A Novel Knowledge-induced Path Planning Strategy for The Mobile Robots

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Summary
Robot path planning is to obtain a most reasonable collision-free path in a certain environment. Existing method can ensure that the solution is the optimal or near-optimal path satisfying some criterion. However, the convergence speed and computation complexity of these methods are limited because they have not utilize knowledge embodied in the problem enough. Therefore, a novel knowledge-induced path planning strategy (KIPP) is proposed. Here, two kinds of knowledge, including explicit knowledge and implicit knowledge, are defined. Explicit knowledge memorizes the information about obstacles which is known in advance. The angle relationship between the path and the obstacles are extracted as implicit knowledge and used to judge and repair the infeasible path. Because the inserted point of repair operator is chosen from feasible region noted in implicit knowledge, the repaired path must be feasible after only repaired once. So computation complexity of this strategy is lower. Taken environment with regular or irregular obstacles as the example, simulation results show that the convergence speed and the precision of the solutions in the proposed strategy are better than other strategies.

Key words:
Knowledge, Repair operator, Evolutionary algorithm, Path planning

1. Introduction

Path planning is an important issue in mobile robotics. It is to find a most reasonable collision-free path for a mobile robot to move from a start location to a destination in an environment with obstacles. This path is commonly optimal in some aspect, such as distance or time. How to find a path meeting the need of such criterion and escaping from obstacles is the key problem in path planning.

Aiming at above problem,researchers have developed many efficient ways to describe environment[1], such as mapping method, free-space method, grid method, topology method and so on. Many optimization methods have adopted to solve above problems, such as genetic algorithm[2-3], particle swarm optimization[4], ant colony algorithm[5-6], and so on. Hu[7] adopts knowledge based genetic algorithm, which incorporating the domain knowledge into its specialized operators, for robot path planning. Though each method has its own strength over others in certain aspects, the performances and computation complexity of them are limited because implicit knowledge embodied in the problem is not used enough. However, it has been proved that implicit knowledge extracted from evolution process can be used to induce evolution operators so as to improve the performance of algorithms[8]. Based on above theories, a novel knowledge-induced path planning strategy for the mobile robots is proposed.

In the strategy, knowledge is classified into two kinds according to their characters and utilized to judge and repair the infeasible individuals so as to decrease computation complexity and improve the convergence speed and the precision of the solutions.

2. Description about Problem

Path planning is to provide a most reasonable trajectory for robots in a certain environment. So a rational description of environment is the basis of this problem. Many methods have been proposed to model the environment. Here, the environment is described by grid.

Suppose robots move in a limited planar space expressed by $\Omega:\{(x,y)\mid x\in[x^L,x^U],y\in[y^L,y^U]\}$. Robots can be considered as a particle and moves in any direction. Its step size is *Tb*. According to the step size, the space is partitioned into uniform grids along X-axis and Y-axis, as shown in Fig.1.

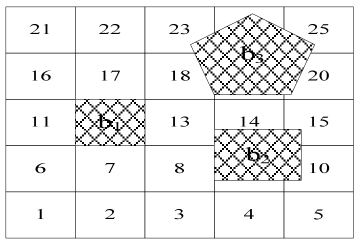


Fig.1 Environment described by grid

In each axis, the number of grid is $N_x=(x^U-x^L)/Tb$ or $N_y=(y^U-y^L)/Tb$. Each grid is labeled by an integer

Manuscript received May 5, 2008.
Manuscript revised May 20, 2008.

$g_l, l \in \lfloor 0, N_x \times N_y \rfloor$ or the coordination of the grid's midpoint (x_{g_l}, y_{g_l}).

$$x_{g_l} = INT\left(l * N_y^{-1}\right) + 0.5 * Tb \qquad (1)$$

$$y_{g_l} = \left(g - INT\left(l / N_y\right) * N_x\right) N_x^{-1} + 0.5 * Tb \qquad (2)$$

In the environment, there are some obstacles distributed in this space usually. They can be described by the convex polygon and the height of them is ignored. Suppose the obstacle set is $B = \{b_k, k = 1, 2, \cdots n_b\}$. n_b denotes the number of obstacles.

The goal of path planning is to find an optimal or near-optimal path from the start location o_{start} to the destination o_{end} escaping from obstacles. Suppose $p_i = (o_{i,1}, \cdots o_{i,j}, \cdots, o_{i,N_{p_i}})$ is a path. $o_{i,j} (j = 1, 2, \cdots N_{p_i})$ is the location composing of a path, which is expressed by g_l or (x_{g_l}, y_{g_l}). The optimal path is shown as follows.

$$\begin{aligned} & p_{best} = \arg\min_i D_{p_i} \\ & s.t \quad p_i \cap b_k = \phi \\ & \qquad o_{i,1} = o_{start}, o_{i,N_{p_i}} = o_{end} \end{aligned} \qquad (3)$$

where D_{p_i} denotes a kind of criterion used to evaluate a path. N_{p_i} is the number of the locations in a path.

3 Knowledge-induced Path Planning Strategy

If any segment of a path crosses any obstacle, we call the path an infeasible individual. Existing methods normally penalize infeasible individuals by lower their fitness, and then repair them by inserting a random feasible location. However, the repaired path is maybe still infeasible. So they are in fact the passive judgment strategies. In order to ensure the feasibility of the repaired path, a novel genetic algorithm-based path planning strategy with knowledge-induced judgment and repair operators is proposed. The pseudo-code of the strategy is described as follows.

```
Begin
  t←0;
  initialize P(t),K(t);
  while (the condition of termination is not satisfied) do
        begin
        evaluate P(t);
        form Ps(t) after crossover and mutation;
        extract K(t);
        judge feasibility of individuals;
        repair infeasible individuals using K(t);
        select P(t+1) from P(t) and Ps(t);
        t←t+1;
    end
  end
```

In the strategy, an active judgment and repair methods are adopted, in which the fitness of infeasible individuals are not penalized. The infeasible paths are repaired according to knowledge embodied in the problem. Therefore, how to extract knowledge and utilize them to judge and repair operators are key steps in the strategy.

3.1 Extraction of Knowledge

Knowledge is used to judge the feasibility of a path and repair the infeasible path escaping from obstacle. So it must memorize the information about obstacles and the relationship between a path and the obstacles.

A. Explicit knowledge

Because the location and shape of static obstacles are known in advance as shown in Fig.1, they are called explicit knowledge.

The shape of obstacles can be regular or irregular. According to the shape and location of obstacles, the grids in the environment are classified into three types: feasible, infeasible and semi-feasible. Suppose *Fg*, *IFg* and *SFg* are feasible, infeasible and semi-feasible grid sets.

$$\begin{cases} g_l \in Fg & b_k \cap g_l = \phi \\ g_l \in IFg & (x_{g_l}, y_{g_l}) \subset b_k \\ g_l \in SFg & ((x_{g_l}, y_{g_l}) \not\subset b_k) \wedge (b_k \cap g_l \neq \phi) \end{cases} \qquad (4)$$

Taken the environment shown in Fig.1 as an example, if there are no obstacles lying in a grid, we call it a feasible grid, such as g16. The grid is infeasible if an obstacle covers it fully or covers its midpoint not whole grid, such as g12 and g19. Otherwise, the grid is semi-feasible, such as g23 and g20.

B. Implicit knowledge

Implicit knowledge describes the angle relationship between a path and the tangent line of an obstacle, as shown in Fig.2. The shadow region denotes an obstacle. The dashed line between two locations, $o_{i,j}$ and $o_{i,j+1}$, denotes the segment of a path $s^i_{j,j+1}$. The tangent lines from $o_{i,j}$ cross the obstacle at the tangent points $c_{i,j}$. The angles between the tangent line and the X-axis are called tangent angles.

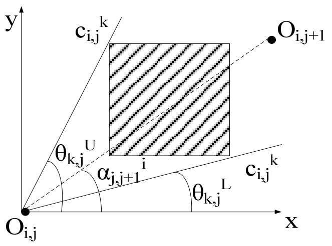


Fig.2 Angle relationship between a path and an obstacle

Definition 1: tangent angle $\theta_{k,j}$

$$\theta_{k,j} = \arctan\left(\frac{y_{T_{i,j}^{k}} - y_{O_{i,j}}}{x_{T_{i,j}^{k}} - x_{O_{i,j}}}\right) \tag{5}$$

That is, tangent angle is the arc tangent of a tangent line. If there are two tangent lines from $o_{i,j}$, the maximum and minimum tangent angles are expressed by $\theta_{k,j}^{U}$ and $\theta_{k,j}^{L}$ respectively.

3.2Knowledge-based Judgment and Repair Operators

According to angle relationship between a path and an obstacle shown in Fig.2, the path p_i with $s_{j,j+1}^{i}$ is infeasible if $s_{j,j+1}^{i}$ crosses b_k. Suppose $\alpha_{j,j+1}^{i}$ is the path angle formed by the path and the X-axis. Judgment rule based on above angle information is achieved.

$$\begin{cases} p_i \quad cross \quad b_k & \theta_{k,j}^{L} < \alpha_{j,j+1}^{i} < \theta_{k,j}^{U} \\ p_i \quad \neg cross \quad b_k & else \end{cases} \tag{6}$$

where
$$\alpha_{j,j+1}^{i} = \arctan\left(\frac{y_{O_{i,j+1}} - y_{O_{i,j}}}{x_{O_{i,j+1}} - x_{O_{i,j}}}\right) \tag{7}$$

It is obvious that as long as the path lies between two tangent lines, the path must cross obstacle. That is, this path is infeasible.

In order to make the infeasible path escaping from the obstacle, repair operator is adopted. It inserts a random location out of the obstacle into the infeasible segment of the path. However, existing repair operators can not ensure the feasibility of the repaired path. So above repair operator shall be repeated until the feasibility of the path is satisfied. This will consume large computation time and lower the performance of the algorithms. The reason for this phenomenon is the randomicity of the inserted location. Aiming at this problem, a novel knowledge-induced repair operator is proposed.

The key of knowledge-induced repair operator is to choose a rational inserted location so as to ensure the feasibility of the repaired paths and decrease the computation complexity. Here, implicit knowledge is utilized to guide the selection of the inserted locations.

According to the judgment rule, as long as the path angle of the repaired segments satisfy the judgment condition of feasibility simultaneously, the repaired path must be feasible. For example, the infeasible segment $s_{j,j+1}^{i}$ is divided into two repaired segments: $s_{j,r}^{i}$ and $s_{r,j+1}^{i}$ after the inserted location $r_{j,j+1}$ is inserted, as shown in Fig.3.

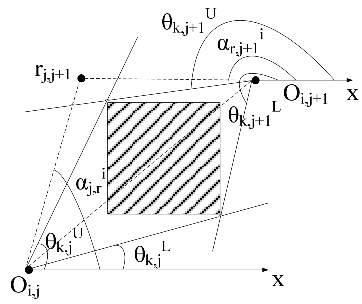


Fig.3 knowledge-induced repair operator

In order to ensure the feasibility of the repaired path, $s_{j,r}^{i}$ and $s_{r,j+1}^{i}$ shall out of the obstacle simultaneously. That is, not only the path angle of $s_{j,r}^{i}$ must satisfy the '¬cross' condition with tangent angle of $o_{i,j}$, but also the path angle of $s_{r,j+1}^{i}$ must satisfy the '¬cross' condition with tangent angle of $o_{i,j+1}$. Therefore, if the inserted location lies in the region, which satisfied above '¬cross' conditions simultaneously, all repaired segments must be feasible. So this region is called feasible region.

Definition 2: feasible region $\Omega_{F_{i,k}}$

$$\begin{aligned} &\Omega_{F_{i,k}} \subseteq (\Omega_{F_{i,k}}^{j} \cap \Omega_{F_{i,k}}^{j+1}) \\ &\Omega_{F_{i,k}}^{j} : \left\{\alpha_{j,r}^{i} \geq \theta_{k,j}^{U} \cup \alpha_{j,r}^{i} \leq \theta_{k,j}^{L}\right\} \\ &\Omega_{F_{i,k}}^{j+1} : \left\{\alpha_{j+1,r}^{i} \geq \theta_{k,j+1}^{U} \cup \alpha_{j+1,r}^{i} \leq \theta_{k,j+1}^{L}\right\} \end{aligned} \tag{8}$$

Because the inserted location chosen from feasible region can ensure the feasibility of two repaired segments of path, there is no need to repair path once more. So knowledge-induced repair operator has lower computation complexity than other methods.

3.3 Evaluation and Evolution Operators

A path is an individual composing of the population. Each individual is described by two forms. One is to express an individual by serial number of grids. That is, $o_{i,j} = g_l$. This form saves the memory capability and is easy to plot the path in simulation. The other form is to express an individual by the coordination of grid, shown as $o_{i,j} = (x_{i,j}, y_{i,j}) = (x_{g_l}, y_{g_l})$. It is used to each evolution operator, compute the fitness and judge the feasibility.

In the paper, distance is adopted as the criterion of the performance. So a path is evaluated by the following fitness function, which computes the length of a path by the Euclidian distance of adjoining points.

$$D_{p_i} = \sum_{j=0}^{N_{p_i}-1} \sqrt{(x_{i,j+1} - x_{i,j})^2 + (y_{i,j+1} - y_{i,j})^2} \tag{9}$$

In evolution process, stochastic tournament selection combining with elite strategy is adopted. That is, the path with lower fitness value is selected as better individual from two individuals, which are chosen from the population stochastically. Single-point crossover operator and mutation operator for real number[9] are used, shown as follows.

$$x'_{i,j} = x_{i,j} \pm 0.5(x^U - x^L)\sum_{m=0}^{q-1} \frac{a(m)}{2}$$

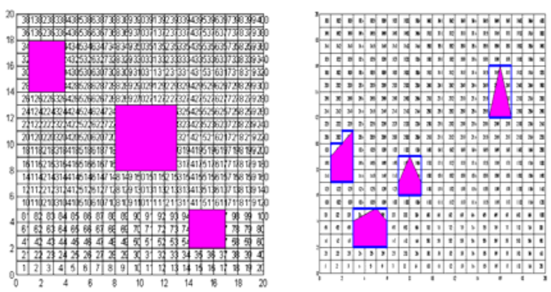
or $$y'_{i,j} = y_{i,j} \pm 0.5(y^U - y^L)\sum_{m=0}^{q-1} \frac{a(m)}{2} \tag{10}$$

where $$a(m) = \begin{cases} 1 & 0 < ra < \frac{1}{m} \\ 0 & \frac{1}{m} < ra < 1 \end{cases}$$

where $ra \in [0,1]$ is a random number. m normally equals to 20.

4 Simulations and Analysis

In order to validate the rationality and feasibility of the path planning strategy proposed in the paper, two different environments with 20×20 grids are used, as shown in Fig.4.



(a) Regular obstacles (b) irregular obstacles

Fig.4 Environments with obstacles

Main parameters used in the strategy are listed in Table.1.

Table 1: Main parameters used in the strategy

Probability of crossover	Probability of mutation	Run times	Termination iteration	
0.6	0.03	20	150	
o_{start}	o_{end}	N_x	N_y	Tb
(1,1)	(20,20)	20	20	1

In order to analyze the performance of the strategy, three indices are adopted. Assume that M1 is the average convergence iteration during twenty run times. M2 is the average iteration as the best solutions appeared firstly during twenty run times. M3 expresses average fitness value of the best solutions during twenty run times.

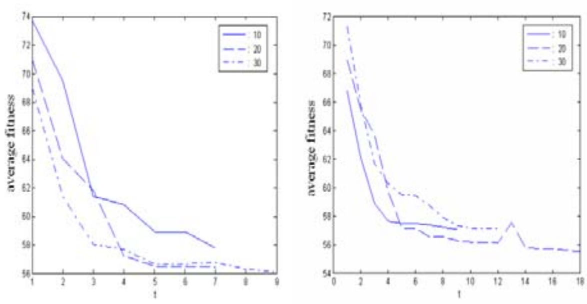
4.1 Comparison of the Performance with Different Population Size

Different population size leads to different performances. Adopted parameters in Tab.1, the performances of the strategy under two environments are compared in Tab.2.

Table 2: Comparison of performance with different population size

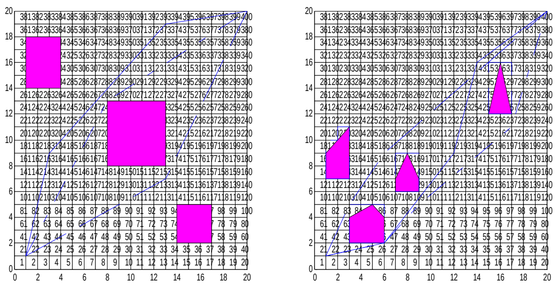
Population size		10	20	30
M1	regular	15.7	11.95	**10.75**
	irregular	16.05	13.6	**9.6**
M2	regular	2.1	4.5	**2.2**
	irregular	6.45	4.05	**2.4**
M3	regular	56.5198	56.4899	**56.475**
	irregular	57.23	57.2275	**56.4188**

The average fitness of population and the best solution with different population size in one run are plotted in Fig.5 and Fig.6.



(a) Regular obstacles (b) irregular obstacles

Fig.5 curves of average fitness



(a) Regular obstacles (b) irregular obstacles

Fig.6 the shortest path in environment

It is obvious that no matter what the population size is, the shortest collision-free path is obtained by the proposed strategy. And along with the increase of the population size, the convergence speed is faster and the length of the path is shorter. The reason for above phenomena is that the initial feasible individuals included in the population are formed randomly. So the population size is more, the distribution of individuals is better. That is, the diversity of the population is better. Therefore, larger population size can improve the performances of the strategy effectively.

4.2 Comparison of the Performance Between Different Methods

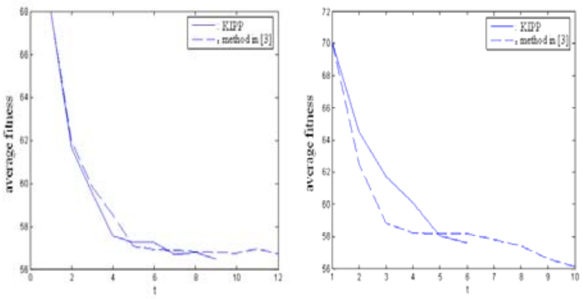
In order to validate the rationality and validity of the strategy proposed in the paper, it is compared with the method in reference [5]. During the simulation, population size is equal to 20. Adopted parameters in Tab.1, the performances of the strategies under two environments are compared in Tab.3.

Table 3: Comparison of performance between different methods

methods		KIPP	Method in [5]
M1	regular	**0.85**	1.1
	irregular	**1**	1.65
M2	regular	**2.95**	3.05
	irregular	**3.9**	4.6
M3	regular	**56.4613**	56.466
	irregular	**56.8439**	57.0211

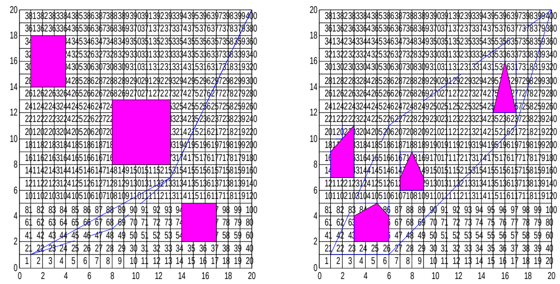
The average fitness of population and the best solution of different methods in one run are plotted in Fig.7 and Fig.8.

It is obvious that the convergence speed and the precision of the solution by the strategy proposed in the paper are better. The reason for above phenomena is that the inserted location in repair operator is chosen randomly in reference[3].However, the guided-inserted location is adopted in repair operator of KIPP. That is, the inserted



(a) Regular obstacles (b) irregular obstacles

Fig.7 curves of average fitness



(a) Regular obstacles (b) irregular obstacles

Fig.8 the shortest path in environment

location is chosen from feasible region extracted in evolution. So the judgment and repair operators of the proposed strategy are more effective, which improve the performances. In a word, the knowledge-induced path planning strategy is valid and rational.

4. Conclusion

Path planning is a key issue for the mobile robots. Its goal is to obtain an optimal collision-free path in a certain environment. Existing method do not utilize knowledge embodied in the problem enough, which limits the convergence speed and computation complexity. So a novel knowledge-induced path planning strategy is proposed. Environment is described by explicit knowledge. Implicit knowledge, which noting the angle relationship between the path and the obstacles, is used to judge and repair infeasible path. Taken environment with regular or irregular obstacles as the example, simulation results show that the strategy proposed in the paper has lower computation complexity, better performance of convergence than other strategies.

This research is at an early stage of study. There still remain several problems to be solved in future such as:

(i) How to extract and utilize implicit knowledge describing common attributes of better individuals in evolution so as to improve the performance of algorithms further.
(ii) Path planning method for mobile robot in an uncertain environment.

Acknowledgment

This work is supported by the Postdoctoral Science Foundation of China (2005037225).

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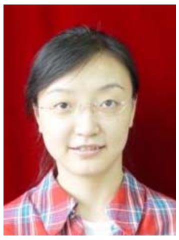

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