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An Optimal Parameters in Path Planning Issue with Artificial Potential Field Based on Evolutions Algorithm

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Abstract. The traditional artificial potential field method's parameter values are usually determined empirically would cause unsmooth planned paths, low calculation efficiency, unreachable goal spots. This study suggests optimization parameters in the artificial potential field in finding the shortest route for mobile robots using the differential evolution algorithm (EA). Three parameters of the positive proportional gain coefficient of the gravitational field, the repulsive field gain coefficient, and the influence distance of obstacles to find the shortest path are considered to modify the infeasible ways of search space in optimizing the algorithm in locating the fastest route. A collision-free path model is constructed by using known global environment information for the mobile robot, and the EA algorithm is used to plan the robot's best path. Compared results show the suggested scheme outperforms the other algorithm in terms of convergence speed and solution quality in handling the collision-free path problem for mobile robots. The experimental results show that the proposed scheme can achieve satisfactory results in terms of convergence and solution quality for different obstacles.

Keywords: Path planning; Artificial potential field method; Evolution algorithm; Optimization

1 Introduction

A mobile robot is a type of robot that autonomously goes from a starting place to a goal point in the presence of obstacles using environmental awareness and behavior planning control [1]. Path planning goal is to find a path from the beginning position to the target position's collision-free path [2][3]. The following are the goals of mobile robot path planning [4]: 1) Using the algorithm, find an optimal path for the robot to travel from its current position to the goal position that does not clash with obstacles [5]; 2) The robot's motion path must comply with the robot simulation [6]. The road should be as smooth as feasible, and the turning amplitude should be modest, among other things [7]. Scholars have given the global path planning problem of mobile robots a lot of attention, and solutions for many path planning difficulties have been developed. The artificial potential field approach assumes that a virtual potential field force exists in the surroundings that influence the robot's movements [4].

Recent studies have found variant repulsive field models, e.g., Dijkstra [8], A* algorithm [9], genetic calculations algorithm (GA) [10], and gravitational search algorithm (GSA) [11], for the developed path planning techniques. The higher the repulsive force in the potential field, the closer the robot is to the obstacle. A threshold is determined when the distance between the robot and the block exceeds. As a result, the offensive potential field functions are considered models' fitness functions for optimization algorithms' artificial possible field methods. [12][13]. The evolution algorithm (EA) [14] is one of the most popular metaheuristic algorithms since that has the advantages such as robustness, simple operation principle, and good optimization performance in the global and parallel search process. Because of the EA algorithm's outstanding performance, the field of evolution becomes a studying hotspot in the optimization domain.

This paper suggests the best dispatching path planning based on combining its solution with the artificial potential field method for solving mobile robots' collision-free shortest path planning problem. A adaptive adjustment parameter is used for the mutation factor of the mutation factor according to the actual optimization process. Simultaneously, the artificial potential field method is used to correct the infeasible solution generated by the differential evolution algorithm's crossover operation, and the corresponding correction strategy is proposed. The experimental results suggest that the proposed approach may obtain satisfactory results for varied barriers in convergence and solution quality.

2 Artificial Potential Field Statement

The path planning purpose is to find a path from the starting and ending positions with the collision-free course of the obstacle environment. A path planning is modeled with the potential field that is the closer the robot to the obstacle would be the repulsive force. The direct distance between the robot and the obstruction is more significant than a specific value that is an offensive force of the barrier to the robot. Therefore, the repulsive potential field function can be calculated as follows.

$$U(q) = \begin{cases} {}^{1}\!/_{2}\, K\left(\frac{1}{\rho(q)} - \frac{1}{\rho_0}\right)^2, & \rho(q) \le \rho_0 \\ 0, & otherwise \end{cases} \tag{1}$$

The field method is a widely used path planning method because its advantages are that the mathematical expressions are concise and clear, the response speed is fast, the real-time performance is good, and the physical meaning is clear. The artificial potential field method also models the repulsive potential field function with q representing the robot's current position t.

$$F(q) = \begin{cases} K\left(\frac{1}{\rho(q)} - \frac{1}{\rho_0}\right) \cdot \frac{1}{\rho^2(q)} \cdot \frac{q-q_0}{\rho(q)}, & \rho(q) \le \rho_0 \\ 0, & otherwise \end{cases} \tag{2}$$

Analyze the impact of parameter settings in the classic artificial potential field method on the final path planning outcome. The principal parameters of the artificial potential field method are optimized to design a shorter and more smooth path. The traditional artificial potential field algorithm's path planning is in the position; *Kr* is the gain coefficient of the repulsion field function; *(q)* is the distance between the robot and the obstacle, and 0 is the most significant distance beyond which the obstruction can impact the robot. The robot's repulsive force in a potential virtual field is calculated with the fundamental premise of the artificial possible field scheme.

3 Potential Field Robot Path Planning Using Evolution Algorithm

This section presents the suggested scheme for automobile path planning with the parameter optimization in the potential fields and using differential evolution algorithm. First, we review the differential evolution algorithm (EA) and then describe the optimization parameter for the path planning problem.

3.1 Evolution Algorithm

The evolution algorithm is mainly referred to as the evolution algorithm (EA) presented in the several following phases [14].

The initial population matrix is generated randomly: $y_{ij} = (y_{i,1}, y_{i,2}, .., y_{i,D})$, i = $(1,2,..,NP)$, where NP is the population size, D is the number of dimensions (D is also the number of path points n, that is, D is set to n). The robot's initial point and target point are (x_0, y_0) and $(x_n + 1, y_n + 1)$ respectively. The initial individual' s. The selection method is as follows. Calculate the length of the starting point and the target point on the x axis as $L = x_{n+1} - x_0$. Compare the size of y0 and $y_n + 1$. The more significant value of the two is $y_{\max}$, and the smaller value is $y_{\min}$. Then the upper bound of the algorithm population is $y_{max+L/2}$, and the lower bound of the population is $y_{\min-L/2}$. Nodes can be randomly selected in turn to form path points by determining $x = \{x_1, x_2, \ldots x_n\}$.

The mutation operation refers to selecting the different individuals that are formulated as follows.

$$v_{i,g} = y_{r1,g} + F.(y_{r2,g} - y_{r3,g}), \tag{3}$$

where g is evolutionary algebra, $r1 \neq r2 \neq r3 \neq i$ and $i = (1,2,\ldots,NP)$, F is the scaling factor. In the differential evolution algorithm, the function of F is to scale the differential mutation vector corresponding to each individual in the population to determine the search range of the current individual. At the beginning of the algorithm, F takes a larger value to keep individuals diverse. In the later stage of the algorithm, F is close to 0. The value of 5 retains good information, avoids the destruction of the optimal solution, and increases the probability of searching for the optimal global solution.

$$F = F_{min} + (F_{max} - F_{min}).r, \tag{4}$$

The crossover operation generates test vectors $u_{i,j,g}$ by crossing the initial target vectors $y_{i,j,g}$ and the mutation vectors $vv_{i,j,g}$, using the binomial crossover method to operate, and at least one component of the test vector is made up of the mutation vector produced. The specific operation is shown in the following formula.

$$u_{i,j,g} = \begin{cases} v_{i,j,g}, & if\ rand(0,1) \leq CR\ or\ j = j_{rand} \\ y_{i,j,g}, & otherwise \end{cases}, \tag{5}$$

where j is the dimension, $j = 1, 2, \ldots, D$; $CR \in (0, 1)$ is the crossover rate, and j_{rand} and is an integer randomly selected in $[1, D]$.

The selection operation is to generate the next-generation population, and the optimal individual is selected according to the fitness value of $f()$ of the target vector $y_{i,g}$ and the test vector $u_{i,g}$. The specific operation is shown in the following equation.

$$y_{i,g+1} = \begin{cases} u_{i,g}, & f(u_{i,g}) < f(y_{i,g}) \\ y_{i,g}, & else \end{cases}, \tag{6}$$

where $f(.)$ is the fitness function; i and $g + 1$ are the target vector of the next generation.

3.2 Evolution Algorithm Combined Potential Field for Path Planning

The attraction between the robot and the goal point decreases as the distance between them decreases. The robot's potential energy is zero when the distance between it and the goal point is zero, so it reaches the target point. The elastic potential field's properties are comparable to those of the potential virtual area. The gravitational potential field function in the potential gravitational field can be the main steps: the potential energy in the elastic potential field is proportional to the distance, and then the gravitational possible field function in the gravitational field potential field can be the main steps as follows.

Step1. The obstacles in some cases of the different environment are set initially, e.g., by circles, squares with a radius and lengths; the coordinate origin is set to (x_0, y_0), (x_m, y_m);

Step 2. The initial point coordinates of the robot in the three environments are $(0, 0)$, and the target point is $(10, 0)$. Parameter settings: For the evolution algorithm, the population size is NP is set to 100, and the termination condition is IterMax; CR and F are set as follows, e.g., $CR = 0.9$, $Fmin = 0.5$. $Fmax=0.9$; individual in the population is generated randomly.

Step 3. Calculate the value of the objective function of the individuals in the population to find their optimal individual population.

Step 4. Mutation operation generates mutation vector, and Boundary condition processing is checked by Eq.(3).

Step 5. Cross operation, cross operation on target vector and mutation vector to generate test vector as in Eq(5).

Step 6. Select in applying Eq.(6), calculate test vector by the objective function; with greedy is the attraction potential and the positive proportional coefficient, and the operation is selected; The distance between the mobile robot and the target point that can get attractiveness.

Step 7. Termination condition: The overall situation is derived from the attractive potential field and the repulsive potential field. Correspondingly, the resultant force Eq (2), the iterative algebra, increases if the maximum algebra is not reached, go Step 3. Otherwise, the output of the optimal individual and its corresponding objective function value with the global outcome.

4 Simulation Experiment and Result Analysis

A simulation experiment of the mobile robot path planning moves is carried out to verify the effectiveness of the proposed scheme by setting obstacle environment and setting the coordinates of the starting point and the target point to respectively. The parameters set for the artificial potential field method greatly influence the path planned by the artificial potential field method. The gravitational field has a positive proportional gain. Coefficients K_r, K_a, and ρ0 are the gain coefficient repulsion field, affecting obstacle distance parameters on the planning path. The EA relevant settings are as follows: the initial population size is set to 40, the maximum number of iterations is 1000, and the crossover probability *CR* and the scaling factor *F* are set to 0.1 and 0.4, respectively.

Table 1. Influence of parameters, e.g., ρ_0 intensity; K_r and K_a setting for the algorithm performance.

ρ_0 intensity			**Constants of Kr, and Ka**		
Values	**Obtained shortest path**	**Iterations no. for a path**	[Kr, Ka]	**Obtained shortest path**	**Iterations no. for a path**
1	49.361	41.08	[0.7,0.8]	45.73	52.63
10	48.121	47.03	[0.6,0.9]	45.96	60.23
40	47.792	49.39	[0.6,0.8]	46.29	59.00
80	47.951	52.03	[0.6,0.7]	45.77	62.89
100	46.195	57.16	[0.5,0.9]	47.15	51.68
150	46.686	59.34	[0.5,0.8]	47.73	68.69
200	46.907	60.61	[0.5,0.7]	47.40	51.97

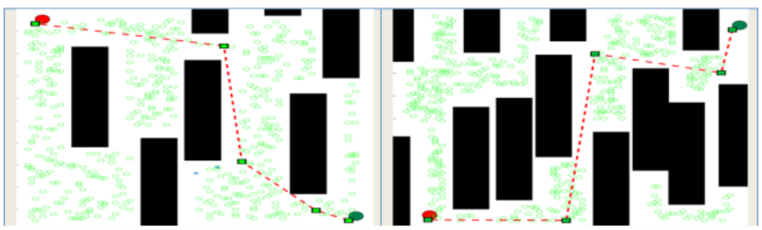
Table 1 shows an example of the influence of parameters, e.g., ρ_0 intensity; K_r and K_a setting for the algorithm performance. The optimized obtained path planning result for the parameters in the artificial potential field method for in the path planned dramatically improves the smoothness of the mobile robot's path. The optimized artificial potential field is compared to the result obtained with the PSO [15], ACO [16], and A* algorithms [9] is shown in Table 2. A shorter, smoother path is reached, and the scheme of obtained parameter settings is also found out unreachable targets is depicted in Figs 1 and 2.

Table 2. Simulation results of the proposed scheme compared with the other algorithms for three scenarios of the setting complex environments in the workspace.

Scenarios	**Algorithms**	**Best**	**Mean**	**Std.**
100×100m complex environment	A*	56.95252	52.96207	1.19232
	PSO	56.00487	53.15206	0.23368
	ACO	57.76607	51.05097	0.14608
	EA	**53.02256**	**50.44013**	**0.01648**
50×50m	A*	47.30760	44.16887	0.8148

complex environment	PSO	46.34112	43.84140	0.30344
	ACO	45.39600	41.06996	0.176
	EA	**44.08749**	**41.95422**	**0.00784**
20×20 m complex environment	A*	42.09452	39.20709	0.70064
	PSO	41.70066	39.62108	0.18448
	ACO	42.24799	37.10396	0.17776
	EA	**40.72964**	**36.84022**	**0.00776**

Table 2 shows the simulation results of the proposed scheme compared with the other algorithms for three scenarios of the setting complex environments in the workspace. From the data in Table 2, it can be shown that the suggested EA's optimal path length produces superior optimization path planning results than the other approaches. The EA algorithm is more feasible and effective than the original algorithm; however, the algorithm's running time is significantly reduced, the number of inflection points is reduced, and the number of iterations is decreased.



a) seven obstacles on the path planning   b) twelve obstacles on the path planning

Fig. 1. An obtained graphical result of the suggested EA scheme for path planning under artificial potential field with serveral significant obstacles and weights

The robot operating environment space is set to MxM m, e.g., $20x20$m, $50x50$m, and $100x100$ m, respectively, in applying the EA scheme for optimal path scheduling. Fig. 1 shows the obtained graphical result of the proposed EA method in different environment settings, e.g., 3 and 6 obstacles, respectively, for artificial potential field path planning. It can be seen that the simulation results show that parameter optimization can significantly improve the performance of the potential synthetic field approaching the target.

5 Conclusion

This study suggested a modification to the evolution algorithm (EA) for path planning optimization of mobile robots based on optimized parameters in the artificial potential field in finding the shortest route of mobile robots. We combined the traditional artificial potential field method with the EA algorithm to optimize the parameters for reducing the path length. The field gain coefficient and the influence distance of obstacles to finding the shortest path are considered by modifying the infeasible search space to optimize the algorithm to locate the fastest route. The simulation results show that parameter optimization can significantly improve the performance of the artificial potential field approaching a target. Compared results show the suggested scheme outperforms the other algorithm in terms of convergence speed and solution quality in handling the collision-free path problem for mobile robots.

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