path planning for a local sensing range of a robot, a dynamic target, and moving obstacles in unknown environments. Path planning in unknown environments is impossible for classic path planning algorithms. It is extremely difficult for heuristic path planning algorithms. We assumed that the only locations of the robot and target are known for the robot, and that the sensing range of a robot is 3 m omni-directional. Figures 19 to 21 respectively show a local sensing range robot path planning for a static target, dynamic target, and a dynamic target with a moving obstacle.

Figure 17 Consumed time steps (see online version for colours)

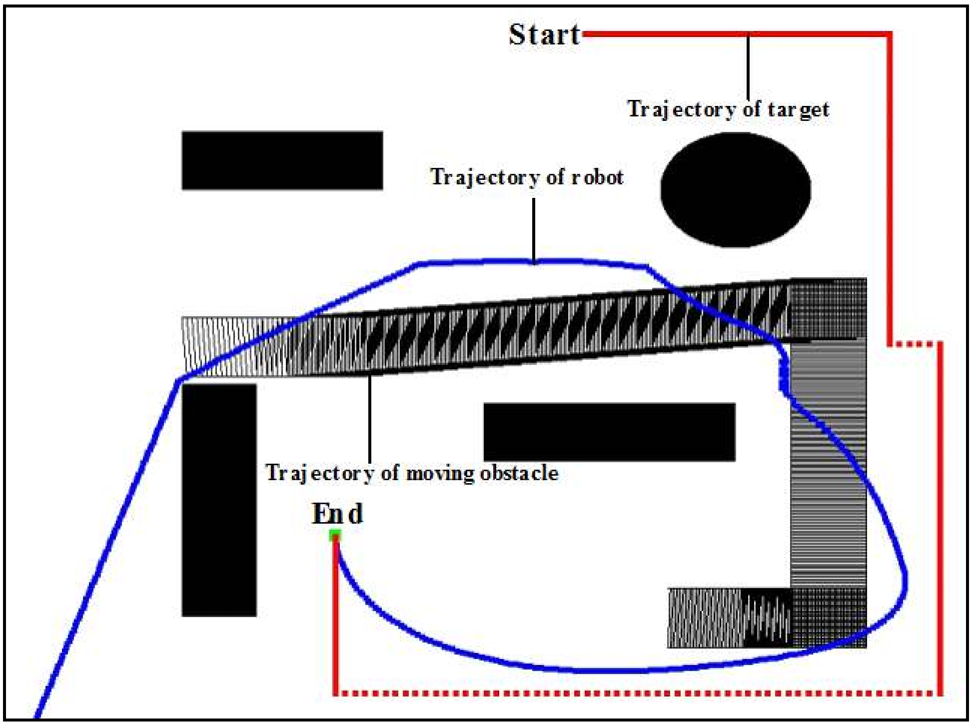


Notes: Black rectangle points represent consumed time steps by improved APF. Red circular points show consumed time steps based on improved APF-based RS method. In most conditions, the improved APF-based RS method consumed fewer time steps to approach a moving target than improved APF, which means that the improved APF-based RS method can conserve more energy for the robot.

Figure 18 Path planning for dynamic target and moving obstacle, (a) improved APF method and (b) improved APF-based RS method (see online version for colours)



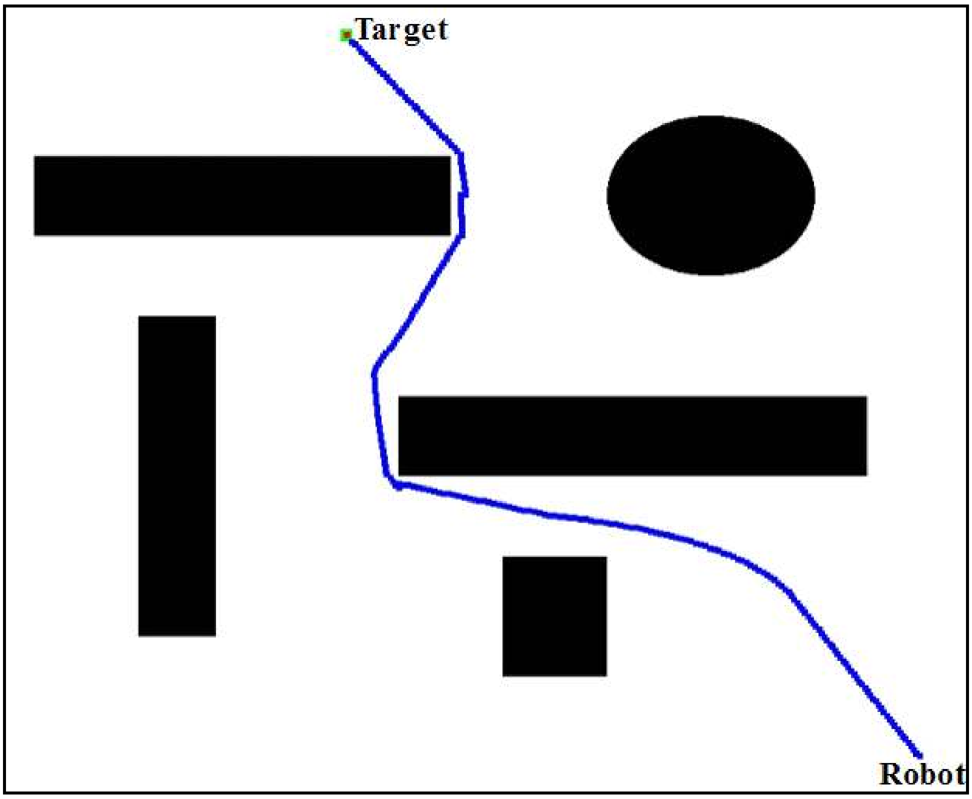
(a)



(b)

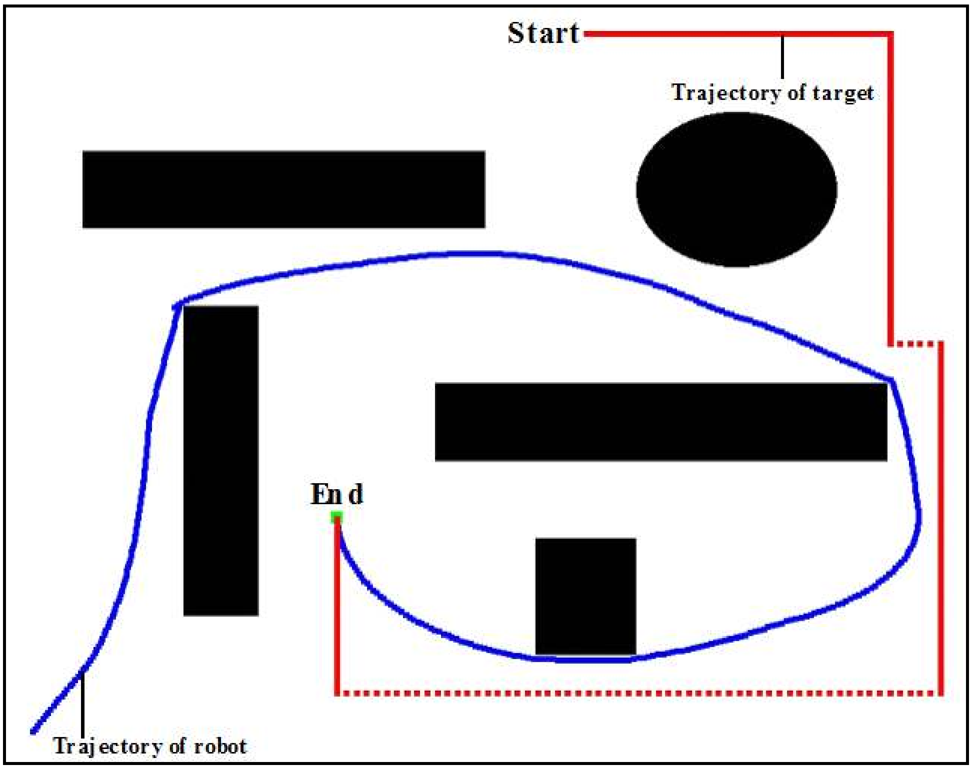
Notes: A partial known environment means information about static obstacles, coordinates of the target and robot are known by the robot, but the robot does not know information related to moving obstacles. Red is the trajectory of the moving target, whereas blue shows the robot trajectory. The initial robot and target positions are (1, 1) and (12, 19). We used improved APF method and improved APF-based RS method to plan a path for a dynamic target at the same conditions.

Figure 19 Path planning of local sensing range for a static target (see online version for colours)



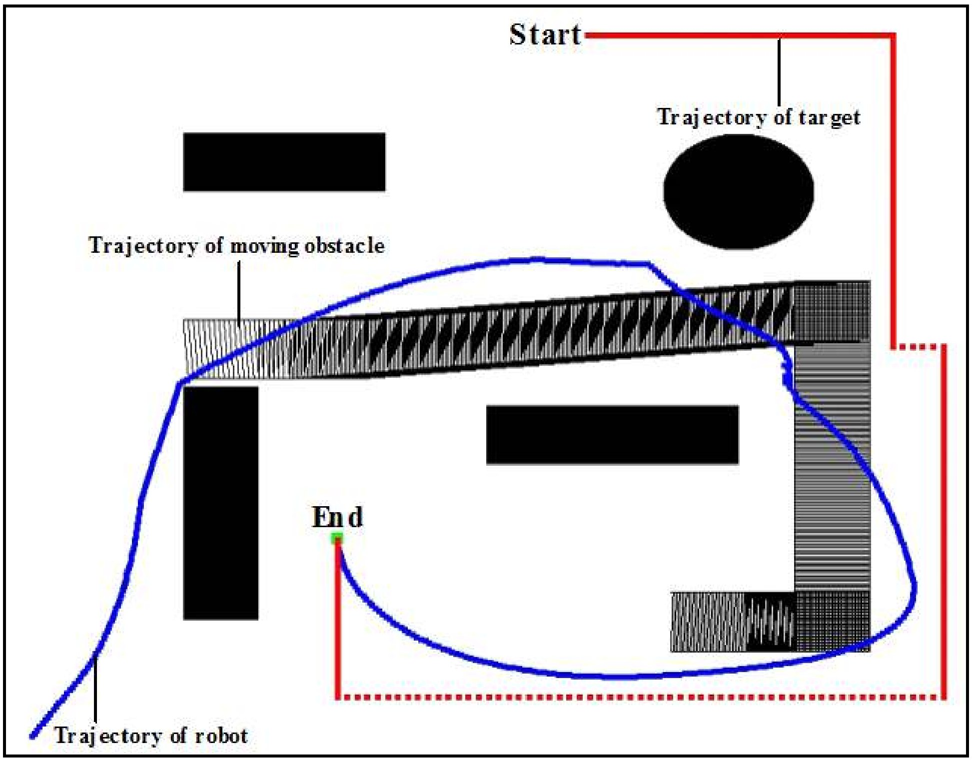
Notes: In an unknown environment, the robot only knows its position and the target's position. Information about obstacles is not known by the robot. The robot's sensing range is 3 m omni-directional. The robot detects its working environment using a sensor. The initial robot and target positions are (19, 1) and (8, 19).

Figure 20 Path planning of local sensing range for a dynamic target (see online version for colours)



Notes: In an unknown environment, the robot only knows its position and the target's position. Information about obstacles is not known by the robot. The robot's sensing range is 3 m omni-directional. The robot detects its working environment by a sensor. Initial positions of the robot and target were (1, 1) and (12, 19).

Figure 21 Path planning of local sensing range for a dynamic target and a moving obstacle (see online version for colours)



Notes: In an unknown environment, the robot only knows its position and the target's position. Information about obstacles is not known by the robot. The robot's sensing range is 3 m omni-directional. The robot detects its working environment using a sensor. The initial robot and target positions are (1, 1) and (12, 19).

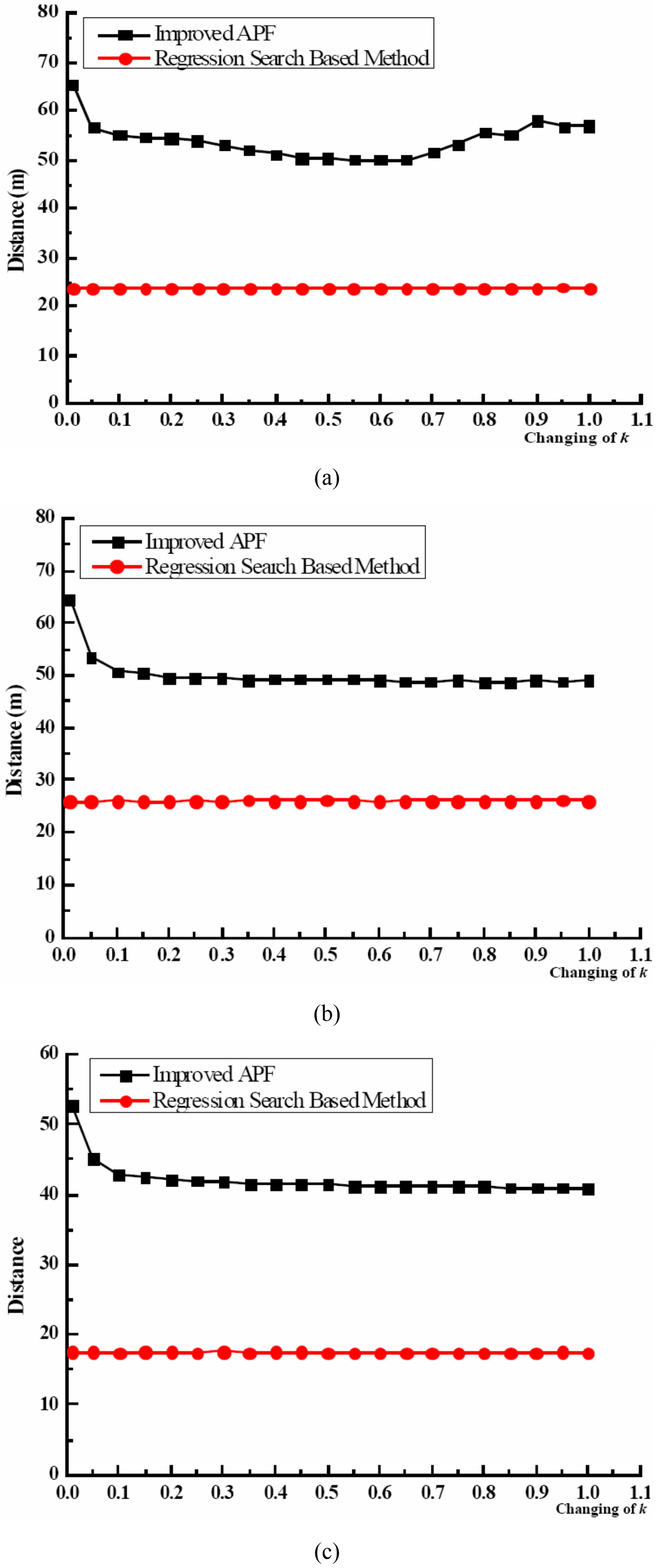
5 Discussion

5.1 Influence of parameters setting

Parameter setting is a troublesome problem for various path planning methods. It is crucial for influence of its capability and applications. The cell size is the key parameter setting for A* algorithm and D* algorithm. When the cell is large, the computational time will increase rapidly, although the distance of the planned path and robot travelled energy are not exactly. An unacceptably long computational time is necessary to obtain an optimal path. Similarly, for a genetic algorithm, a colony optimisation algorithm, neural network, a particle swarm optimisation and many others, the parameter setting is the most difficult problem that strongly influences these methods' performance and practicality. To reduce the computational time and to obtain the optimal planned path, some methods demand the use of a learning method to determine the values of parameters before path planning.

As other path planning methods, we must set several parameters in advance for our improved APF-based RS method. The main parameters which affect the performance of our method are k for attractive potential, and η and ρ_0 for repulsive potential. Other parameters are set to guarantee that a robot avoids obstacles and approaches the target. The changing of these parameters does not affect the performance. Nor do the distance of the planned path, computational time or robot travelled energy. Because of the very simple characteristics of such methods, the changing of parameters has almost no affect on the computational time, only changing the distance of the planned path and the robot travelled energy. As a result of our assumptions for a robot in a simulation experiment as an omni-directional robot, we consider that the robot travelled energy is the same as the planned path distance. Therefore, we analysed how changes 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 Figures 22 to 24. The results showed that the changing of the three parameters slightly affects the distance of the improved APF method, but there is almost no influence of improved APF-based RS method. The figures show that although we should choose parameters for improved APF method carefully 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. It is easy to extend the use of our method to many other planning problems.

Figure 22 Influence of k, (a) Case 1, (b) Case 2, and (c) Case 3 (see online version for colours)

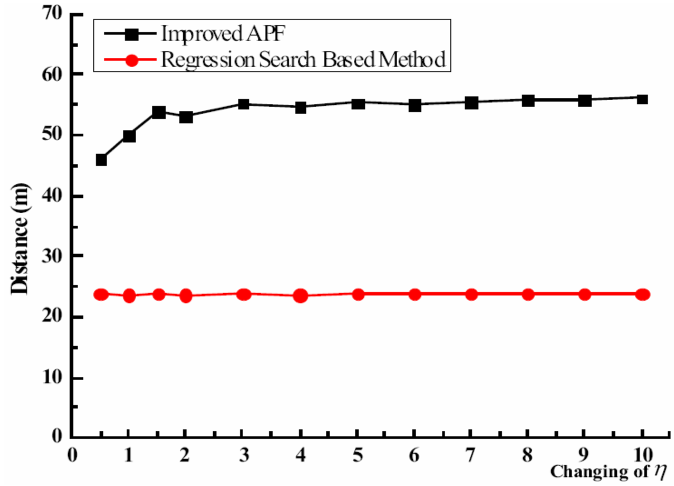


Notes: Other parameters are set as follows:

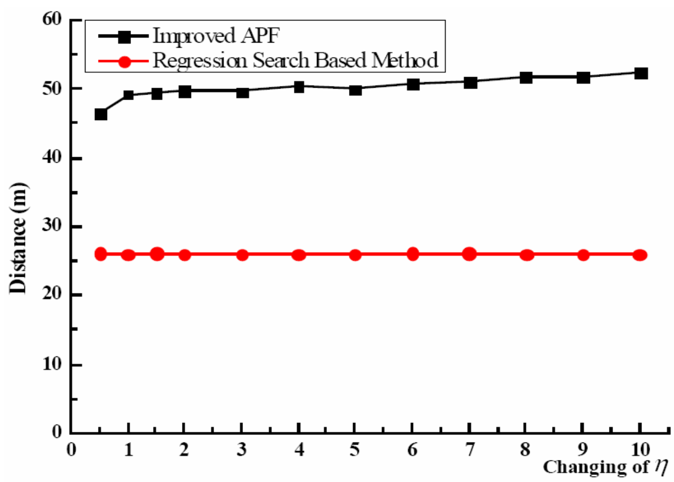
Free configuration space (C-space)	d	η	ρ_0	d_{Ob}	d_{gr}	D_0	ΔS
20 × 20 m	3.0	2.0	0.5	0.4	0.6	0.2	0.1

(a) Initial robot and target positions are (4, 19) and (12, 1). (b) Initial robot and target positions are (3, 2) and (17, 17).
(c) Initial robot and target positions are (2, 10) and (13.2, 4).

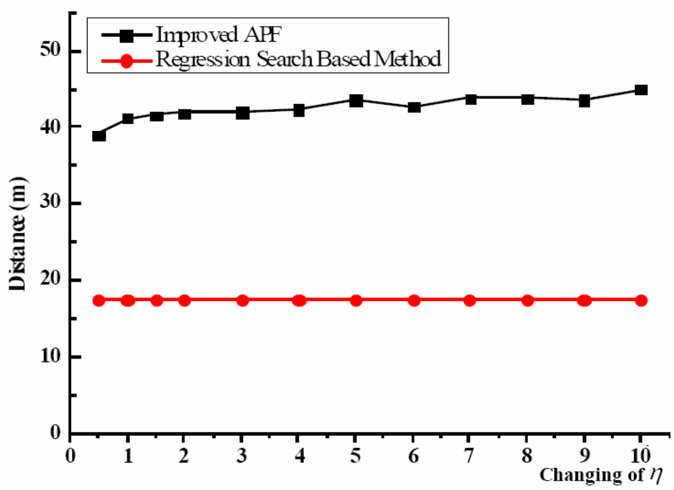
Figure 23 Influence of η in (a) Case 1, (b) Case 2, and (c) Case 3 (see online version for colours)



(a)



(b)



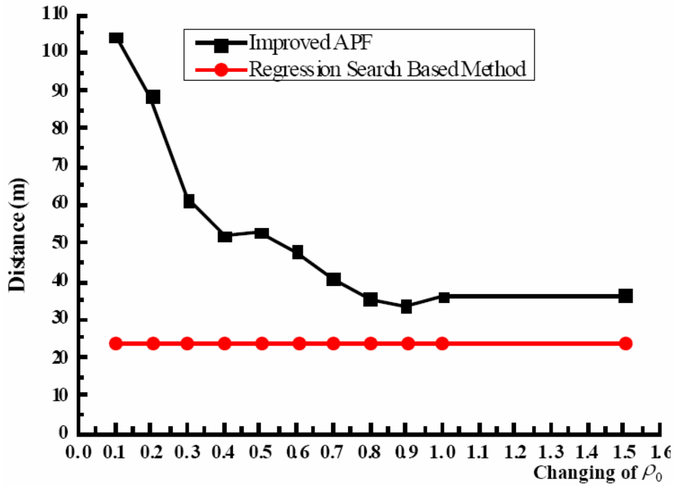
(c)

Notes: Other parameters are set as follows:

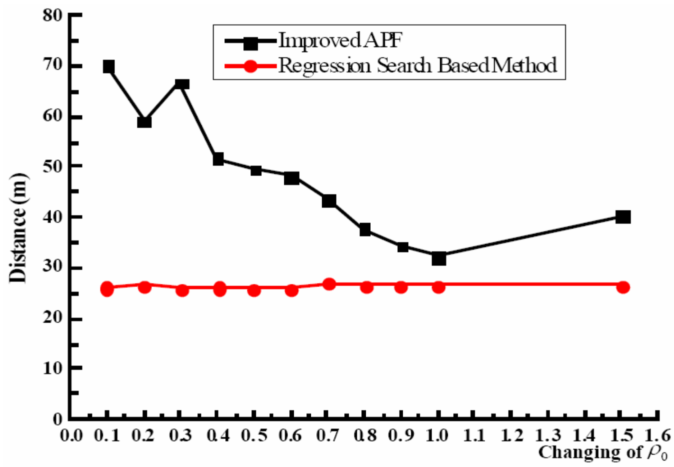
Free configuration space (C-space)	k	d	ρ_0	d_{Ob}	d_{gr}	D_0	ΔS
20 × 20 m	0.3	3.0	0.5	0.4	0.6	0.2	0.1

(a) Initial robot and target positions are (4, 19) and (12, 1). (b) Initial robot and target positions are (3, 2) and (17, 17).
(c) Initial robot and target positions are (2, 10) and (13.2, 4).

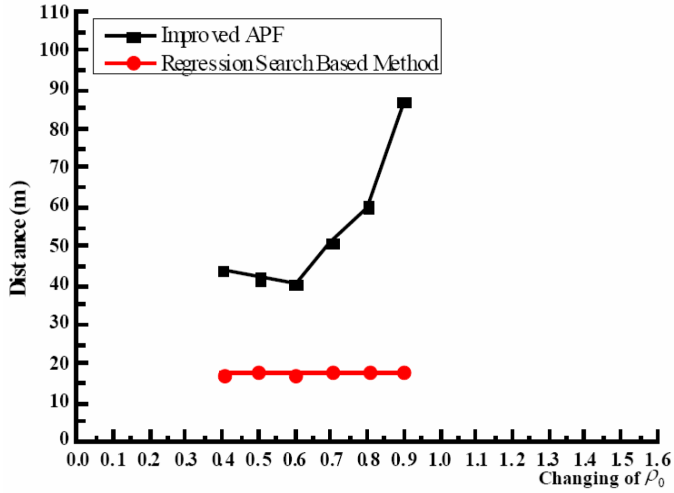
Figure 24 Influence of ρ_0, (a) Case 1, (b) Case 2, and (c) Case 3 (see online version for colours)



(a)



(b)



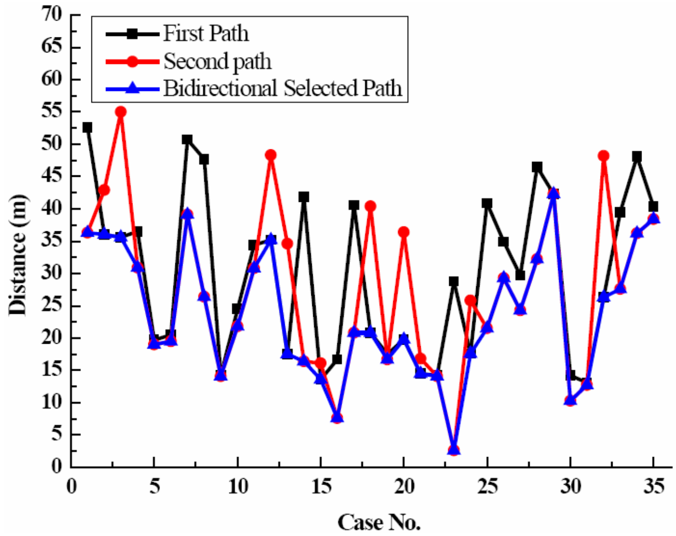
(c)

Notes: Other parameters are set as follows:

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

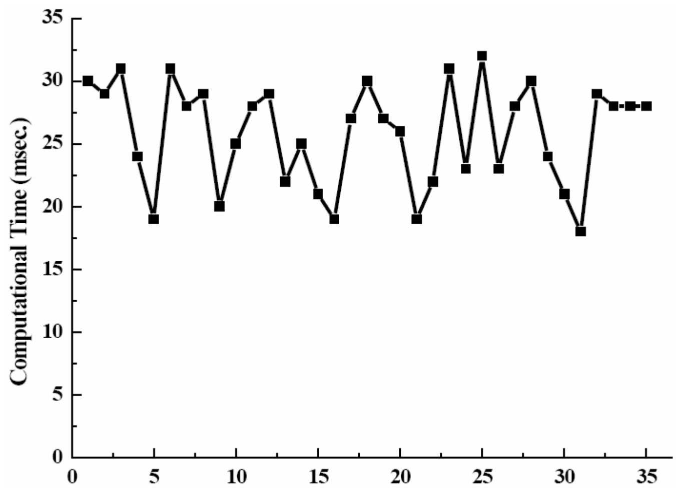
(a) Initial robot and target positions are (4, 19) and (12, 1). (b) Initial robot and target positions are (3, 2) and (17, 17).
(c) Initial robot and target positions are (2, 10) and (13.2, 4).

Figure 25 Bidirectional improved APF method (see online version for colours)



Notes: The first path is planned from the robot location to the target position. The second is planned from the target position to the robot location. A difference exists 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 described above, improved APF takes only a few milliseconds to plan a valid path, while bidirectional improved APF need ten times that of the improved APF to compute a better path. This is an acceptable computational time for small scale multiple robots systems, but for real-time middle-scale and large-scale distributed multi-robot systems, an overly long computational time is undesirable according to common path planning problem criteria.

5.2 Bidirectional improved APF

Several researchers (Zhang et al., 2006a; Uyanik, 2010) have proposed a bidirectional APF method for robot path planning. The bidirectional APF method has three steps: First, plan a path from the robot location to the target position. Secondly, plan another path from the target position to the robot location. Finally, compare the distance of the two paths; then select the shorter one as the planned path. This method invariably selects a shorter distance path. Therefore, in this paper, we use the bidirectional path planning method based on our improved APF method to assess its performance. Figures 25 and 26 present the simulation results. As the figures show, the bidirectional improved APF method can select the shorter distance path in every condition as earlier reports have described (Zhang et al., 2006a; Uyanik, 2010) described. However, the computational time is too long to obtain a better path. As described earlier (Figure 15), our proposed improved APF method only consumes a few milliseconds to compute a valid path. In contrast, the bidirectional improved APF method spends ten times that computational time to calculate a better path compared to the improved APF method. This is an acceptable computational time for small-scale multiple robots systems, but for real-time middle-scale or large-scale distributed multi-robot systems, an overly long computational time is undesirable according to common path planning problem criteria.

6 Conclusions

Path planning problems are important robotic problems for autonomous mobile robots must solve to accomplish given tasks. An effective improved APF-based RS method was proposed to obtain a global sub-optimal or optimal path without local minima, oscillations and non-reachable target problems in various environments: completely known, partially known, unknown, static, and dynamic environments. Redefined potential functions and improved wall-following methods were used to eliminate the three fatal problems for conventional APF. Because the computed path by improved APF method is not the shortest distance, we developed a RS method to optimise the planned path, and proved through simulation experiments that a safe, optimal and collision-free path can be produced for an autonomous mobile robot. The results demonstrated that our improved APF-based RS method is feasible and efficient to solve the mobile robot path planning problem. Moreover, we verified that our method is applicable for real-time path planning: a dynamic target, moving obstacles, and the local robot sensing range.

In future work, we will attend to smoothing of the planned path, improving our method for a more complex environments and making it suitable for large-scale distributed multi-robot coordination systems. We also intend to reduce the consumed computational time of the bidirectional improved APF method. Actually, our regression research method (RS method) is useful to reduce the distance of the planned path, with calculations using other path planning methods.

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