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Multi-Robot Formation Control Based on Leader-Follower Optimized by the IGA

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Abstract: *To improve the efficiency of multi-robot formation control, a new formation control algorithm based on leader-follower optimized by the immune genetic algorithm (IGA) is put forward in this paper. Firstly, the formation control is realized by leader-follower algorithm. Then, the proportion coefficients k_1, k_2 in leader-follower is optimized by the immune genetic algorithm. Finally, the optimized proportion coefficients k_1 and k_2 is used in the leader-follower algorithm to finish the multi-robot formation control. Compared with other three formation control algorithms (i.e. GA, simple leader-follower algorithm, behavior algorithm), the experimental results of multi-robot formation control in two environments show that the formation control performance at time and step finishing formation of the proposed formation control algorithm is obviously improved, which verifies the validity of this algorithm.*

Keywords: *Multiple robots, Formation control, Leader-follower, Immune genetic algorithm*

I. Introduction

In recent years, the multi-robot system has attracted more and more attention. The formation control is one of the key technologies in multi-robot systems. The existing formation control methods mainly include the leader-follower algorithm [1], behavior-based control algorithm [2] and virtual structure algorithm [3]. Li *et al*. [4] put forward a multi-robot formation control based on dynamic leader and enhance the ability of multi-robots to deal with emergencies. However, the algorithm has poor adaptability in complex environments. Aiming at the formation control of multi-robots, Zhang *et al.* [5] proposed a quick converging distributed algorithm for generating arbitrary shape of multi-robots. However, the leader and followers are relatively independent of each other, and it is difficult for the proposed algorithm to find feasible space when the obstacles are dense. He *et al*. [6] proposed a distributed formation control approach to formation maneuvers. In the control approach, based on virtual structures, formation feedback is incorporated in the formation control scheme to increase the robustness of the formation. However, because the formation movement of multi-robots simulates a virtual structure, the approach is limited in application range. In order to further improve the formation control efficiency of the leader-follower algorithm, the immune genetic algorithm is introduced to optimize the proportion coefficients k_1, k_2 of the leader-follower algorithm in this paper. The experimental results show that the formation control efficiency of the proposed leader follower algorithm optimized by IGA is significantly improved.

II. Formation Control Based on Leader-Follower

The leader-follower method [7] is described as: In a multi-robot team, a leader is set. The rest of the robots are designated followers, and follow the movement of the leader. Let l_e and φ_e be the expected straight-line distance and expected included angle between the leader and a follower, respectively. The purpose of the formation control is to make the actual detection distance l and included angle φ between the leader and a follower equal to the l_e and φ_e.Let (x_0, y_0), θ_0, v_0 and ω_0 be the position coordinate, direction angle, velocity and angular velocity of the leader.Let (x_i, y_i) and θ_i be the position coordinate and direction angle of the ith follower. The ith follower can finish its formation control by calculating its forward speed v_i and angular velocity ω_i.
The kinematics equation of the ith follower can be described:

$$\begin{cases} \dot{l}_i = v_i \cos\gamma_i - v_0 \cos\varphi_i + d_i\omega_i \sin\gamma_i \\ \dot{\varphi}_i = \dfrac{1}{l_i}(v_0 \sin\varphi_i - v_i \sin\gamma + d_i\omega_i \cos\gamma_i - l_i\omega_0) \\ \dot{\theta}_i = \omega_i \end{cases} \tag{1}$$

where, d_i is the distance between the leader point and the reference point of the ith follower. $\gamma_i = \varphi_i + \theta_0 + \theta_i$.
According to the closed loop characteristics of the leader-follower formation control, we can conclude:

$$\begin{cases} \dot{l}_i = k_1(l_e - l_i) \\ \dot{\varphi}_i = k_2(\varphi_e - \varphi_i) \end{cases} \tag{2}$$

where, k_1 and k_2 are the proportional control coefficients.
According to Eq.(1) and (2), the velocity v_i and angular velocity ω_i of the ith follower can be obtained.

$$\begin{cases} \omega_i = \dfrac{\cos\gamma_i}{d_i}[k_2 l_i(\varphi_e - \varphi_i) - v_0 \sin\varphi_i + l_i\omega_0 + p\sin\gamma_i] \\ v_i = p_i - d_i\omega_i \tan\gamma_i \end{cases} \tag{3}$$

where, $p_i = \dfrac{v_0 \cos\varphi_i + k_1(l_e - l_i)}{\cos\gamma_i}$.

In the multi-robot formation system, the velocity and angular velocity of each follower robot can be achieved according to Eq.(3). Then the multi-robot formation control can be completed.

III. Multi-Robot Formation Control Optimized by Immune Genetic Optimization

3.1 Immune genetic optimization algorithm

The genetic algorithm (GA) [8] is a kind of global random search algorithm, and is commonly used to generate high-quality solutions to optimization and search problems by relying on bio-inspired operators such as mutation, crossover and selection. The immune genetic algorithm (IGA) [9] is a novel optimization algorithm based on artificial immune theory, and is designed on the basic framework of genetic algorithm by combing with immune operators (such as antibody stimulation and suppression, vaccine extraction and inoculation, and so on.), which can effectively enhance the search efficiency and search precision of genetic algorithm.
The flow of IGA is shown in Fig.1.

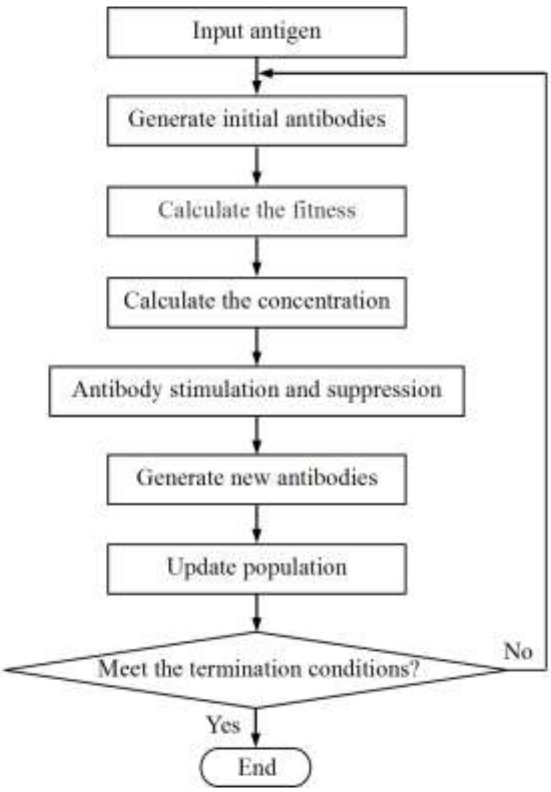


Fig. 1 Flow of immune genetic algorithm

3.2 Immune selection based on information entropy

In order to reflect the diversity of antibodies in the population, the information entropy is introduced in this paper. The affinity between the antibody and the antigen, and the affinity between different antibodies are calculated based on the information entropy.
The average information entropy of the entire population is defined as:

$$H(N) = \frac{1}{M}\sum_{j=1}^{M} H_j(N) \tag{4}$$

$$H_j(N) = \sum_{i=0}^{1}(-p_{ij}\lg p_{ij}) \tag{5}$$

$$p_{ij} = \frac{\text{Total number of symbol } i \text{ at } j\text{th position of } N \text{ antibodies}}{N} \tag{6}$$

where, M is population size, H_j is entropy from jth position of N antibodies, and p_{ij} is probability whose symbol is i from jth position of N antibodies.
Let $\boldsymbol{A}_{ij}$ be the similarity between individuals s_i and s_j.

$$\boldsymbol{A}_{ij} = \frac{1}{1+H(2)} \tag{7}$$

where $H(2)$ can be obtained through Equations (4), (5) and (6) when N = 2.

3.3 Calculation of the expected reproduction rate[10]
The concentration of antibody $\boldsymbol{x}$ is defined as

$$D_x = \frac{1}{N}\sum_{j=i}^{N} Q_{ij} \tag{8}$$

Where

$$Q_{ij} = \begin{cases} 1 & A_{ij} > \gamma \\ 0 & otherwise \end{cases} \tag{9}$$

and γ is the preset threshold value of the similarity.
The affinity between antigen and antibody [8, 9] is defined as:

$$Af_x = Fit(\boldsymbol{x}) + Pra(\boldsymbol{x}) \tag{10}$$

Where, Fit($\boldsymbol{x}$) is the fitness of antibody $\boldsymbol{x}$. $Pra(\boldsymbol{x})$ is the excitation value of an antibody which is next to the local or global optimal points.
The expected reproduction rate (Err) of antibody $\boldsymbol{x}$ can be described as:

$$E\text{rr}(\boldsymbol{x}) = \frac{Af_x}{D_x} \tag{11}$$

3.4 Optimization flow of the proportional control coefficients of leader-follower algorithm
Step 1 Initialize algorithm parameters: antibody size M, selection probability, crossover probability, mutation probability, threshold value γ, maximal evolutionary generation $k_{\max}$, and so on. $k \leftarrow 0$.
Step 2 Generate initial operation population and memory population.
Step 3 Calculate the expected reproduction rates Errs of all antibodies in operation population.
Step 4 Execute selection operation.
Step 5 Execute crossover operation.
Step 6 Execute mutation operation.
Step 7 Calculate the expected reproduction rates Errs of all antibodies in new operation population and memory population.
Step 8 Select better antibodies to update the operation population and memory population.
Step 9 Judge whether the terminating condition is satisfied. If not, $k \leftarrow k+1$, go to Step 4, otherwise end.
The termination condition is stated as: The specified $k_{\max}$ is reached.

IV. Immune optimization test and result analysis

In order to verify the validity and superiority of the proposed multi-robot formation control based on immune genetic optimization, the triangle formation control simulations in two environments are executed. The simulation results are compared with those of the GA, leader-follower algorithm and behavior algorithm.The proportional coefficients k_1 and k_2 in leader-follower algorithm are 0.22 and 0.20 respectively after optimization of IGA. The coefficients k_1 and k_2 optimized by GA are 0.20 and 0.20 respectively. The evolutionary curves of optimal solutions of IGA and GA are shown in Fig. 2. The evolutionary curves of average solutions of IGA and GA are shown in Fig. 3. From Fig.2 and Fig.3, it can be seen that the optimization ability of IGA is stronger than that of IGA.

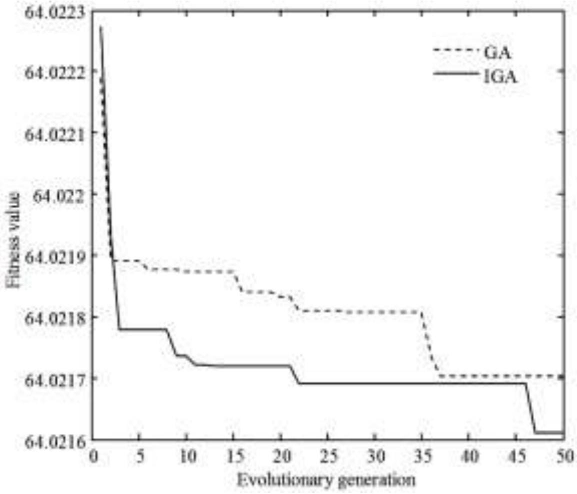


Fig.2 Evolutionary curves of optimal solutions

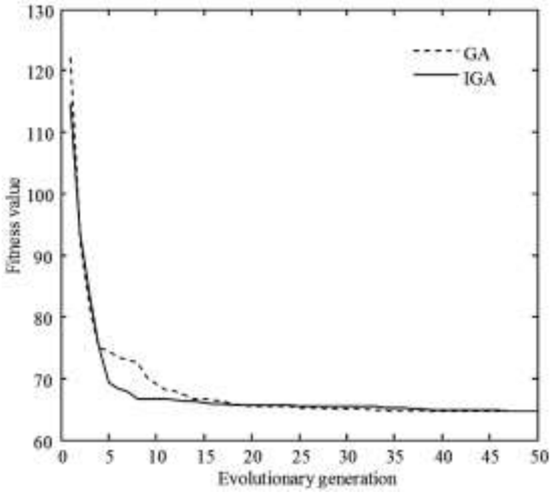
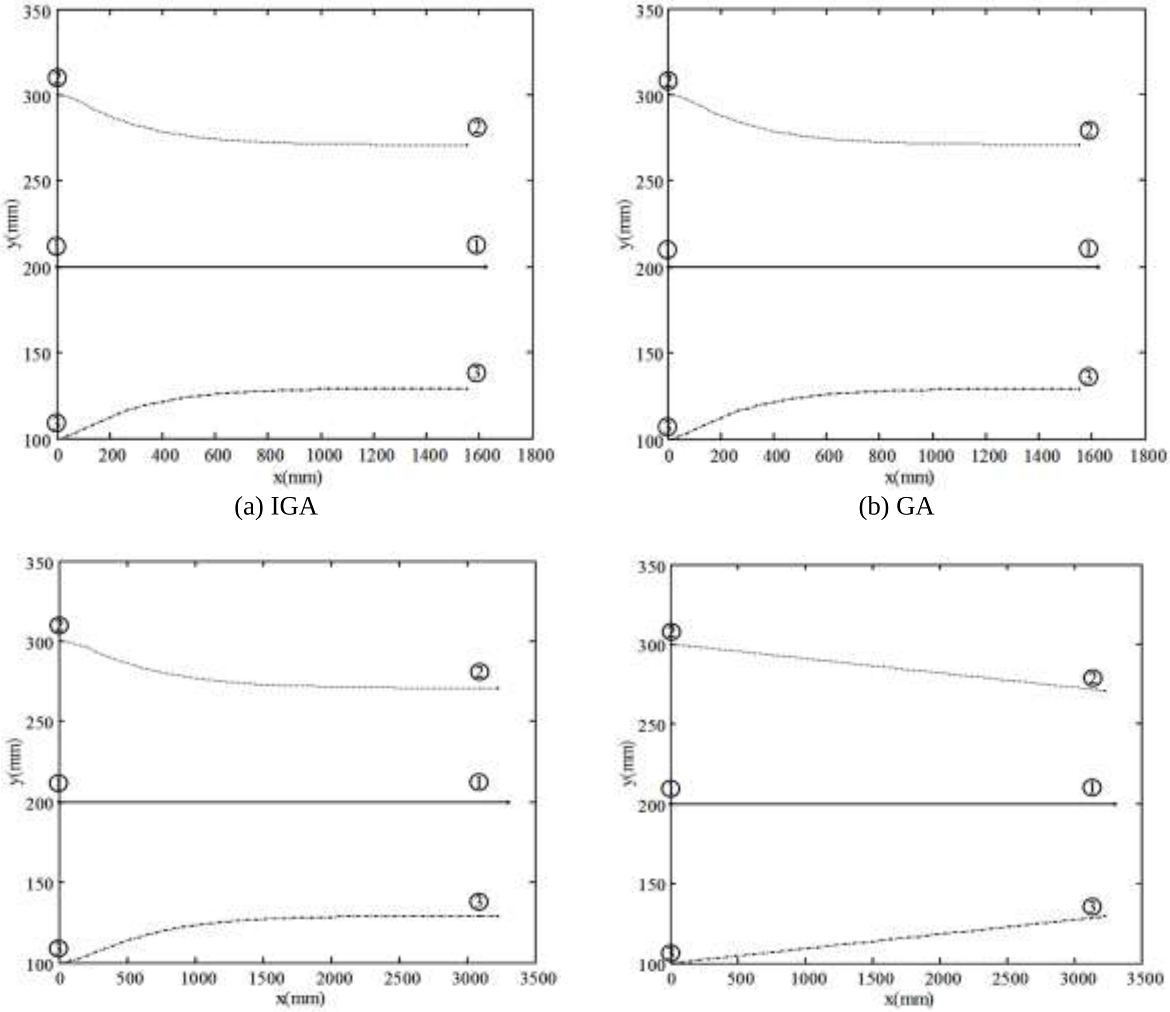


Fig. 3 Evolutionary curves of average solutions

Fig.4 gives the formation control results of four algorithms (i.e. IGA, GA, leader-follower and behavior) in an environment with three robots. Fig.5 gives the formation control results of four algorithms in an environment with six robots. Form the two figures, it can be seen that all robots can complete the formation control successfully through their respective algorithms. However, different algorithms have resulted in different control results.



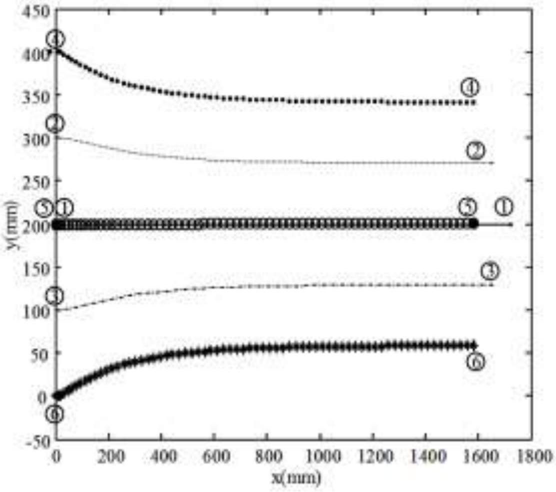
(a) IGA

(b) GA

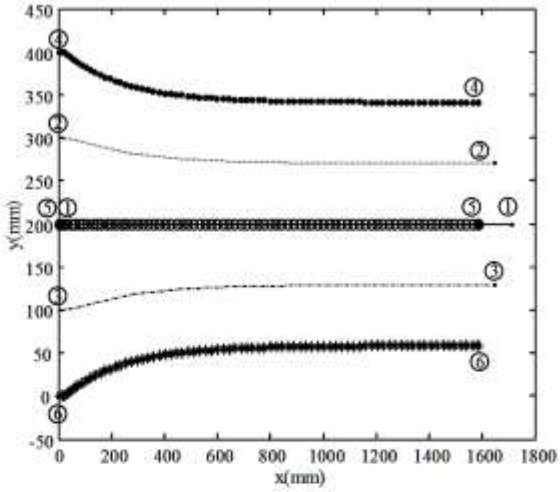
(c) Leader-follower algorithm

(d) Behavior algorithm

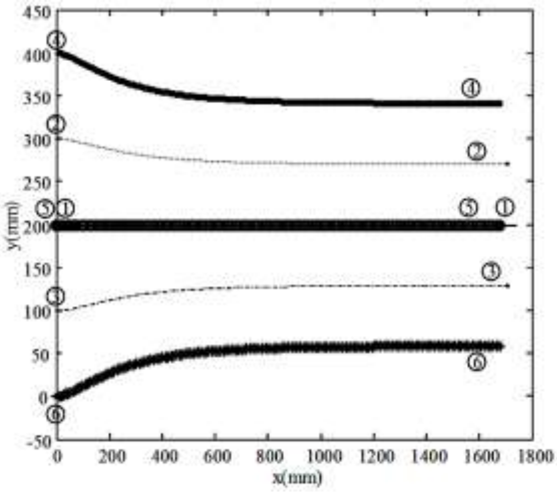
Fig.4 Formation simulation of three robots



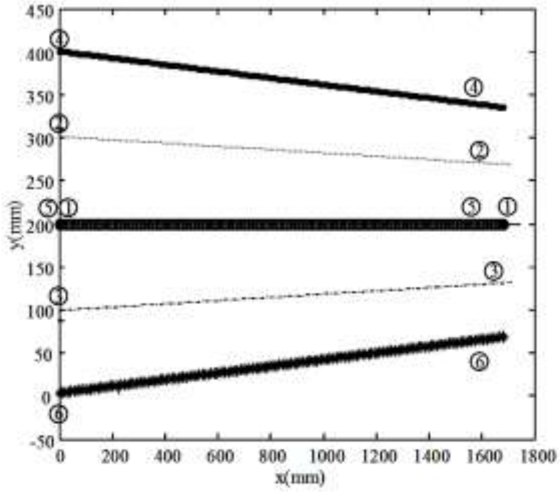
(a) IGA



(b) GA



(c) Leader-follower algorithm



(d) Behavior algorithm

Fig.5 Formation simulation of six robots

Table 1 gives the performance comparison of formation control among four algorithms in two environments. From the table, we can see that, although the traditional control algorithms (i.e. leader-follower and behavior) have completed formation control, their control performance (i.e. time and step finishing formation) are significantly lower than the intelligent algorithms (i.e. IGA and GA). As for IGA and GA, it can be seen that their formation control effect is basically the same in simple environment with only three robots. However, in the environment with six robots, we can see that the IGA plays a powerful optimization capability and its formation control result is better than that of GA, which verifies the validity of the IGA in the formation control.

Table1 performance comparison of formation control among four algorithms

Performance	**Number of robots**	**IGA**	**GA**	**Leader-follower algorithm**	**Behavior algorithm**
Time finishing formation	3	33	33	66.5	70.5
	6	35.5	36.5	78	82
Step finishing formation	3	66	66	133	141
	6	71	73	156	164

V. Conclusions

In the traditional leader-follower algorithm, the proportion coefficients k_1, k_2 is obtained by trial and error. The random coefficients affect the formation control effect to a great extent. In order to improve the formation control efficiency of the simple leader-follower algorithm, the immune genetic algorithm is introduced in this paper. The proportion coefficients k_1, k_2 are taken as the antibodies, and optimal solutions are obtained through the immune optimization. Finally the optimized proportion coefficients are used in the leader-follower algorithm. The parameter optimization results show that the IGA not only can complete the global optimization of k_1 and k_2, but also its optimization ability is stronger than that of the genetic algorithm. Furthermore, the simulation results of formation control in two environments also show that the formation control results of IGA are the best, which further verifies the validity of the IGA in the parameter optimization of leader-follower algorithm.

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