Proceedings of the 35th Chinese Control Conference
July 27-29, 2016, Chengdu, China

Parameters Optimization of Multi-UAV Formation Control Method based on Artificial Physics

FU Yu, WANG XiangKe, ZHU HuaYong, YU YangGuang
National University of Defense technology, Changsha, 410073, China
E-mail: xkwang@nudt.edu.cn

Abstract: In this paper we focus on the optimization of the artificial physics based formation control algorithm, for the multiple Unmanned Aerial Vehicles(UAVs) formation control. It is known that time optimization is very important in many applications of the formation related problems. Therefore, in this paper, an optimization method using genetic algorithm is proposed to tune the parameters automatically for the formation control algorithm based on the artificial physics, in order to optimize the formation forming process and improve the time performance of the proposed formation control method. The simulation results demonstrate the feasibility and effectiveness of the proposed method in solving the optimal formation control problem for multiple UAVs.

Key Words: unmanned aerial vehicle, formation control, time-optimal control, artificial physics

1 Introduction

The formation control problems of multiple Unmanned Aerial Vehicle (UAV) systems have attracted growing interest in recent years, due to its extensive applications in both civilian and military fields. The capability of keeping multiple unmanned vehicles in a designed geometric pattern provides favorable capability multiplying effects for tasks where a single vehicle is difficult to accomplish or too costly[1]. In recent decades, various methods have been proposed to solve the formation control problems, such as the leader-follower strategy, the virtual structure strategy, the behavior-based strategy, the artificial field strategy and the graph-based strategy[2][3].

The artificial physics method, proposed by William M.Spears, is a new and attractive method in the multi-agent coordination problem[4]. It is used to self-organize swarms of mobile robots into hexagonal and square lattices. Inspired by the law of universal gravitation, the virtual forces between two agents are defined. Through the attractive and repulsive forces between two agents, the swarms can exhibit the convergence and avoidance behavior[5][6]. As many advantages such as self-assembly, fault-tolerance, self-repairs, briefness and distribution as there may be, the artificial physics method also has shortcomings such as easily plunging into a local optimal solution, longer settling time and rough trajectories[7]. What's more, most of the research on the artificial physics method has only focused on how to make the multiple agents reach the desired formation, without considering to optimize the performance indexes, such as the formation time, and the evolutions of the trajectories. Whereas, it is known that the optimization of the performances is very important in many applications for multiple UAV coordinations. For example, it is always expected that the multiple UAVs are to form the desired formation pattern as soon as possible after taking off.

In order to overcome the shortcomings of traditional artificial physics, we have modified the artificial force laws of the traditional artificial physics, and designed a new artificial-physics-based formation control strategy in the previous work[8]. However it has not considered the optimization problem of formation control neither. As an important resource for formation control problem, time performance is one of the key indexes for the Multi-UAV formation system. A main contribution of this paper is that an optimization method using genetic algorithm is proposed to tune the parameters automatically for the formation control method based on the artificial physics, in order to make the formation form as fast as possible. The simulation results have shown that the time performance of the formation control based on artificial physics has greatly improved with the proposed parameter optimization method.

The rest of this paper is organized as follow. In Section 2, we introduce the basic principles of traditional artificial physics and the modified artificial force laws in our previous work. Section 3 gives the mathematical description of multiple UAVs formation control problem, and define the time performance index. Section 4 provides the formation time-optimal control method with genetic algorithms in details. The simulation results are presented to illustrate the proposed approach in Section 5. And our concluding remarks are contained in the final section.

2 Artificial Physics Framework

In this section, we will introduce some basic notions of the artificial physics framework and the formation control method based on artificial physics developed in our previous work. In the artificial physics method, the virtual physics forces are defined to drive a swarm of UAVs to a desired configuration, which is one that minimizes the potential energy of overall system, and the system acts as a molecular dynamics($\overrightarrow{F} = m\overrightarrow{a}$)simulation[9].

2.1 The Standard Formation Model

The standard formation is defined as a regular polygon with n sides, as shown in Fig. 1. The UAVs are deposited on the circumcircle evenly, and the length of each side is equal to L. The circumcenter of the polygon is in a desired position x_c, which acts as the virtual leader of the formation. R is the radius of the circumcircle of the polygon. In the rest of the paper we use five UAVs as an example to design the formation controller and carry out the simulations. Our aim is to drive the five UAVs to form a standard formation shown in Fig. 1.

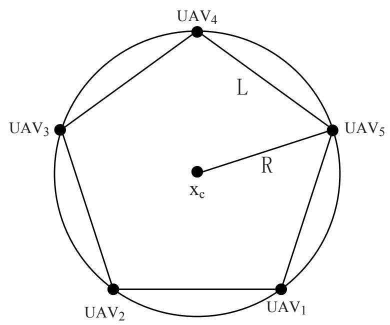


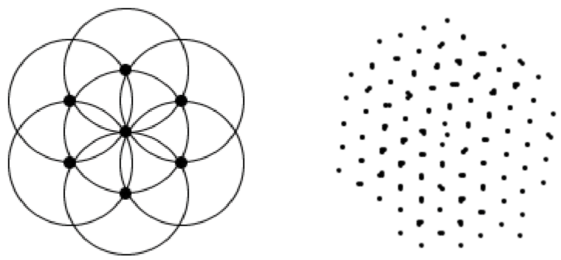
Fig. 1 The standard formation

2.2 Formation control method based on Artificial Physics

In the traditional artificial physics framework, each agent exerts virtual forces upon others. Imitating the Newtonian gravitational force law, the artificial force can be defined as:

$$F_{ij} = G\frac{m_i m_j}{r^p} \tag{1}$$

where F_{ij} is the magnitude of force between two agents i and j, m_i is the mass of the i_{th} agent, r represents the range between two agents, p is some power, and the "gravitational constant" G is set at initialization. The direction of the force is determined by the magnitude of r, the force is repulsive if r < R and attractive if r > R. Each agent has a range of only 1.5R. Thus each agent can be considered to have a circular "potential well" around itself. Finally, under this force law,seven agents will form a hexagon formation shown in Fig. 2(a), and the agents will form a hexagonal lattice with the number of the agents increasing, as Fig. 2(b) shows.



(a) (b)

Fig. 2 (a)The hexagon formation.(b)The hexagonal lattice.

Actually,by the traditional artificial physics force law, the agents cannot form the desired formation like the standard formation shown in Fig. 1, because in the standard formation, the distance between two adjacent UAVs on the circumcircle is not equal to R.

Therefore, we modified the artificial physics force law in our previous work. In order to make the five UAVs form the standard formation shown in Fig. 1, firstly, we define the force law between the circumcenter x_c and UAV$_i(i = 1, \cdots, 5)$ on the circumcircle as follows:

$$f_{ic} = G_1\frac{(||\overrightarrow{r}_i|| - R)\overrightarrow{r}_i}{||\overrightarrow{r}_i||} \tag{2}$$

where f_{ic} is the force between x_c and UAV$_i(i = 1, \cdots, 5)$; G_1 is the "gravitational constant" of f_{ic}; $\overrightarrow{r}_i = \overrightarrow{p}_i - \overrightarrow{p}_c$ is the relative position vector; $\overrightarrow{p}_i$ is the position vector of UAV$_i$; and $\overrightarrow{p}_c$ is position vector of x_c. As we can see, if $||r_i|| > R$, it will produce an attractive force to drive the UAV$_i(i = 1, \cdots, 5)$ toward the x_c; to the contrary, if $||r_i|| < R$, a repulsive force will work. So the UAV$_i(i = 1, \cdots, 5)$ will be deposited on the circumcircle eventually.

In order to avoid collision, we define the repulsive force between two UAVs as follow:

$$f_{ij} = \begin{cases} G_2\frac{(||\overrightarrow{r}_{ij}|| - L)\overrightarrow{r}_{ij}}{||\overrightarrow{r}_{ij}||} & \text{if } ||\overrightarrow{r}_{ij}|| < L \\ 0 & \text{if } ||\overrightarrow{r}_{ij}|| \geqslant L \end{cases} \tag{3}$$

where f$_{ij}$ is the repulsive force between the UAV$_i$ and UAV$_j$; G_2 is the "gravitational constant" of f_{ij}; $\overrightarrow{r}_{ij} = \overrightarrow{p}_i - \overrightarrow{p}_j$; and $\overrightarrow{p}_i$ and $\overrightarrow{p}_j$ are the position vectors of the UAV$_i$ and UAV$_j$ respectively.

In fact, there are infinite possible polygons lying on the same circumcircle due to the freedom of rotation. So we add the attractive point X* with an attractive range of L* to eliminate the freedom of rotation as Fig. 3 shows.

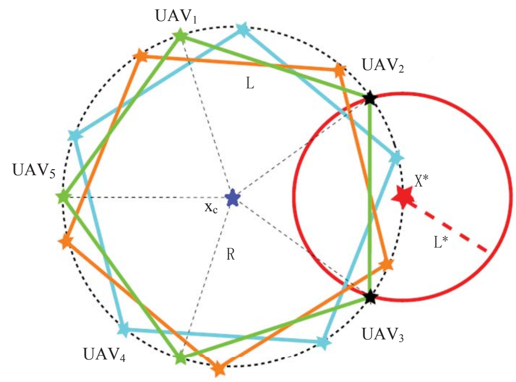


Fig. 3 The standard formation with an attractive point

If the distance between the UAV$_i$ and X* is less than L*, the attractive point will exert an attractive force on the UAV. Meanwhile, other UAVs will adjust their positions to maintain the standard formation.The force between the UAV in the attractive range and X* is :

$$f_{io} = G_3(\overrightarrow{p}_i - \overrightarrow{X}^*) \tag{4}$$

G_3 is the "gravitational constant" of f_{io}.

By combining (2), (3) and (4), we can get the sum force applied on the UAV$_i$:

$$f_i = \sum_{j=1, j\neq i}^{5} f_{ij} + f_{ic} + f_{io} \tag{5}$$

It has proven that the five UAVs driving by the force defined in (5) form the exclusive standard formation shown in Fig. 1.

In fact, in our formation control method based on artificial physics, the virtual force exerted on each UAV can be set as control input of the corresponding UAV, i.e., the desired velocity vector of the UAV. According to the definition, the value of the virtual force is greatly influenced by the value of the "gravitational constant". In our previous work, the "gravitational constants" G_1, G_2 and G_3 are all set at initialization without considering to optimize the performance indexes. In order to get the optimal time performance of the proposed formation control method, we will present an optimization method to tune the parameters automatically in the rest of this paper.

3 Formation Time-optimal Control Problem

Without loss of generality, the considered multiple UAVs formation is flying at a certain high level. Assume that the number of the UAVs in the formation is N. Note that in this paper we set $N = 5$. The initial time is set to be $t_i = 0$, the terminal time $t_T = T$. the control input for UAV$_i$ is u_i, i.e., the desired velocity vector of the UAV. According to our formation control method introduced in the previous section, the value of u_i depends on the sum of the virtue force vector f_i acted on the UAV$_i$. Then the formation control input vector can be defined as:

$$U = (u_1, \cdots, u_N) = \{U(t)|\forall t \in [0, T]\} \tag{6}$$

Assume that the state vector of UAV$_i$ is x_i, including the coordinates and the heading angle of the UAV$_i$. Therefore, the state vector of the over all system is defined as:

$$X = (x_1^T, \cdots, x_N^T)^T \tag{7}$$

And the formation system dynamic can be described as:

$$\dot{X}(t) = f(t, X(t), U(t)) \tag{8}$$

Considering the initial state $X(0) = X_0$, the state of the overall system at any time $t \in [0, T]$ can be determined by the following form:

$$X(t) = X(0) + \int_0^{t^-} f(\tau, X(\tau), U(\tau))d\tau \tag{9}$$

Generally, for the optimal control problem, the payoff function can be expressed in the following form:

$$J(U) = \Phi[X(T), T] + \int_0^T L(X(t), U(t), t)dt \tag{10}$$

where $\Phi[X(T), T]$ represents the terminal performance index, which is determined by the terminal time T and the terminal state $X(T)$, and the dynamic performance index $L(X(t), U(t), t)$ is determined by state vector $X(T)$ and the control vector $U(T)$. For the formation time-optimal control problem, the payoff function can be defined as:

$$J(U) = T \tag{11}$$

it can be seen that the sooner the UAVs form the desired formation, the smaller the value of the payoff function will be.

Meanwhile, the system has to satisfy some constrains, the control inputs are usually constrained by[10]:

$$U_{min} \leq U(t) \leq U_{max}, \forall t \in [0, T] \tag{12}$$

And the terminal constraint of the formation system $g(U, T)$ can be defined as:

$$g(U, T) = \sum_{i=1}^{N} ||(\overrightarrow{p}_i - \overrightarrow{p}_c) - \overrightarrow{p}_i^T|| = 0 \tag{13}$$

Where $\overrightarrow{p}_i$ is the position vector of UAV$_i$; and $\overrightarrow{p}_c$ is position vector of the center point x_c, $\overrightarrow{p}_i^T$ is the desired relative vector of UAV$_i$ with respect to the center x_c at the terminal time T.

In summary, the formation time-optimal control problem can be expressed as finding a continuous control input U to minimize the payoff function (11) under the restrictive conditions (12) and (13), given the initial state of the formation system. For the proposed formation control method based on artificial physics, as discussed in the above section, the control inputs are determined by the defined virtual force applied on the UAVs. According to our formation control method based on artificial physics and the definition of the virtual force (2), (3) and (4), the problem of finding the optimal control input U can be transformed into finding the optimal parameter set $G_{optimal}$, that is, finding the optimal "gravitational constants" G_1, G_2 and G_3.

4 Formation Time-optimal Control Method

Genetic algorithm is an optimization technique that mimics the process of the natural selection. It is one of the evolutionary algorithms, which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, selection, mutation, and crossover.

4.1 The formation time-optimal control structure

The structure of the formation time-optimal control method is shown in Fig. 4. The formation control module contains the formation control method that produces the control input $U(t)$ and the formation model which can be expressed by formula (8). The genetic algorithm receives the formation time T and the formation state $X(t)$, calculate the fitness function, and then produces the optimal parameter set $G_{optimal}$ for the formation control method after the iterations.

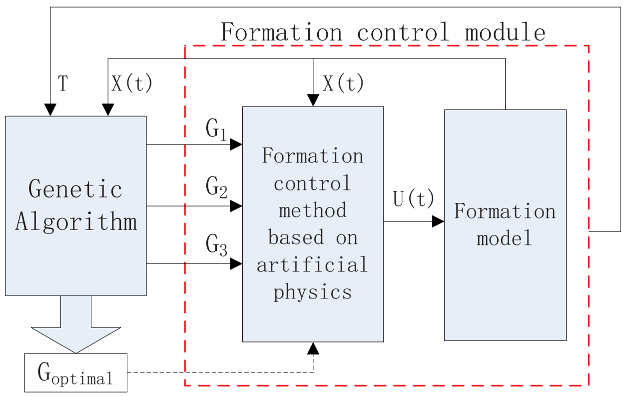


Fig. 4 Formation time-optimal control structure

As discussing in the previous sections, the formation time-optimal control problem is transformed into the control parameter optimization problem. According to the proposed formation control method based on artificial physics and the definition of the virtual force, with the optimal control parameter set $G_{optimal} = \{G_1, G_2, G_3\}$, we can get the optimal formation control input $U(t)$ and make the UAVs form the desired formation pattern as soon as possible, thereby, minimizing the payoff function (11).

4.2 The formation control parameter optimization method using genetic algorithm

In genetic algorithm, the potential solutions are called chromosomes. The evolution usually starts from a population of randomly generated individuals, and is an iterative process, with the population in each iteration called a generation. In each generation, the fitness of each chromosome in the population is evaluated, which is usually the value of the objective function in the optimization problem to be solved. The more fit individuals are stochastically selected from the current population, and each individual's genome is modified (recombined and mutated) to form a new generation. The new generation of candidate solutions are then used in the next iteration of the algorithm, and the iterative process terminates when the maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. In our formation control parameter optimization method, we use genetic algorithm to search the optimal parameter set $G_{optimal}$ for the formation control method. The parameter optimization process using genetic algorithm is shown in Fig. 5.

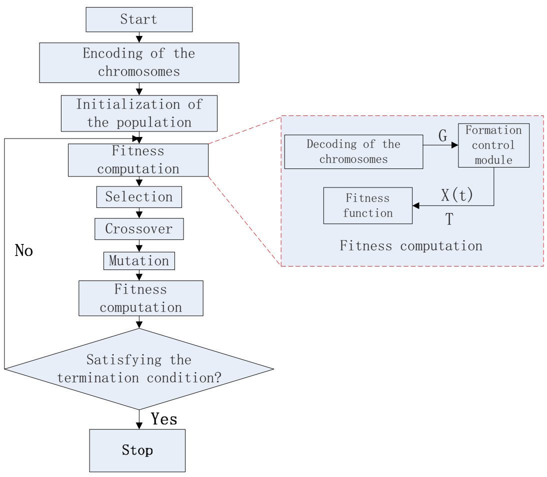


Fig. 5 The parameter optimization process using genetic algorithm

(1)Encoding of the chromosome

The control parameter set can be expressed as:

$$G = \{G_1, G_2, G_3\} \tag{14}$$

where G_1, G_2, G_3 are the "gravitational constants" of the virtual force (2), (3) and (4) defined in the previous section.

The potential solutions of $G_{optimal}$ can be encoded in binary as strings of 0 and 1. Thus, the chromosome P can be encoded into a $3M$ bits binary string using every M bits to represent a parameter.

(2)Initialization of the population

Given the population size and the max iteration, initialize the chromosomes randomly.

(3)Fitness computation

Considering of the constrains of the formation system, define the extended payoff function as follows:

$$J_{extend} = T + \delta \times \hat{g}(U,T) \tag{15}$$

where T represents the terminal time, that is, the time that the UAVs cost to form the desired formation pattern, δ is the punishment constant coefficient of terminal constraint of the formation system, and $\hat{g}(U,T) = \sum_{i=1}^{N} ||(\overrightarrow{p}_i - \overrightarrow{p}_c) - \overrightarrow{p}_i^T||$, if δ is a positive number and big enough(for example 10^7), it is clear that the value of the fitness function will be extremely small when the terminal constraint (13) is not satisfied, and the corresponding chromosome will be very likely removed out by the genetic operators. Only when the terminal constraint is satisfied, the punishment value is 0, and $J_{extend} = T$, the corresponding value of fitness function can be big enough to make the chromosome survive to the next generation. Thus the primitive payoff function (11) and the constraints condition (13) are equal to expression (15). The fitness function can be defined as:

$$F = \frac{1}{J_{extend}} \tag{16}$$

The fitness computation process can be seen in Fig. 5, firstly, we get the value of the control parameter set $G = \{G_1, G_2, G_3\}$ from the decoding of the chromosomes, and set the control parameters to the formation control method based on artificial physics in the formation control module, then the formation control module produces the terminal time T and the state $X(t)$ of the formation system and sent them to the fitness function to compute the fitness of the corresponding chromosome.

For the control input constraint (12), it can be satisfied by setting the threshold of $U(t)$ in the formation control module.

(4)Selection

During each generation, a proportion of the existing population is selected to breed a new generation. Individual solutions(chromosomes) are selected through a fitness-based process, where fitter solutions are more likely to be selected. In this paper, we adopt Roulette wheel selection method. Roulette wheel selection is a common technique that implements the proportional selection strategy, as in all selection methods, the fitness function assigns a fitness to chromosomes. This fitness level is used to associate a probability of selection with each individual chromosome, if F_i is the fitness of chromosome P_i in the population, its probability of being selected is as follows:

$$PS_i = \frac{F_i}{\sum_{j=1}^{K} F_j} \tag{17}$$

Where K is the number of the population size, it clear that the chromosome with a higher fitness will be less likely to be eliminated.

(5) Crossover

Crossover is a probabilistic process that exchanges information between two parent chromosomes for generating two child chromosomes[11]. Many crossover techniques exist for chromosomes which use different data structures to store themselves. In this paper two-point crossover with a fixed crossover probability is used, the two-point crossover calls for two points to be selected on the parent chromosomes, everything between the two points is swapped between the parent chromosomes, producing two child chromosomes, the process is shown in Fig. 6.

(6) Mutation

Mutation is a genetic operator used to maintain genetic

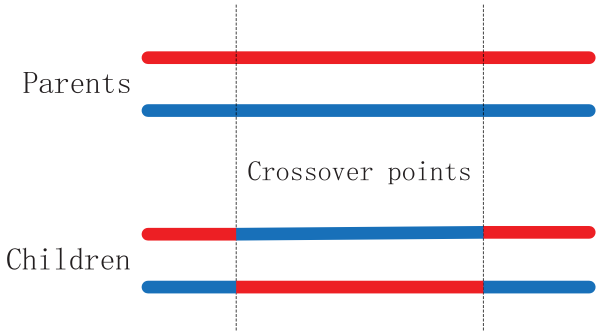


Fig. 6 Crossover

diversity from one generation of a population of genetic algorithm chromosomes to the next. For binary representation of chromosomes, a bit gene is mutated by simply flipping its value(i.e. if the genome bit is 1, it is changed to 0 and vice versa). In this paper, the mutation takes place at random positions on the chromosomes with a fixed mutation probability.

(7)Termination criterion

In this paper the processes of the fitness computation, selection, crossover, and mutation are executed for a maximum number of iterations. The best chromosomes (determined by the fitness value) in the population of each generation are stored as the potential solutions, and the final solution is the best one among these potential solutions.

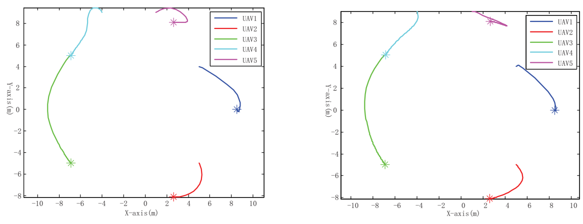
5 Simulation Results

In order to verify the feasibility and effectiveness of our proposed formation time-optimal control method, we have implemented our simulations using Matlab R2013a on a personal computer with 6GB RAM and 2.7GHz Core CPU under Microsoft Windows 7. The proposed formation time-optimal control method is all coded in Matlab language, while the formation control module with our formation control method based on artificial physics is implemented in Simulink environment, and the parameter optimization method using genetic algorithm is written in the M-file.

In our simulation, in order to satisfy tradeoff between accurate estimation and computational complexity, the population size of the genetic algorithm is set to be 100, the max iteration is set to be 100, the mutation probability $\mu_m = 0.1$, the crossover probability $\mu_c = 0.95$. Considering five UAVs moving at a certain high level, giving the arbitrary initial positions of the five UAVs, after the time-optimal control, the UAVs can form the desired standard formation shown in Fig. 1, the length of the regular polygon of the standard formation is set to 10m, the range of each formation control parameter in $G = \{g_1, g_2, g_3\}$ is set to $[0, 100]$. The Simulink stop time is set to 26s.

We have done two sets of experiments. One is without the formation control parameter optimization method and the other is with the formation control parameter optimization method. Fig. 7(a) shows the final positions of the UAVs with the trajectories showing the forming process of the standard formation. In this case, the formation control parameters are set initially without the formation control parameter optimization method.

Fig. 8 shows the position evolution process of the five UAVs without using the formation time-optimal control method, if the precision of the control input is set to 0.01, we can get that the formation time is 22.8s.



(a) (b)

Fig. 7 The formation forming process

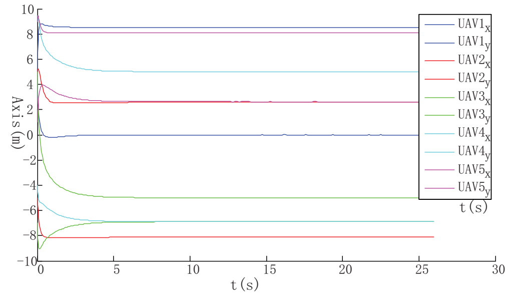


Fig. 8 The evolution of positions of the five UAVs without using the formation time-optimal control method

Fig. 7(b) shows forming process of the standard formation using the formation time-optimal control method. It is clear that the standard formation is formed in both cases. Fig. 9 shows the position evolution process of the five UAVs using the formation time-optimal control method. If the precision of the control input is set to 0.01 too, we can get that the formation time is 3.7s. It is obvious that the time performance has been greatly improved.

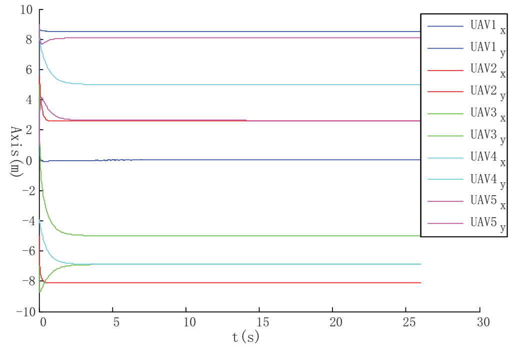


Fig. 9 The evolution of positions of the five UAVs using the formation time-optimal control method

Fig. 10 describes the relationship between the fitness and the iterations. It shows that the fitness reach the maximum, meaning that the formation time has converged to the minimum.

Based on the simulation results and analysis, it is obvious that our proposed formation time-optimal control method based on modified artificial physics with control parameter optimization method using genetic algorithm is advantageous over the basic artificial physics method and greatly improves the time performance of the formation system.

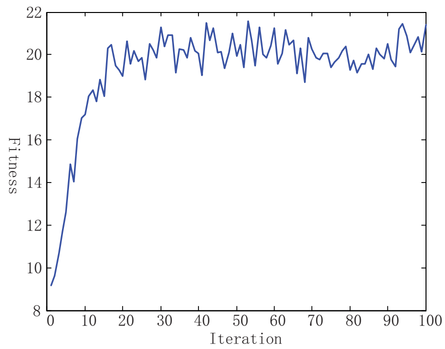


Fig. 10 The relationship between the fitness and the iterations

6 Conclusions

In this paper, we have proposed a formation time-optimal control method based on artificial physics with control parameter optimization using genetic algorithm. Driven by the designed controller, UAVs can form the desired standard formation, and the time performance has greatly improved. The simulation results demonstrated the feasibility and effectiveness of our proposed formation time-optimal control method. As a future work, we will continue our efforts to find better solutions in order to shorten the optimization time, and to make the trajectories smoother. Applications on the real UAVs formation with the proposed method are considered as well.

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