An Improved Shuffled Frog Leaping Algorithm for Robot Path Planning

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***Abstract*—Path planning problem is one of the most important and challenging issue in robot control field. In this paper, a path planning method based on an improved shuffled frog leaping algorithm is proposed. In the proposed approach, a novel searching strategy based on the median strategy is used to avoid local optimal solution problem in the general shuffled frog leaping algorithm. Furthermore, the fitness function is modified to make the path generated by the shuffled frog leaping algorithm smoother. In each iteration, the globally best frog is obtained and its position is used to lead the movement of the robot. Finally, some simulation experiments are carried out. The experimental results show the feasibility and effectiveness of the proposed algorithm in path planning for mobile robots.**

***Index Terms*—Shuffled frog leaping algorithm, Robot path planning, Searching strategy, Fitness function.**

I. INTRODUCTION

Mobile robot is a very important subject in theoretical research and the applications in practice. With the development of the science and technology, the robots have been used widely in industrial production, environmental detection, home service, and so on [1], [2]. Path planning is a key issue in the robotic research field, and the goal of path planning is to find a suitable collision-free path from a start position to a target for the mobile robot in an environment with some obstacles [3], [4].

To deal with this problem, many methods have been developed, such as the artificial potential field method, the neural network method, and the genetic algorithm method [5]–[7]. Each method has its own advantages over others in certain aspects, but also shows some limitations. For example, the path planning methods based on the artificial potential field method often get into the local optimum problem, because they lack global information [8]. The computation of the traditional neural network methods is very complex, which isn't suitable for path planning in dynamic environment.

To overcome the shortcomings of those approaches above, researchers have explored a variety of solutions. Recently, more and more bioinspired intelligent methods have been proposed for robot path planning, which is the development trend in the robot control field. For example, Cai, et al. [9] presented a path planning algorithm based on biphasic ant colony algorithm with fuzzy control, where the environment is dynamic. Yang and Meng [10] proposed a bioinspired neural network based on a shunting model for the robot navigation in unknown environment. Hassanzadeh, et al. [11] proposed a shuffled frog leaping algorithm based robot path planning method in partially unknown environments. But the obstacles in [11] are supposed as points, the shape and the size of the obstacles are not taken into account, which will affect the safety of the robot during the movement.

In this paper, an improved shuffled frog leaping algorithm is proposed to achieve the task of path planning. Shuffled frog leaping algorithm is a new type of bioinspired intelligent optimization algorithm, which has been tried to solve the mobile robot path planning problem, due to its advantages of fast searching and easy implementation. In order to avoid the local optimal solution problem, an improved shuffled frog leaping algorithm (ISFLA) is developed in this study. The ISFLA is based on a new searching strategy. In addition, the function of the fitness is improved. Some simulation experiments were conducted in various situations. The results of the simulation experiments show the efficiency of the proposed approach.

The rest of the paper is organized as follows: Section II introduces the general shuffled frog leaping algorithm; Section III is focused on the improved SFLA for robot path planning; Section IV presents the simulation experiments for various situations; Finally, the conclusion is given in Section V.

II. THE GENERAL SHUFFLED FROG LEAPING ALGORITHM

Shuffled Frog Leaping Algorithm (SFLA), which was originated from the research on food hunting behaviors of frogs, is a population based meta-heuristic computing technology. SFLA is developed firstly by Eusuff and Lansey in 2003 [12]. The SFLA based methods have some good performances of both the PSO based methods and the genetic based algorithms [13], and have been successfully applied to various optimization problems in engineering, such as the task scheduling problem, the traveling salesman problem, and the unit-commitment problem [14]–[16]. The basic working principle of the SFLA based method is introduced as follows.

A. Initialization

The first step of SFLA is to randomly generate an initial population of frogs within the feasible solution space. A solution in this space is considered as a frog. The number of frogs in this population is denoted as F. The position of the ith frog is represented as

$$X_i = (x_{i1}, x_{i2}, ..., x_{id}) \tag{1}$$

where d is the number of variables within a solution.

B. Partition

This process is to divide all the frogs into m memeplexes. Before this process, the frogs need to be sorted in a descending order based on their fitness. Then the frogs are put into these memeplexes by the strategy as follows: each frog is put into one memeplex according to its sequence sequentially. When the last memeplex has one frog, the next frog is put into the first memeplex again. This process continues till all the frogs are divided into these m memeplexes, and each memeplex contains n frogs.

C. Updating

This process is to update the position of the frog with the worst fitness in each memeplex, which is defined as X_w. The updating formula is as follows:

$$D = rand() \cdot (X_b - X_w) \tag{2}$$

$$X_w^{new} = X_w^{current} + D, (-D_{max} \leq D \leq D_{max}) \tag{3}$$

where X_b is the frog with the best fitness in each memeplex, and $rand()$ is a function to generate a random number in the range of [0,1]. If this process doesn't produce a better solution, then a frog with the global best fitness (defined as X_g) will be used. The detail updating rule can be viewed in [11].

D. Shuffling

This process is to conduct a global search after the local search finished. All frogs in the population are remixed, then the processes of partition and updating introduced above are proceeded repeatedly until the defined convergence criteria is satisfied.

III. THE IMPROVED SFLA FOR ROBOT PATH PLANNING

A. The improved SFLA based on the median strategy

In the general SFLA based method, the worst solution is updated by the best solution in the memeplex. As we know, individuals can share all of the information carried by other individuals during the search of food and benefit from the entire search process [17]. According to this theory, this paper proposed an improved SFLA (ISFLA) based on the median strategy for the updating. The basic idea of this searching strategy is that the worst frog (solution) is no longer simply updated by the most optimal frog of the memeplex. It will make full use of all information carried by this memeplex. Namely, the worst frog is updated by the frog in the center of the memeplex. Assuming the center of each memeplex is

$$X_c = (x_{c1}, x_{c2}, \cdots, x_{cd}) \tag{4}$$

where the element of X_c is calculated by

$$x_{cj} = \sum_{i=1}^{n} x_{ij} \Big/ n, (j = 1, 2, \cdots, d) \tag{5}$$

Within each memeplex, the worst performance frog is updated according to the following simple rule:

$$D = rand() \cdot (X_c - X_w) \tag{6}$$

In the proposed ISFLA, the frog leaping rule is composed by (3) and (6). Based on the proposed median strategy, the worst frog draws on the experience of all frogs within the neighborhood, not simply by the optimal frog within the neighborhood, which can avoid the SFLA to trap in local optimum.

B. The robot path planning based on ISFLA

The robot path planning problem in a partially unknown environment is investigated in this paper. The information of the target and the obstacles can be detected during the path planning. During the path planning, the distances between the robot and the target or the obstacles in the environment are measured by the robot sensors. In general, the path planning is aimed at reaching to the target without colliding with the obstacles. In this paper, ISFLA is used to solve the path planning problem. During the path planning process based on ISFLA, the globally optimized frogs in each iteration are generated, which are used to lead the robot to their positions in sequence. The path planning task in this paper is described as follows. (1) In the path planning task, there is a target, which is denoted as T, and its coordinate is (x_T, y_T). (2) In the environment, there are N obstacles, which are denoted as $O = \{O_1, O_2, \cdots, O_N\}$; these obstacles have different shapes and sizes. (3) The robot have some onboard sensors, and the detecting range of these sensors is limited.

The fitness function of a frog X_i in this paper is expressed as follows:

$$f(X_i) = \omega_1 * e^{-\min\limits_{O_j \in O} \|X_i - O_j\|} + \omega_2 * \|X_i - T\| \tag{7}$$

where ω_1 and ω_2 are constants; $\|\cdot\|$ is Euclidean distance between two positions. It can be seen from (7) that the fitness value of a frog will become smaller when the frog is near the target. On the other hand, the fitness value will become larger when the frog is close to the obstacles. That is to say the robot will select the positions which are next to the target and move away from the positions which are near the obstacles.

Remark: The main reason to use the exponential function as the fitness function is that the fitness value calculated by the exponential function is smaller than the reciprocal function [11] in the same range, which is more suitable for the path planning problem.

The workflow of the proposed path planning approach is summarized as follows:

1) Initialization. Set the initial values of the parameters, such as the number of frogs F, the number of memeplexes m, the maximum step size $D_{\max}$, and so on;

2) Generate the initial population. The robotic current position is used as the center of the circle area A, whose radius is the detecting radius of the robotic onboard sensors. Then F frogs are generated as the initial population in this circle area A.

3) Calculate the fitness of each frog by (7) and then sort them in a descending order according to their fitness.

4) Partition the frog population. Divide F frogs into m memeplexes, The strategy of the partitioning is showed in Section II;

5) Local searching. The worst frog of each memeplex is updated by the proposed median strategy, it is proceeded until reaching to the number of iterations L;

6) Shuffling process. After the local searching of all memeplexes have been finished, all frogs in the population are into shuffling process. And the position of the optimal frog is used as the next position of the robot.

7) Determine whether the robot reaches to the target, if not, turn to step 2), otherwise the path planning task is ended.

IV. Experimental studies

In order to verify the feasibility and effectiveness of the proposed approach, some simulation experiments under static and dynamic environment are conducted respectively, using a computer with 4.0 GHz physical memory and 3.2 GHz CPU clock speed. In these experiments, the robot and the target are expressed by small circle and triangle. The main parameters of the ISFLA are the same as the SFLA [18]. Most of these parameters are set according to the literature [11], and some of them are designed by experiences from the experiments. The parameters in all the experiments are the same, which are listed in Table I.

TABLE I
The parameters of ISFLA.

Parameters	Value	Remarks
F	60	The number of frogs
m	6	The number of memeplexes
n	10	The number of frogs in each memeplex
$D_{\max}$	2	The maximum step size
L	10	The number of generations for each memeplex
G	100	The number of shuffling iterations
ω_1	5	The inertia weight
ω_2	12	The inertia weight

A. Under static environment

In order to test the basic performance of the proposed approach, the first simulation is conducted. The area of the environment is 20×20 (m^2), and the start point of the robot is $(0,\ 0)$, the position of the target is $(16,\ 19)$. The detecting range of the robotic onboard sensors is 2m. The initial positions of the target, the robot and obstacles are shown in Fig. 1. To show the advantages of the proposed ISFLA, it is compared with the general SFLA (see [11]), and the parameters of the general SFLA are the same as the proposed approach. Because the initialization of the frogs is random, each experiment is conducted 10 times. The experimental results are listed in Table II and the path planning results of the two methods in one experiment are shown in Fig. 2.

The results in Table II show that the average length of the path obtained by the proposed approach is less than that of

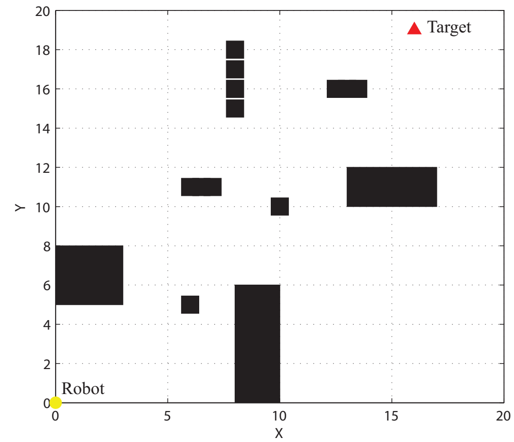

Fig. 1. The initial positions of the target, robot and obstacles in the first experiment.

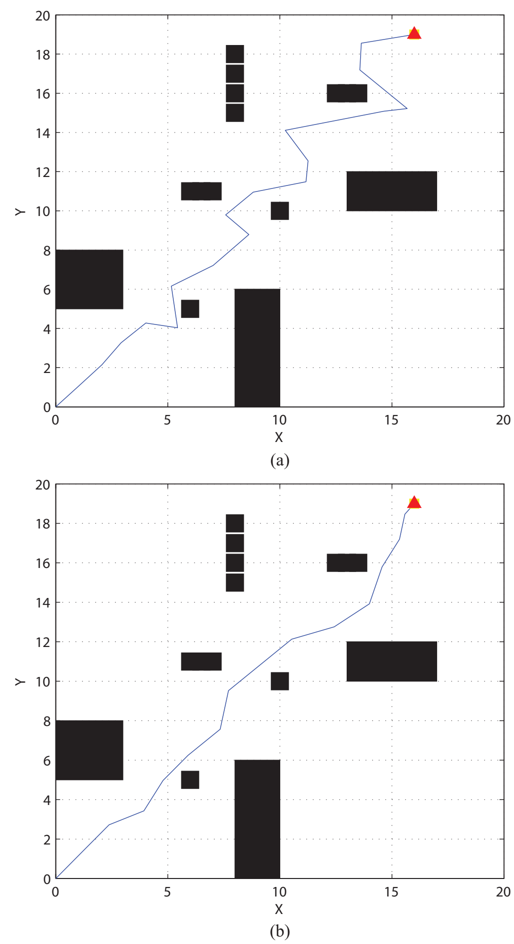

Fig. 2. The experimental results of path planning under static environment: (a) based on the general SFLA method; (b) based on the proposed ISFLA method.

TABLE II
THE EXPERIMENTAL RESULTS OF 10 REPETITIONS UNDER STATIC ENVIRONMENT.

The path planning method	The minimum path length	The maximum path length	The average path length	The average time used in the task	The times to change the direction
The general SFLA	25.88m	39.31m	32.31m	53.56s	16
The proposed ISFLA	25.20m	26.53m	25.79m	46.91s	14

the general SFLA based method. The main reason is that the fitness function based on the exponential function in the proposed approach can make the path smoother than the reciprocal function (see Fig. 2). The average times to change the direction of the proposed approach is less than the general SFLA based method, namely the energy consumption of the robot navigated by the proposed approach is less than that of the robot navigated by the general SFLA based method. The experimental results show that the proposed approach can deal with the path planning problem under static environment more efficiently than the general SFLA based method.

B. Under dynamic environment

To further test the efficiency of the proposed approach in some complex applications, this experiment is conducted, where the target is movable. The initial position of the target is $(8, 18)$, the target will move from the left side to the right side of the environment. The initial positions of the target, the robot and obstacles are shown in Fig. 3. In this experiment, the velocity of the target is set as 0.5(m/s). The comparative results of this experiment are shown in Table III and the path planning results of the two methods are shown in Fig. 4.

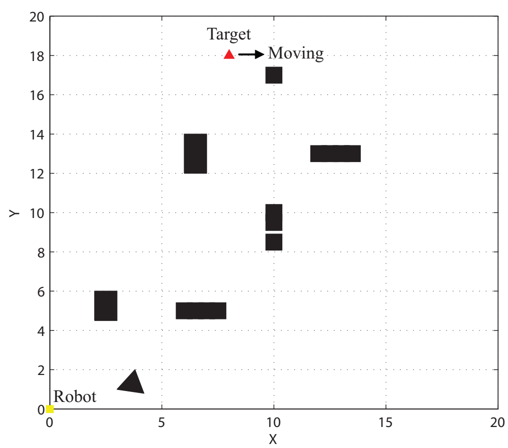

Fig. 3. The initial positions of the target, the robot and obstacles for the path planning under dynamic environment.

The results in Table III show that the proposed approach has a good ability to follow the target and avoid the obstacles. In this dynamic environment experiment, the proposed SFLA method generated the initial frogs within the detection range of the robot, which can ensure the path of proposed approach smoother than the path generated by the general SFLA based method. The times to change the directions of the general SFLA based method increased very much, while the times to change the directions of the proposed approach is almost the same as that in the static environment experiment (see Tables II and III). This performance of the proposed approach is very important for the robot path planning especially when the obstacles are dense (see Fig. 4). The results of this experiment show that the robot navigated by the proposed approach can reach to the target faster than the general SFLA based method in the complex environment.

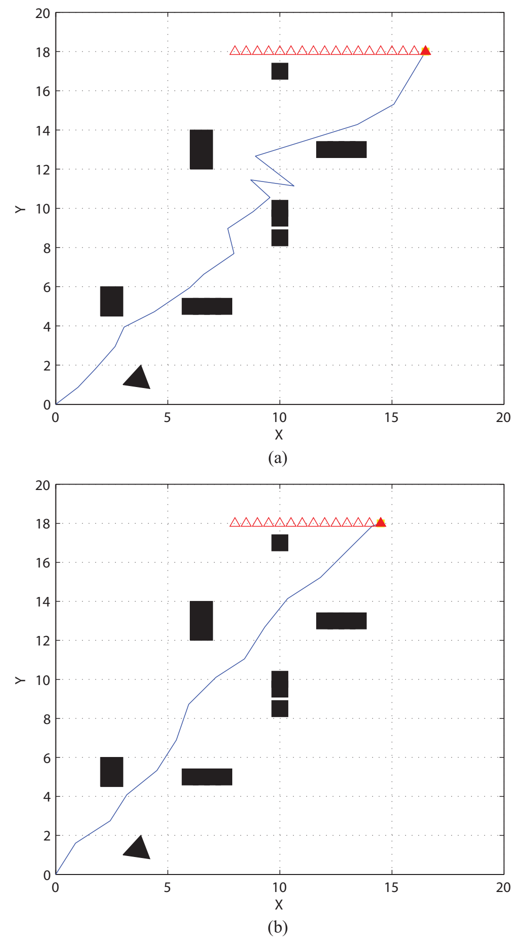

Fig. 4. The experimental results of path planning under dynamic environment: (a) based on the general SFLA method; (b) based on the proposed ISFLA method.

TABLE III
THE EXPERIMENTAL RESULTS OF 10 REPETITIONS UNDER DYNAMIC ENVIRONMENT.

The path planning method	The minimum path length	The maximum path length	The average path length	The average time used in the task	The times to change the direction
The general SFLA	27.45m	34.91m	32.01m	57.99s	18
The proposed ISFLA	22.95m	24.16m	23.39m	43.18s	14

V. CONCLUSIONS

In this paper, an improved shuffled frog leaping algorithm is proposed to solve the robot path planning problem. A new searching strategy based on median strategy is presented. And a novel fitness function which shortens the path length is proposed in the SFLA based method. During the process of the IFSLA, the globally best frogs in each iteration are generated, and their positions are used to lead the robot. The experiments show that the proposed approach is effective and efficient both in static environment and in dynamic environment. The proposed approach has wide applications in the robot control field, such as the hunting and fire disaster response by robot in unknown environment [19]–[21].

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