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Multi-robot hunting strategy based on FIS and artificial immune algorithm[①]

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Abstract

A combination strategy of multi robot hunting in dynamic environment based on a fuzzy inference system (FIS) and artificial immune algorithm is proposed. By analyzing relative relation of hunters and escaper, abstract data is gathered to describe the relative location and relative motion state of the robots, which in turn forms the beginning stage of the fuzzy rule. The artificial immune algorithm optimizes and generates the rule data base and adaptive design considers factors in measuring the hunting efficiency. The optimized rules are applied to the hunting task and the results show that the algorithm can effectively actualize hunting of multiple mobile robots.

Key words: multi-robot hunting, fuzzy inference system (FIS), artificial immunity, fuzzy rule database

0 Introduction

With the development of robotics, multi robot system has attracted attention of scholars at home and abroad because of its high flexibility. As a typical multi robot task, multi robot cooperating rounded up can actualize the invaders captured, security patrols, raise the degree of intelligence forces combat equipment if developed in the military field. In the field of industrial control, it can improve the degree of automation of the factory, reduce the risk of manual operation for some work, and adjust the precision and efficiency of production.

Ref. [1] proposed an algorithm for rounded up through simulating the interaction among antibody B cells in the human immune system. Ref. [2] proposed a hunting method based on a multi-robot learning mode. Ref. [3] suggested a new multi-agent reinforcement learning approach which is proposed to learn the optimal behaviors among cooperative agent teams. Fuzzy inference system (FIS), as a rule based intelligent controller, has been widely used in robot control. Based on the fuzzy rule database within the fuzzy inference system, Refs[4-7] used genetic algorithms to study methods for optimizing fuzzy control function and rules of control, which improved the performance of the fuzzy controller to a certain extent.

In Ref. [8], fuzzy data rules in the fuzzy logic system was obtained by adjusting the genetic algorithm and achieved successful hunting in an environment with obstacles. In Ref. [9], ant colony algorithm was used to optimize the membership function as well as the rules of the fuzzy control system, which optimized fuzzy inference system overall and achieved good results. Ref. [10] showed that a controller using adaptive HFRBS can learn a suitable control policy using a fewer number of fuzzy rules for both a supervised and reinforcement learning problem and is not sensitive to the layout as with uniform representation.

All of the studies mentioned above have actualized the multi-robot hunting strategy, but there are some limitations. Firstly, due to the fact that the problem of multi-robot was over-simplified, the effectiveness of the strategy could not be guaranteed. Secondly, the robot motion was too abstract in some of the learning algorithms. They did not consider the constraints on robot kinematics, thus it could not reflect the mobile robot in the environment of realistic running state. The feasibility of the algorithm is therefore difficult to verify. Furthermore, due to the fact that the fuzzy rules are not independent, singling optimization of fuzzy rules cannot guarantee the overall optimization of the fuzzy rule database. Finally, the search space in some optimization methods was too large, which had made it difficult to ensure the efficiency of the algorithm.

Inspired by the limitations in the current literature, this paper proposes a strategy of multi-robot hun-

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ting combining the fuzzy inference system and artificial immune algorithm. With the premise of fully considering the environment factors and robot motion information, the fuzzy inference system establishes a model of the multi-robot hunting task. The fuzzy rule database is set up by both expert knowledge and artificial immune optimization algorithm and it is optimized to design appropriate strategies for the escaper. Finally, the feasibility is validated through the simulation program.

1 Multi robot hunting task

1.1 Multi robot hunting task description

Multi-robot hunting task refers to multiple robot rounding up the escaper by cooperating and finally completes the capture. The task is different from the simple robot approaching task. The multi-robot hunting task emphasizes on the cooperation of multi robots. As shown in Fig. 1, there are multiple hunting robots and one escaping robot, each hunting robot has a range of perception and they can share information including the location and direction of movement of hunting robots and escaper by communicating with one another. The escaper has the same perceptive and mobile ability.

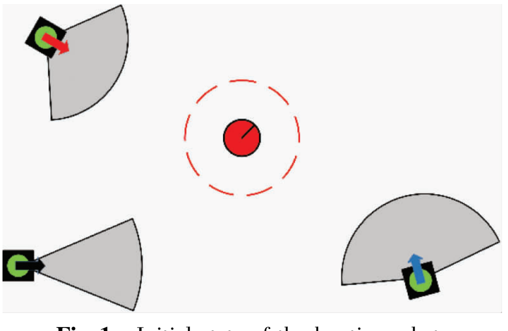

Fig. 1 Initial state of the hunting robots

When hunting robots find the escaper, they start the rounding up process and the escaper starts to escape. At last, the encirclement is formed by the hunting robots and the escaper either cannot move or can move but unable to escape from the encirclement. At this time, the task of hunting is completed as shown in Fig. 2.

1.2 Robot motion mode

In multi-robot hunting task, robot motion module uses independent drive to the left and right wheel. It achieves the robot movement through speed control of the robot left and right wheel. At the same time, the robot' smotion needs to be constrained by the dynamics. The robot's motion behavior is defined as the following 5 groups of forms, as shown in Fig. 3.

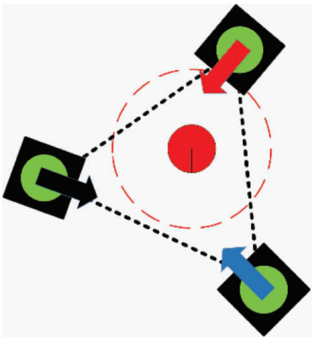

Fig. 2 The hunting task is completed

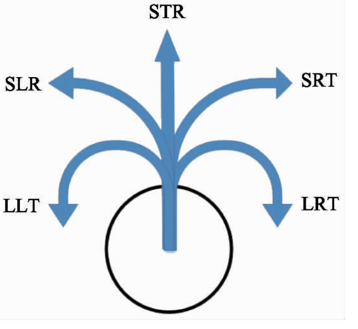

Fig. 3 The motion behavior of the wheeled robot

Each of these arrows represents the direction of the robot's motion. They denote the forward motion of the mobile robot, the left / right small steering and the left / right large steering. Each movement reflects the direction and amplitude of the robot through the speed difference between the left and right wheel.

2 Multi-robot hunting strategy

2.1 Fuzzy inference system based on rounding up the state description

Fuzzy inference system (FIS) can constitute an intelligent controller based on rules. Through reasoning a series of rule database with embodied knowledge, the fuzzy system solves complex reasoning problems with a fuzzy nature and continuous and accurate output can be obtained. Because people want robots with human intelligence, the fuzzy inference system fits the human thinking habit, and it does not require the establishment of an accurate mathematical model. By replacing mathematics variables with linguistic variables, it is made easily for transforming the knowledge into the rule database and limiting the human thinking strategies within the aspect of control. Thus, the fuzzy inference system is suitable for controlling complex environments and it is widely used in mobile robot motion control. Moreover, the fuzzy inference system is fast and can satisfy the requirement of the multi robot system.

For multi-robot hunting problem, to analyze three rounded up robots and one escaping robot as the experimental objects, it is needed to consider an overall coordination among multi robots. The movement of each robot is influenced and restricted by the movement of others. To gain a comprehensive and effective description of the whole state of rounding up, it is needed to gather necessary data from the environment abstractly, so that the data can not only fully describe the state of multi-robot in the hunting task, but also avoid unnecessary data redundancy.

For multi-robot hunting task, the capturing state is mainly reflected in the relative relationship among the robots. This mainly includes two aspects. One is the relationship between the hunters and the escaper. The other is the relationship between the hunters and the escaper involving relative distance, relative orientation and relative motion. Similarly, the relationship among the hunters involves the relative distance, relative orientation and relative motion.

In the relations mentioned above, the relative orientation and the hunter-hunter relative orientation can be expressed using relative position of the hunting robots which is used to describe the relative distribution of multi-robots; the hunters-escaper relative motion and the hunter-hunter relative motion can be expressed by the relative motion of the escaper which is used to describe the relative motion of multi-robots; the hunter-hunter relative distance can be described through the multi-robot relative orientation and the escaper-hunter relative distance. Thus, factors used to describe the capture are simplified as the following three aspects: multi-robot relative orientation, multi-robot relative motion, the escaper-hunter relative distance.

In order to fully cover the above factors so that the hunting task can be accurately described through data, the following data are used as description of the capturing state. As shown in Fig. 4, three dark boxes are the hunting robots; the middle circle represents the escaping robot; the arrows represent the moving direction of

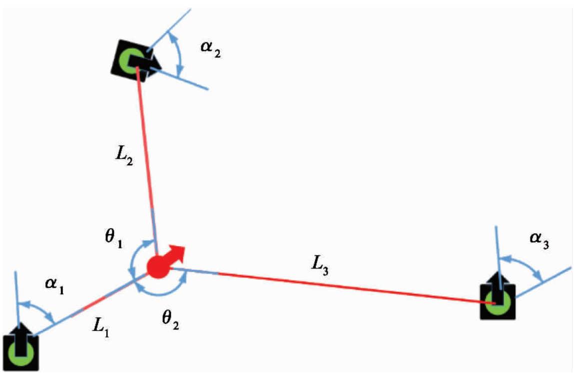

Fig. 4 The data description of the multi robot hunting task

the robot where No. 1 robot is the benchmark. θ_2, θ_3 represent the angle between the hunting robots (No. 2 and 3) and the escaper's position in relation to No. 1 hunting robot. It refers to the relative relations of multi-robots. α_1, α_2, α_3 are angles between the moving direction of the hunting robot and the escaper, which describes the relative motion of multi-robots. The distance between the hunting robot and the escaper is L_1, L_2, L_3 respectively.

The value of the input angle and the value of distance are fuzzed based on the membership function in Fig. 5 and Fig. 6.

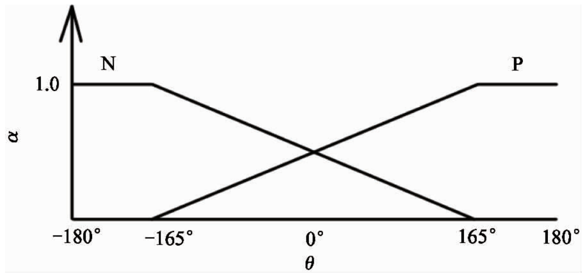

Fig. 5 The membership function between α and θ

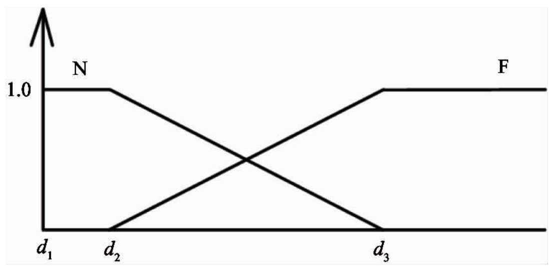

Fig. 6 The membership function of L

The focus of the multi-robot hunting task is to effectively control the robots and to make them collaborate with each other to accomplish the task. Therefore, the design of fuzzy rules in the fuzzy inference system needs to fully reflect the overall behavior of the multi-robot control. The seccedent in this design includes the set of 3 hunting robot R: {$R1$, $R2$, $R3$}, wherein $R1$, $R2$, $R3$ indicate the motion behavior of hunting robot 1, 2 and 3, respectively. The specific meaning is selected from the alternative forms of a group of left and right wheel speeds. It is described in detail in Section 2.2.

After confirming the antecedent and seccedent of the fuzzy inference rules, the specific fuzzy rules can be designed. The j_{th} rule R_j is as follows:

If L_{ie} is A_1^j, $\cdots$, α_l is A_{n-1}^j, β_m is A_n^j, then output is $\{R_1, R_2, R_3\}$

where, L_{ie} represents the distance between hunting robot i and the escaper; α_l represents the angle of the moving direction between the hunting robot l and the escaper. β_m represents the angle between hunting robot m taking the escaper as the center. A_n^j represents the n_{th} fuzzy set of j_{th} rules. Output is a collection that contains three sets of motion of hunting robots, in which each robot's motion is a group of left and right wheel speed mentioned earlier. Through matching the rules in the database, the overall fuzzy inference is achieved. Finally, through linear superposition of the fuzzy rules in the database, the overall final output is obtained.

The fuzzy rule database is formed by a series of the above procedures, which embodies the intelligent strategy of control in the fuzzy inference system. For multi-robot hunting problems, in order to ensure that the rules cover all situations, the rule base is formed by the combination of permutation and combination according to the input quantity and the corresponding fuzzy set number. But there is a certain degree of difficulty in the generation rule database. First of all, the amount of input data in the fuzzy inference system is tremendous; second, the rules in the database cover all possible rounding up situation, which is difficult to be visualized by expert knowledge; finally, even if rule database can be generated by expert knowledge, because there is a certain connection between rules, there is no guarantee that the rules of expert knowledge given is the optimal solution. Considering the above factors, an optimized algorithm is used to generate fuzzy rules database. After determining the order of each rule of input and optional output results, through matching the artificial immune algorithm, the optimal output for each fuzzy rule is selected. The optimization of the rule database is actualized.

2.2 Fuzzy system optimization based on artificial immune algorithm antibody

2.2.1 The encoding of fuzzy rules

The transformation of the artificial immune algorithm of a problem to be solved to the operational search space is called coding. In the view of the design of the fuzzy rule database in this paper, the problem to be solved is the relative relation of the antecedent and seccedent of each rule. Thus, after knowing the order of the antecedent in the fuzzy rule database, the task is to code the seccedents and describe a specific individual of rule database. Here, the needed antibody for the generation of the artificial immune algorithm using the method of real encoding is used. According to the N_{th} rule in the database of fuzzy inference system, each rule corresponds to one output. The output of the N_{th} rule and the affinity form the antibody in the artificial immune algorithm.

Each rule of gene contains information of three hunting robots, as well as one group in the five groups of the left and right wheel speed mentioned earlier. Three groups of the left and right wheel form the control of cooperation among the hunting robots.

The number of hunting strategies is reflected in the simulation environment. When the population size is larger, more hunting strategies are generated and it is easy to find the most optimal solution. The antibody is formed according to this method, and the population of the immune process is formed by a certain number of antibodies.

In this paper, although rules in the fuzzy rule database are large and it is difficult to be made by expert knowledge, some of the rules can still be given directly by expert knowledge, which will not only reduce the number of rules needed for the optimization algorithm, but also reduce the amount of calculation in the process of actual optimization. It avoids the reduction of affinity caused by the randomness of all individuals in the algorithm. Therefore, in the initialization stage of the individual, gene bits given by non expert knowledge are generated randomly while the gene given by expert knowledge is initialized based on the expertise. By initializing the population using expert knowledge, the individual affinity is improved to a certain extent, which in turn reduces the adverse impact of individuals with lower quality on the overall optimization. Thus, it can improve the efficiency of the algorithm.

2.2.2 Immune algorithm

The artificial immune algorithm regards the problem and constraints as antigen. The solution of the problem is regarded as the antibody. At the start of the algorithm, the initial population is randomly generated to a given number of adopted operators such as selection, reproduction, crossover, variation, and vaccine access to manipulate the population to evolve and produce offspring better than the parent. The significant advantage of the artificial immune algorithm is the fact that it can converge to the global optimal solution with probability 1 under certain circumstances.

Clonal selection The clone selection operator is actualized through roulette algorithm. Roulette selection is also known as the proportional selection operator.

$$P_i = f_i / \sum_{i=1}^{n} f_i \tag{1}$$

In the population, the probability that the individual selected is proportional to its value of fitness function. If the population size is n and the fitness of the i_{th} individual is f_i, then the probability of the individual being selected is P_i. Through the clonal selection method above, multiple selections are conducted based on the fitness of the individual and population B_k with the same scale as the parent is generated.

Variation operation Conducting random selection and random variation to the gene bits in the antibodies of population B_k given by non-experts. In each variation, random variation occurs in the motion behavior of all three robots contained in the gene position, namely re-selecting the motion behavior in five groups of left and right wheel speed, ultimately forming population C_k, and calculating the fitness of population C_k.

Population recombination Outstanding individuals in population of A_k and C_k were retained with a certain proportion. Moreover, new individuals were joined to make the size of the population to reach n and form new population A_{k+1}. The added individuals were generated similarly as in the initialized stage so that each individual newly added contained expert knowledge.

2.2.3 Affinity calculation

Affinity describes the matching degree between the antibody and the antigen. In this paper, affinity is given in the effectiveness of completing the multi robot hunting task using fuzzy inference system with the optimized rules. The artificial immune algorithm is used to optimize rules of the fuzzy inference system. Thus, the specific evaluation index is to describe the effect of operating fuzzy inference system. Affinity calculation needs to consider the overall advantages and disadvantages of the rounding up state and the number of steps used.

In order to ensure the effectiveness of the rounding up process, various factors need to be considered. This paper mainly focuses on the maintenance of the hunting state and the effect of encirclement. In Fig. 7, the squares represent the hunting robots; the circle at the center area represents the escaping robot; the small circles represent the position of the geometric center formed by hunting robots. The distance between the i_{th} hunting robot and escaping one is a L_{ie}, which is used to measure the formation of the contractile ring; and the distance between i_{th} and j_{th} hunting robot is S_{ij}, which is used to measure the even distribution of the hunting robots; the distance between the geometric center of the hunting robots and the escaping one is denoted by C.

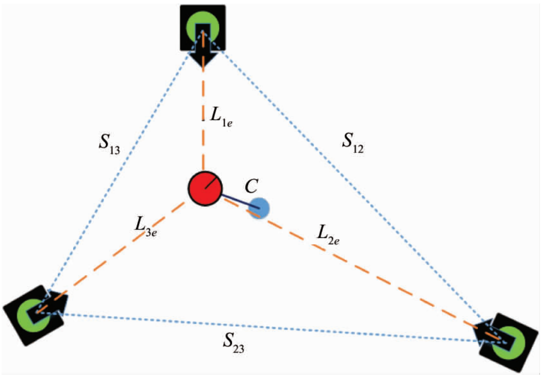

Fig. 7 The parameter of affinity

The operation of the three evaluation criteria above needs fuzzy inference system. It also requires the record of the overall changes of three parameters after each step of movement. Together, they form a comprehensive evaluation of the final affinity. The specific design of the function for affinity calculation is as follows.

$$f = Fitness - \sum_{n=1}^{N} (\omega_1 \cdot C + \omega_2 \cdot \sum_{i=1}^{3} | S_i - S_{avg} | + \omega_3 \cdot \sum_{i=1}^{3} \Delta L_i) + F_p \tag{2}$$

In Eq. (2), *Fitness* is the default initial affinity of the antibody, and N is the total number of steps calculated by the fuzzy inference system. C is the distance between the escaper and hunter formed by the geometric center. S_i is the distance between the robots and S_{avg} is the average value of the distance between the robots. The distribution of the hunting robots is measured by $S_i - S_{avg}$. $\triangle L$ represents the moving distance of i_{th} robot in one step. With the superposition of multiple steps, the total distance of the final movement of the robot is obtained. ω_1, ω_2 and ω_3 are the coefficients of proportionality, which are used to adjust the weight of each evaluation index to the final evaluation. F_p as the reward function, when completing the rounding up within the step number n according to the hunting success criteria, the individual reward will be given. $F_p = 5000$, otherwise F_p is 0. This can ensure the completion of the individual task to be early discovered and preserved.

For each individual, the initial provides a higher level of affinity. With the ongoing work, the affinity will continue to reduce according to the affinity function of the design. According to the setting of the affinity function, first, the total number of steps of the outstanding individuals is small thus the value of $\sum_{i=1}^{3} \Delta L_i$ is relatively small; secondly, the distribution of the outstanding individual hunting robots is even, thus the value of $\sum_{i=1}^{3} | S_i - S_{avg} |$ is smaller; finally, the hunting circle formed by outstanding individuals is more effective, thus the C value is relatively small. Overall, when the individual is more outstanding, its subtracted value based on the initial affinity value is smaller, which provides higher degree of the affinity for the more outstanding individuals.

To determine the success of the hunting, the 3 factors mentioned above need to be taken into the consideration. When the distance is less than a certain threshold ($\varepsilon_s, \varepsilon_l, \varepsilon_c$) and the hunting is successful, the specific threshold is set by the running speed of the robot and the actual environment.

$$((x_i - x_j)^2 + (y_i - y_j)^2)^{\frac{1}{2}} \leqslant \varepsilon_s \tag{3}$$

$$((x_i - x_e)^2 + (y_i - y_e)^2)^{\frac{1}{2}} \leqslant \varepsilon_l \tag{4}$$

$$((x_e - x_c)^2 + (y_e - y_c)^2)^{\frac{1}{2}} \leqslant \varepsilon_c \tag{5}$$

Here, x_i and y_i represent the coordinates of the i_{th} robot, x_e and y_e represent the coordinates of the escaper.

2.3 Artificial immune algorithm flow

After the improvement of the artificial immune algorithm and the combination of the fuzzy inference system, the implementation steps of the algorithm are summarized as follows:

(1) According to the hunting environment of multiple hunting robots, a fuzzy inference system is established. Through ensuring the input and output variables and fuzzy sets, the antecedent of the rule database is formed by permutation and combination.

(2) According to the seccedent of each rule in the fuzzy rule database, antibody is generated and injected with expert knowledge, which in turn forms fuzzy rule database with a certain scale. Initial parent population A_k is formed.

(3) Calculate the evolutionary algebra in the current parent population and the affinity of all the fuzzy rule databases in A_k. The specific calculation is conducted by the deduction of the fuzzy system. If the conditions are satisfied, then the operation is terminated and the result is output. Otherwise, the calculation would continue.

(4) According to the fuzzy rule database and the affinity among hunting robots, the clonal selection of A_k is operated. Through multiple clonal selection, temporary population B_k is obtained and its size is the same as A_k.

(5) Mutation of B_k is operated according to a certain probability. If a mutation occurs, the motion behavior of the three corresponding robots of the gene site would change too. Population C_k is formed after the mutation. The affinity of the antibody in C_k is calculated and sorted. The best individuals m are selected to constitute C_m.

(6) Generation of a new parent population A_{k+1}. The population is constituted by A_k^* (n optimal fuzzy databases in A_k), C_m (m optimal fuzzy rule databases in population C) and D_r (r newly added fuzzy rule databases), namely $A_{k+1} = A_k^* + C_m + D_r$, Then, return to step (4).

The fuzzy rule database is generated through the artificial immune algorithm described above. Then the optimal antibody and the optimal fuzzy rule database are got by analyzing it. Finally, the task of multi-robot hunting can be operated based on this fuzzy rule database.

3 Simulation and analysis

The algorithm simulates the multi-robot hunting task through the simulation program. The simulation environment parameters are set according to the actual situation.

Fig. 8 indicates the initial state of multi-robot hunting. The hunting robots in three corners round up the escaper in the center, and they find each other. While the hunting robots proceed the round up, the escaper tries to run away according to certain strategies.

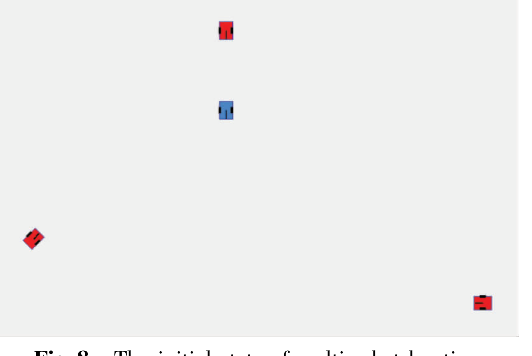

Fig. 8 The initial state of multi-robot hunting

Based on the fuzzy rule database after the artificial immune optimization, the hunting robots gain environmental information and begin rounding up.

After a period of time, hunters effectively actualize the round up with relatively few steps, as shown in Fig. 9. During the process of hunting, the motion trajectory of any robot is smooth and hunters move without

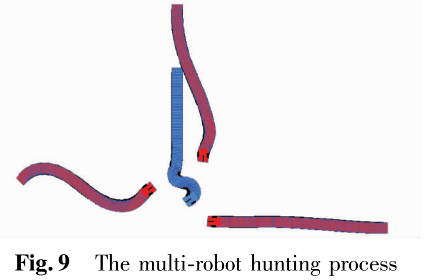

Fig. 9 The multi-robot hunting process

obvious turning back or substantial changes. The overall effect of hunting is good.

Fig. 10 shows the adaption value of the most optimal antibody among all experimental generations during the process of optimization, as well as how much the average fitness has changed with the evolution algebra. In Fig. 10, the horizontal coordinate indicates the evolution algebra in the last experiment; the vertical coordinate indicates the degree of affinity after the unification process. As shown in Fig. 10, the average degree of fitness fluctuates to a certain extent to maintain the diversity in the population during the implementation of the algorithm. Yet with the increase of the evolving algebra, the degree of affinity in the optimal antibody population shows a decreasing trend, until convergence occurs to the overall optimal solution (i. e., the fitness is 1).

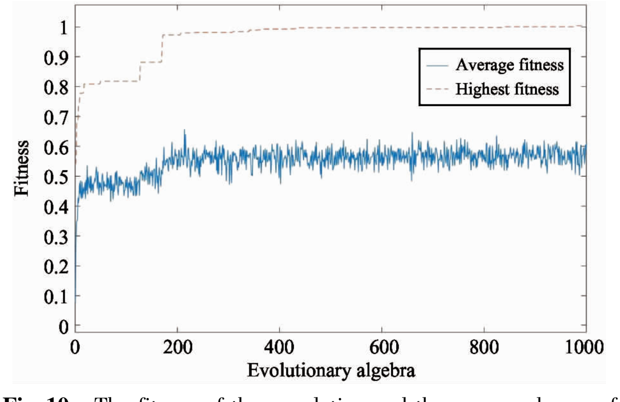

Fig. 10 The fitness of the population and the average degree of fitness in the population changes with the change of the evolutionary algebra

In the case of multi-robot hunting strategy, to verify the validity and applicability of the method, the experiment is conducted in different environments. Fig. 11 and Fig. 12 are two experiments in different initial states under the condition that the hunters and escaper have discovered each other. It is shown that the hunters have completed the rounding up process and the trajectory has no obvious change of reentrant.

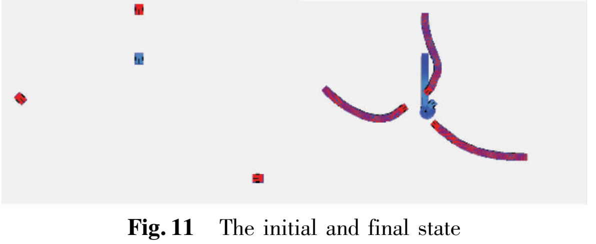

Fig. 11 The initial and final state

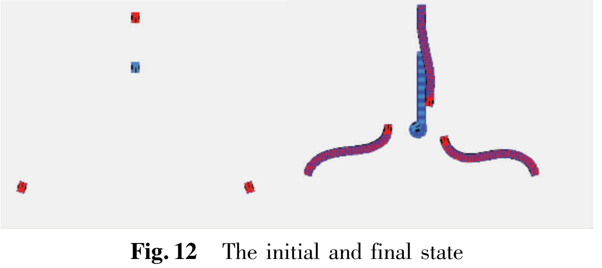

Fig. 12 The initial and final state

In order to analyze the effectiveness of the hunting process, various factors are taken into account. This experiment mainly focuses on the maintenance of the hunting state and the effectiveness of encirclement. As shown in Fig. 7, the hunting effect is evaluated mainly by three parameters L_{ie}, S_{ij} and C. The hunting strategy is evaluated considering the data from the three aspects.

Fig. 13, Fig. 14 and Fig. 15 show that three different lines respectively represent the three different experiments including the changes of evaluation parameters. The horizontal coordinate is the number of steps, and the vertical coordinate shows the normalized distance. As shown, during the whole hunting process, the initial values of evaluative parameters are district. However, the distance among hunters and the distance between hunters and the escaper decrease as the motion steps increase steadily, which reflects the trend of maintenance of the hunting state as well as contraction

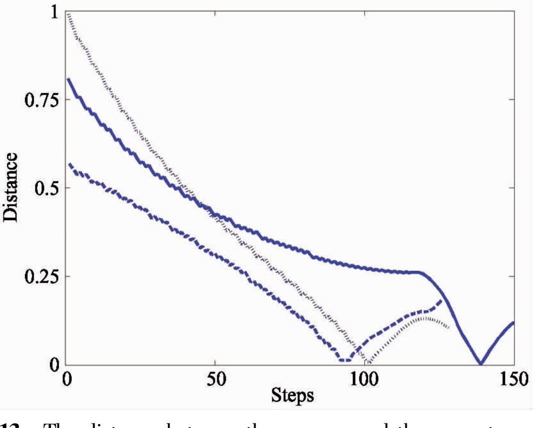

Fig. 13 The distance between the escaper and the geometry center

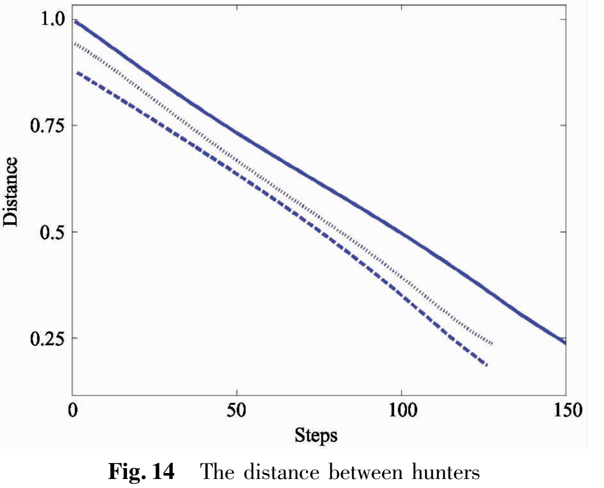

Fig. 14 The distance between hunters

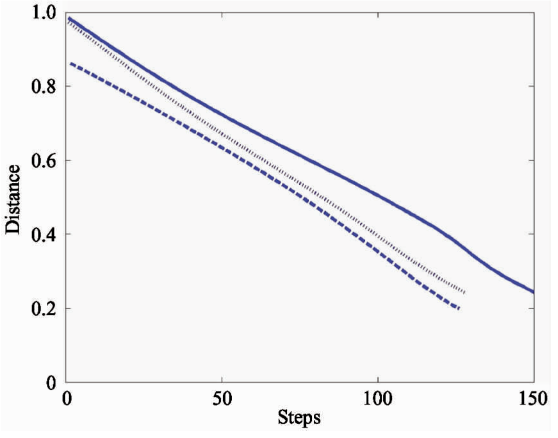

Fig. 15 The distance between hunters and the escaper

during the process of hunting. The small fluctuation of the geometry center distance between the hunter and the escaper is mainly due to the unpredictable motions of the escaper once it perceives hunters. But as the hunting proceeds, a lower value will eventually be reached.

4 Conclusion

The multi-robot hunting task is studied. Through collecting information about the environmental data, the hunting states at different moments are abstracted. In addition, the overall control of multiple hunters is achieved through the fuzzy inference system (FIS). By using the artificial immune algorithm, the majority of rules in the fuzzy rule database are calculated in accordance with a certain degree of adaptation. Some intuitive rules are set by expert knowledge, which reduces the computational complexity in the optimization process. Meanwhile, the connection between the rules is ensured by coding the whole fuzzy rule database as an optimized individual. The simulation program is used to carry out the experiment and the environment of the simulation program is proportionally reduced according to the parameters in the actual environment. The motion of robots is consistent with the constraints of motion models. Multiple simulation experiments have been performed under different initial conditions, which verifies the feasibility of the algorithm and achieved good results.

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