OBSTACLE AVOIDANCE FOR MOBILE ROBOTS USING ARTIFICIAL POTENTIAL FIELD APPROACH WITH SIMULATED ANNEALING

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ABSTRACT

The artificial potential field methods provide simple and effective motion planners for practical purpose. However, there is a major problem with artificial potential field approach. It is the formation of local minima that can trap the robot before reaching it's goal. The avoidance of local minima has been an active research topic in potential field path planning. As one of the powerful techniques for escaping local minima, simulated annealing which has been applied to local and global path planning. In this paper, we present and apply the mobile robot path planning technique which integrate the artificial potential field approach with simulated annealing to mobile robot.

1. INTRODUCTION

The problem of moving in space while avoiding collisions with the environment is known as obstacle avoidance or path planning. The obstacle avoidance problem is important for a mobile robot. The goal of collision-free path planning is to find a continuous path of a robot from the initial position to the goal position, while avoiding collision with the obstacles[1,2].

Path planning is studied extensively in robotics and previous related work can be classified into complete and heuristic techniques. The basic problem with the complete algorithms is that they are computationally intractable. Among heuristic (incomplete) approaches, the artificial potential field (or simply APF) methods provide simple and effective motion planners for practical purpose[3, 4, 5].

The application of artificial potential fields to obstacle avoidance was first developed by Khatib. This approach uses repulsive potential fields around the obstacles(and forbidden regions) to force the robot away and an attractive potential field around goal to attract the robot. Consequently, the robot experiences a generalized force equal to the negative of the total potential gradient. This force drives the robot downhill towards its goal configuration until it reaches a minimum and it stops. The artificial potential field approach can be applied to both global and local methods[3].

The global methods assume a priori knowledge of the workspace and are usually based on the construction of the robot's configuration space which shrinks the robot to a point. However, the global methods require that two main problems be addressed. first, the obstacles must be mapped into the robot's configuration space. Second, a path through the configuration space must be found for the point representing the robot. To generate these path, the artificial potential methods surrounds the configuration space obstacles with repulsive potential energy functions, and places the goal point at a global energy minimum. The point in configuration space representing the robot is acted upon by force equal to the negative gradient of this potential field, and driven away from obstacles and to the minimum[1, 3].

The global methods have several disadvantages. The algorithms necessary for global methods are computationally intensive. Also, the computational costs of global APF methods increase at lease quadratically as a function of the robot's degree of freedom. Thus , they are suited only for off-line path planning and can not be used for real-time obstacle avoidance[1].

A viable alternative to global methods is provided by local ones. Local methods employ the use artificial potential functions like those discussed previously. However, local potential field methods capture local information in real-time to keep the robot away the local obstacles in the Cartesian space of the robot. Consequently, the local methods circumvent the complexity of configuration space construction and representation.

However, there is a major problem with APF approach. It is the formation of local minima that can trap the robot before reaching it's goal. The avoidance of local minima has been an active research topic in potential field path planning. The main classes of treatments include: 1) the redefinition of the potential functions with no or a few local minima; and 2) the utilization of efficient search techniques with the capability of escaping from local minima[3].

The first class of treatments include: repulsive potential functions with circular thresholds of Gaussian shapes, the navigation function, the superquadratic potential function, and numerical potential field of Barraquand etc. These solutions have been shown that the local minima can be removed but at the cost of increased computational complexity. The second class of treatments employ different search techniques such as best-first, random, valley-guided, and constrained-motion techniques. But these techniques are usually slow and unrelialbe for on-line purpose and also for robots of high degree of freedom[5, 6, 7].

On the other hand, one of the powerful techniques for escaping local minima has been shown to be simulated annealing which has been applied to local and global path planning[3, 8].

In this paper, we apply the path planning technique which integrate the artificial potential field approach with simulated annealing to mobile robot through simulation and experiment using real mobile robot system. For evaluate the performances of this approach, it is compared with the path planning method using only potential field.

2. ARTIFICIAL POTENTIAL FIELD APPROACH

In the path planning of a robot, potentials are expressed in Cartesian workspace of the robot. Obstacles to be avoided are surrounded by repulsive potential functions and the goal point is surrounded by an attractive well. These potentials are added to form a composite potential. The robot moves in this field of forces as shown Fig. 1.

As one type of attractive potential function, quadratic well is most widely used. It is simple and provides a linear control raw with constant gain. Also, we use quadratic well as attractive potential function.

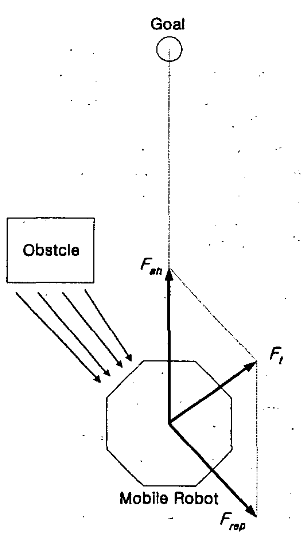


Fig. 1. Force in the artificial potential field

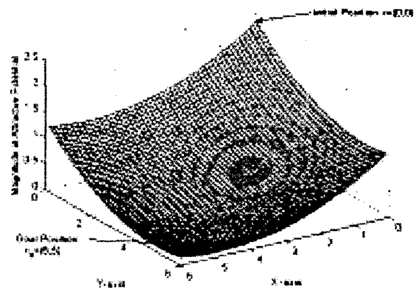


Fig. 2. Attractive potential

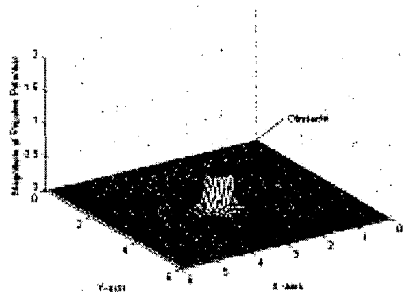


Fig. 3. Repulsive potential

The quadratic well U_{att} is described by

$$U_{att}(\mathrm{x}) = \frac{1}{2} k_a |\mathrm{x} - \mathrm{x}_d|^2$$

where k_a is constant, x is the position vector of robot, and x_d is the position vector of goal. Fig. 2. shows used attractive potential.

The force F_{att}, from this potential may be obtained by the gradient:

$$F_{att} = -\nabla U_{att} = -k_a |\mathrm{x} - \mathrm{x}_d|$$

The second category of potentials, repulsive potentials, are necessary to repel the robot away from obstacles that obstruct its path of motion in the global attractive well. It has generally been recognized that a repulsive potential should have limited range of influence. This prevents an object from affecting the motion of the robot when it is far away from the object. Also, the potential function and its derivative must change smoothly and never become discontinuous[1, 3].

In this study, We use following artificial potential field, FIRAS function proposed by Khatib[4].

$$U_{rep}(\mathrm{x}) = \begin{cases} \frac{1}{2} k_r \left(\frac{1}{\rho} - \frac{1}{\rho_0} \right)^2 & \text{if } \rho \leq \rho_0 \\ 0 & \text{if } \rho > \rho_0 \end{cases}$$

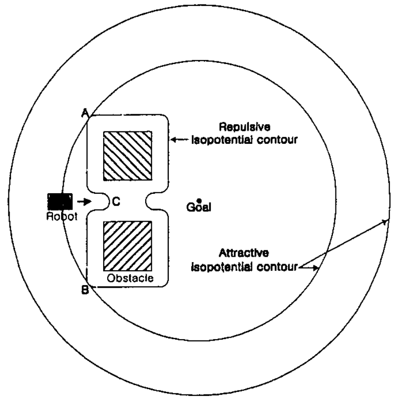


Fig. 4. Local minimum

where ρ_0 represents the limit distance of the potential field influence and ρ is the shortest distance to the obstacle. the selection of the distance ρ_0 will depend on the robot speed and on its deceleration ability. Fig. 3. shows used repulsive potential.

The force F_{ref} is described by

$$F_{ref} = -\nabla U_{ref} = \begin{cases} k_r\left(\frac{1}{\rho} - \frac{1}{\rho_0}\right)\frac{1}{\rho^2}\frac{\partial \rho}{\partial x} & \text{if } \rho \leq \rho_0 \\ 0 & \text{if } \rho > \rho_0 \end{cases}$$

The major drawback of the potential-based method is the existence of the local minima in the potential function.

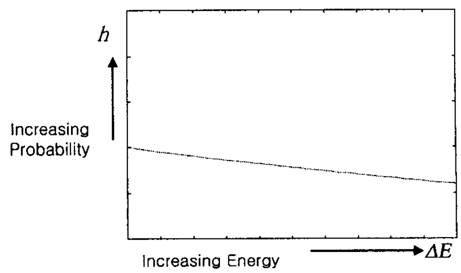
In Fig. 4, point A, B, C have the same repulsive potential. However, since point C has lower attractive potential, the robot will move to point C. Then, the repulsive force of two obstacle becomes stronger, and the robot cannot go to the goal which is the global minimum point but stays at the local minimum point called the local well[8, 9].

The local well usually exists when the radius of the attractive potential contour is larger than the radius of the repulsive potential contour.

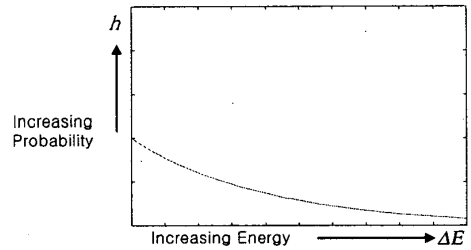
3. ARTIFICIAL POTENTIAL FIELD APPROACH WITH SIMULATED ANNEALING

The operation of artificial potential field methods is basically a gradient descent search, The search is directed towards minimizing the total potential function and therefore artificial potential field methods can be considered as steepest descent optimization procedures. However, the artificial potential field path planners may be trapped in local minima.

One solution to the local minima problem is provided by the simulated annealing algorithm which was first proposed by Metropolis et al. Kirkpatrick at al. and Cerny modified the original algorithm by letting the temperature decrease to zero with the term simulated annealing coined in[3, 10].



(a) high temperature



(b) Low temperature

Fig. 5. Uphill move acceptance probability

With the simulated annealing approach[10], at each step a new solution P' is chosen randomly from a set of neighbours of the current solution P. The new solution is accepted unconditionally if $U(P') \leq U(P)$ or else with (uphill move) probability of $e^{-\Delta/T}$ where $\Delta = U(P') - U(P)$. Here U is the cost function (i.e. potential function), and T denotes the temperature. If P' is not accepted, the algorithm proceeds to the next step the temperature is decreased by cooling rate r. This is repeated until a smallvalue near zero is reached or escape from the local minimum has occurred. Therefore the probability that an uphill move of size Δ will be accepted diminishes as the temperature reduces as shown Fig. 5.

When trapped in a local minimum, simulated annealing is applied. The simulated annealing algorithm for local planning consists of the following steps:

1. Set $P = S$ (local minimum or start-point for simulated annealing).
2. Set $T = T_0$.
3. While $T \geq T_f$ and not escaped, perform this loop:
   - 3.1. Pick random neighbour P' of P.
   - 3.2. Calculate $U(P')$, the potential at P'.
   - 3.3. Set $\Delta = U(P') - U(P)$.
   - 3.4. If $\Delta \leq 0$, set $P = P'$.
   - 3.5. If $\Delta > 0$, set $P = P'$ with probability $e^{-\Delta/T}$.
   - 3.6. $U(P') \leq U(S)$, then successful escape.
4. If not escaped, then return failure, else escape.

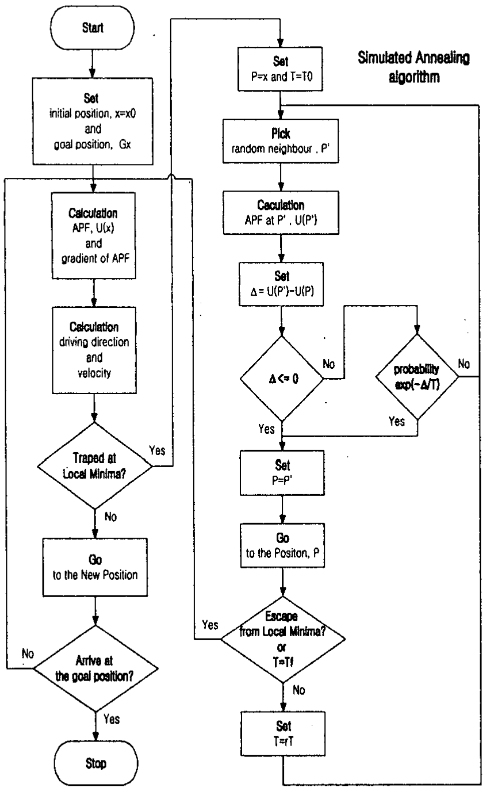


Fig. 6. Path planning algorithm

After the robot escapes from the local minimum, it follows the negative gradient. This procedure is repeated until the goal is reached. Fig. 6. shows entire path planning algorithm.

4. SIMULATIONS AND EXPERIMENTS

To evaluate the performance of the proposed algorithms, computer simulations and experiments were peformed. Table 1 and Table 2 show simulation conditions and parameters.

If local minimum is not occur, robot can reach goal using artificial potential field methods (Fig. 7), but when local minimum is occur it is trapped local minimum (Fig. 8). However, robot can escape local minimum using simulated annealing (Fig. 9)

This is verified through experiments. Fig 10 shows the mobile robot used in experiments. It has 5 ultrasonic sensors and a gyro sensor and its speed is 0.7 m/s. Table 3 shows experiment parameter. In the experiments, we can obtain similar result with the simulations (Fig. 11, Fig. 12, Fig. 13)

Table 1. Simulation conditions

Robot size	Obstacle size	Start point	Goal point	Robot speed
0.5m × 0.5m	2m × 2m	(1m,1m)	(30m,22m)	1m/s

Table 2. Simulation parameters

k_a	k_r	ρ_0	T_0	T_f	r
0.1	0.05	0.8m	10	0.1	0.99

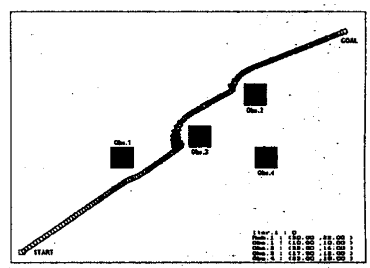


Fig. 7. Simulation : Using APF

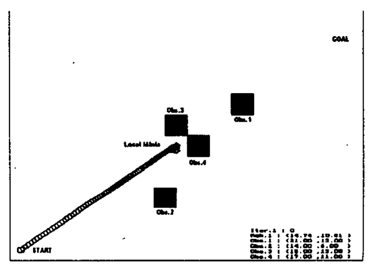


Fig. 8. Simulation : Using APF

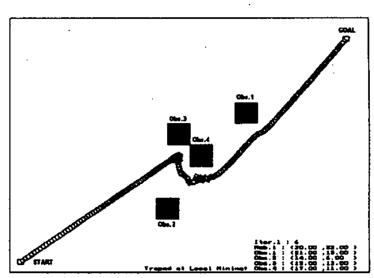


Fig. 9. Simulation : Using APF&SA

Table 3. Experiments parameter

k_a	k_r	ρ_0	T_0	T_f	r
0.1	0.015	0.8m	10	0.1	0.99

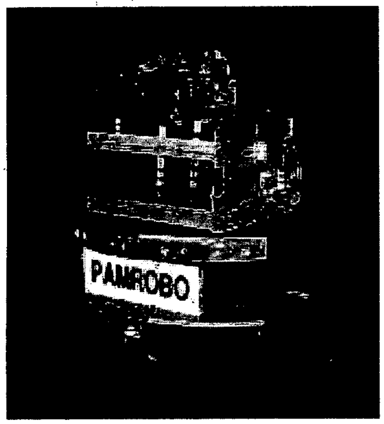


Fig. 10. The robot for experiments

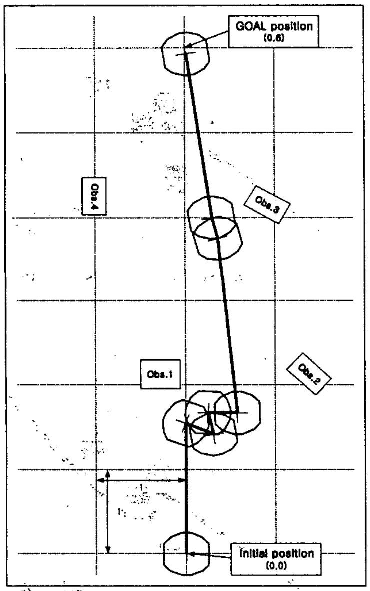


Fig. 11. Experiments : Using APF

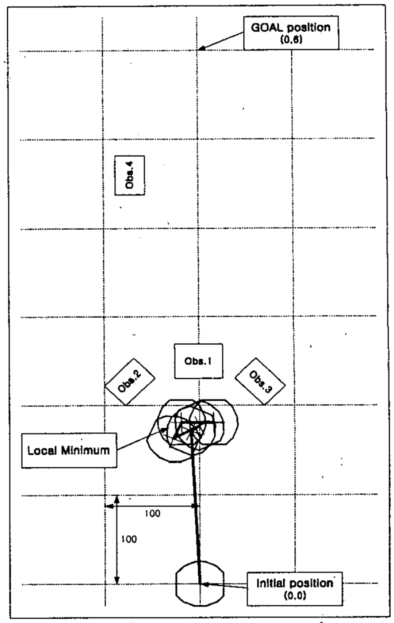


Fig. 12. Experiments : Using APF

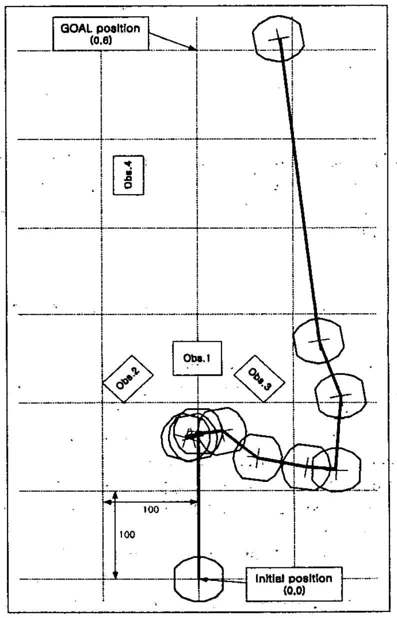


Fig. 13. Experiments : Using APF&SA

5. CONCLUSION

We presented and applied the path planning methods which integrate the simulated annealing approach into artificial potential field path planning. The simulated annealing technique provide the capability of escaping from any possible local minimum. The simulation and experiment results showed local minimum problem occurred in the artificial potential methods will be overcome using simulate annealing approach.

6. REFERENCE

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