Differential Evolution Based Multi-agent Formation Fault Reconstruction

Zirui Liao, Shaoping Wang, Jian Shi, and Qiwang Weng

Abstract The fault reconstruction of second-order multi-agent formation systems under lost communication is studied. Aiming at the specific scenarios of dynamic tracking of multi-agent systems, a mixed-integer programming algorithm based on differential evolution (DE) is proposed according to the characteristics of both continuous kinematic variables and discrete topological variables in the kinematics of UAV formation to ensure the optimization and timeliness. Then, the simulation platform is built and tested in the scene of dynamically tracking. Eventually, the theoretical results are verified by simulation examples. The results show that the method proposed in this paper can ensure that the formation make appropriate adjustments to achieve dynamic target tracking in the process of dynamic target tracking under complex circumstance.

Keywords Multi-agent · Dynamic tracking · Differential evolution · Fault reconstruction

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1 Introduction

Formation control of multi-agent systems has received considerable interests in recent years due to its broad potential applications in civilian and military areas, such as target search and localization [1], surveillance [2], reconnaissance [3], radiation detection [4] and so on. Meanwhile, many formation control methods have been introduced in the past few years, including leader–follower [5, 6], behavior [7], virtual structure-based [8] approaches and so on. Besides, with the development of UAV technology and the increasing demand for formation control of UAV swarm systems, more and more researchers are concentrated on solving the formation problems for UAV swarm systems [9].

Fault reconstruction is another research hotspot for UAV swarm systems. At present, the fault reconstruction of multi-agent formation is generally solved online. Thus, it is the focus of research to solve the problem based on optimal performance, that is, the calculation and solution of optimization problem. Chen et al. [10] studied the problem of efficient reconstruction in the shortest time under complex dynamic circumstance, and iteratively solves optimization problems using a hybrid particle swarm strategy. Tian et al. [11] solved the problem of efficient formation reconstruction in the shortest time according to genetic algorithm. Xiong et al. [12] optimized the genetic algorithm and proposed a new hybrid algorithm theory. This algorithm combines control parameterization and time discretization (CPTD) to solve the formation reconstruction problem based on the genetic algorithm. Shunsaku et al. [13] used Dijkstra's algorithm on the shortest time optimization problem to obtain the optimal path for multi-agent reconstruction. And [14] uses WoBinGO (Work Binder Genetic algorithm-based Optimization) framework for solving optimization problems over a grid, which provides significant speed-up when dealing with problems that have computationally expensive evaluations.

Differential Evolution (DE) algorithm is often used to solve the global optimization problem of continuous variable linear programming [15]. DE is also a heuristic model based on biological evolutionary selection. Once the fitness function is set, the offspring will be screened repeatedly and eventually the most adaptable individuals are preserved [16]. However, compared with other heuristic algorithms, DE is more suitable for two types of linear programming problems: continuous optimization and combinatorial optimization problems. This exactly corresponds to the mixed integer parameters of UAV formation kinematics. Therefore, DE is proposed in the paper to solve this characteristic, making it closer to the engineering practice.

The rest of this article is organized as follows: Sect. 2 states the problems and the specific researches mentioned in this paper. Section 3 introduces the multi-agent formation fault reconstruction approaches, including scenario design, reconstruction framework and details of evolution algorithm. Section 4 conducts experimental and simulation analysis on the reconstruction scenarios with differential evolution algorithm combined, verifying the effectiveness of the proposed method. Finally, relevant conclusions are drawn in Sect. 5.

2 Problem Statement

Assuming that the original multi-agent formation is circular, in which r is the radius of the circular formation and φ is the phase angle of each formation where the agents are located. The communication network of multi-agent formation is described as $G = \{V, S, W\}$, where the information source vertex set $V = \{v_1\, v_2 \ldots v_N\}$ corresponds to each agent one by one. And the communication relationship between agent i and agent j can correspond to an edge $e_{ij} = (v_i, v_j)$ in the graph, thus the input matrix D, the adjacency matrix W and the Laplace matrix $L = D - W$ can be obtained.

Then, it is worth mentioning that this paper mainly concentrates on reconstruction of multi-agent formation, and the influence of system dynamics can be ignored compared with the adjustment time required by reconstruction. Therefore, it is assumed that the agent ith is a three-dimensional and second-order motion system, whose three-dimensional position is described as $s_i(t)$ and the velocity of the agent is noted as $v_i(t)$. And its matrix summary form can be expressed as $\xi_i = [s_{xi}\ v_{xi}\ s_{yi}\ v_{yi}\ s_{zi}\ v_{zi}]$. At the same time, Multi-agent time-varying formation can be represented by a set of function $h_i(t)(i = 1, 2, \ldots, N)$. For a given formation $h(t)$ and the dynamic trajectory of the tracked target $c(t)$, the multi-agent formation can realize the tracking control of the time-varying formation if the multi-agent formation can achieve the following state (at any initial state):

$$\lim_{t\to\infty}(\xi_i(t) - h_i(t) - c(t)) = 0(i = 1, 2, \ldots, N) \tag{1}$$

There are two kinds of failures in such multi-agent formation system, that are agent failure and lost contact with neighbor agent. For the first case, the agent should connect another agent and rebuild the connection under communication fading. For the second case, the most important thing is how to regroup the rest agents and keep the target at the formation center. This paper focuses on such two failure conditions and find the corresponding formation reconstruction method to guarantee the tracking target.

For the first type of failure, topology reconstruction is required. The corresponding mathematical expressions are as follows:

$$\begin{aligned} \max f^1 &= \max\{R, Q, C\} \\ &= g(a_{ij}) + f(\sqrt{\Delta S_x^2 + \Delta S_y^2}) + k \times \sum \Delta a_{ij} \end{aligned} \tag{2}$$

Subject to:

$$\sqrt{\Delta S_x^2 + \Delta S_y^2} < d_{\max} \tag{3}$$

where R, Q and C refer to network connectivity, communication quality and conversion cost respectively; a_{ij} is the status between two nodes; S_x and S_y are continuous variables representing the flight position in m; V_x and V_y are also continuous variables representing flight velocity in m/s; $d_{\max}$ and k are fixed values respectively representing maximum communication distance and switching cost factor in m.

For the second type of failure, both formation and topology reconstruction are required. The corresponding mathematical expressions are as follows:

$$\min f^2 = \min\{E\} = f(r, \theta, V_{it}) \tag{4}$$

Subject to:

$$V_{\max} < M_v \tag{5}$$

$$\sqrt{\Delta S_x^2 + \Delta S_y^2} < M_S \tag{6}$$

where E refers to enclosure error; flight position S_x, S_y and flight velocity V_x, V_y are the same as above while formation geometries r, θ and V_{it} are non-negative continuous variable; M_v and M_s are fixed values respectively representing safety distance constraint and maximum speed constraint in m and m/s.

3 Proposed Approaches

3.1 Scenario Design

Assuming that four agents work together to capture the target in a diamond formation shown in Fig. 1. Two fault scenarios are proposed as follows:

- Scenario 1: Every agent in the multi-agent formation is functional, while a communication link is interrupted due to terrain occlusion and other problems between two agents. At this moment, topology reconstruction and adjustments should be made to delete the link with low communication quality and connect to another agent with high communication quality, as shown in Fig. 1:
- Scenario 2: An agent in a multi-agent formation fails and couldn't form the formation. At this moment, the agent should be abandoned to perform topology reconstruction and adjustment, maintaining the task execution capability of the formation. In the meanwhile, considering the reduction of the number of agents in the formation, the formation shape should be adjusted and the encircling circle should be contracted to achieve better encircling effect. The specific scenario is shown in Fig. 2:

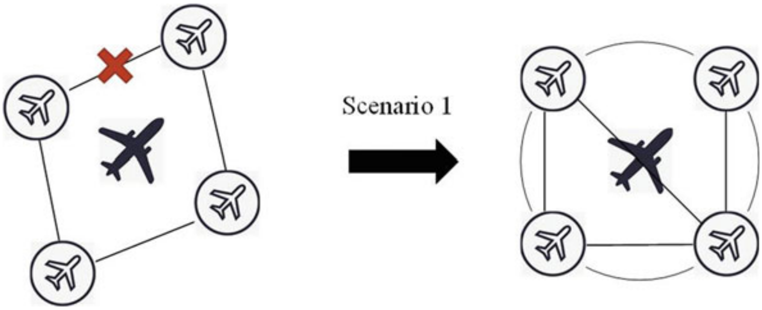

Fig. 1 Formation fault scenario 1

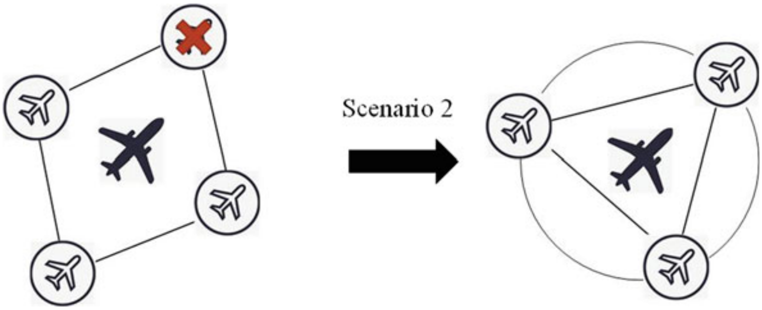

Fig. 2 Formation fault scenario 2

3.2 Reconstruction Framework

In order to describe the decision process of fault reconstruction, it is assumed here that the formation after the reconstruction decision is circular.

The fault reconstruction control of multi-agent formation refers to the completion of rapid reconstruction decisions under the constraints of rapidity, security, and dynamic connectivity of the communication network under fault scenario, so that the multi-agent formation can maintain certain formation ability and task execution ability in the whole task cycle. Taking multi-UAV formation as an example, the fault reconstruction process is described as follows: each UAV publishes flight information (including communication status, its own position and speed, etc.) in real time during the task and the airborne equipment will calculate the satisfaction effect of task reachability and communication reliability in real time. Once the problems such as node position deviation, node communication loss and formation control failure occur, the airborne equipment will make the best reconstruction decision in time, and correspondingly take actions such as adjusting communication topology, changing formation, removing and recovering fault nodes, maintaining the task execution capability of the formation. Figure 3 shows the fault reconstruction framework of multi-agent formation under fault scenario:

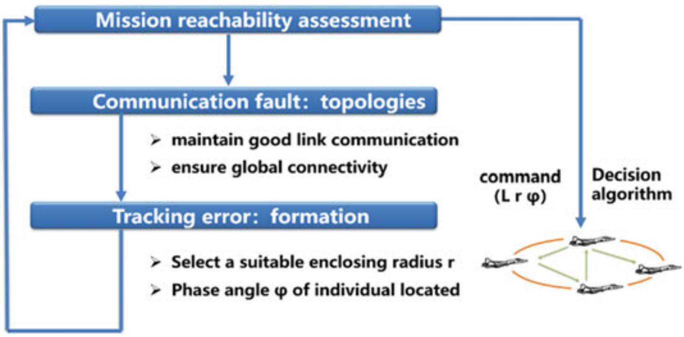

Fig. 3 The overall fault reconstruction framework

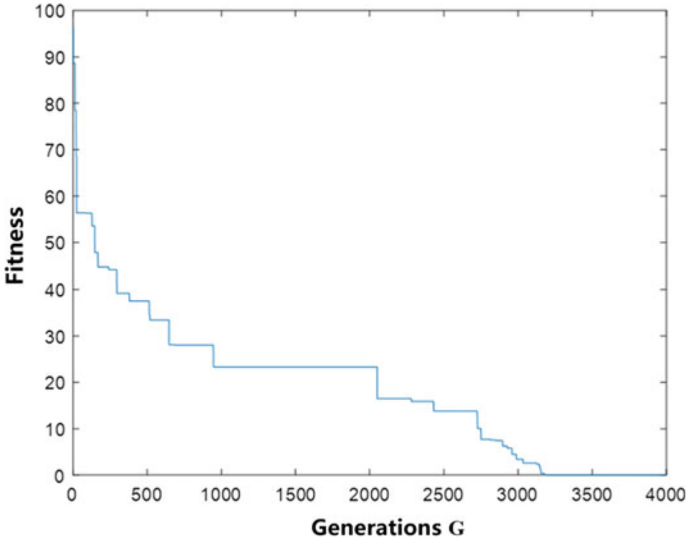

Fig. 4 Fitness changes with evolution generations

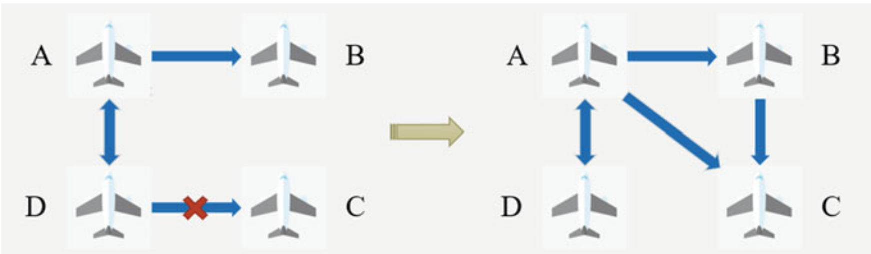

Fig. 5 Formation topological reconstruction under link fault

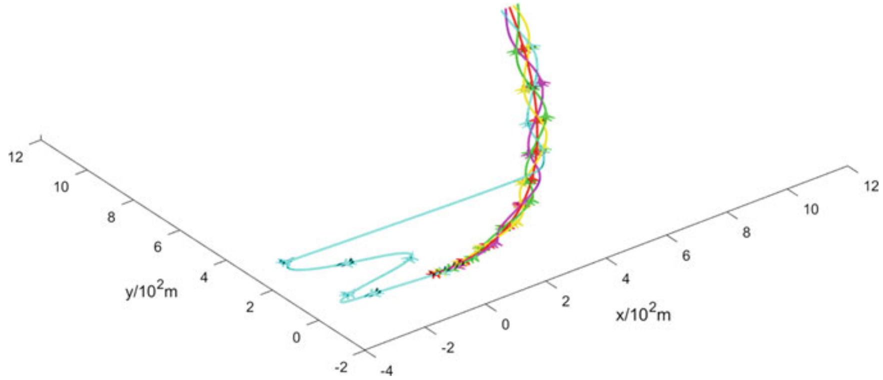

Fig. 6 Trajectory of formation link reconstruction

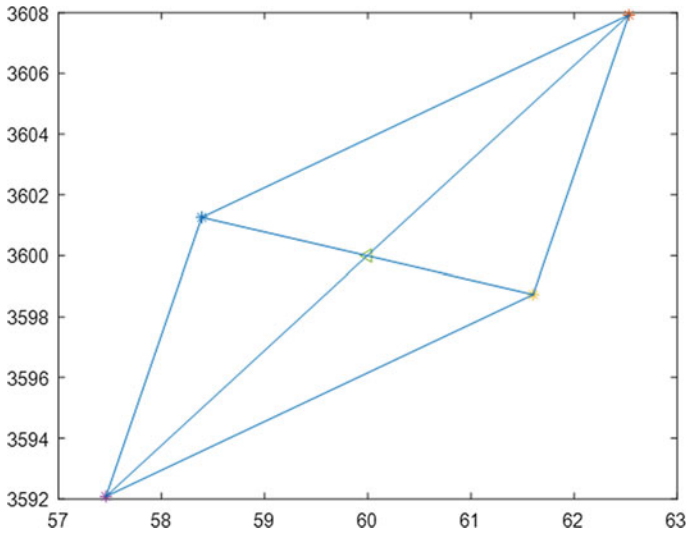

Fig. 7 Diagram of formation after reconstruction

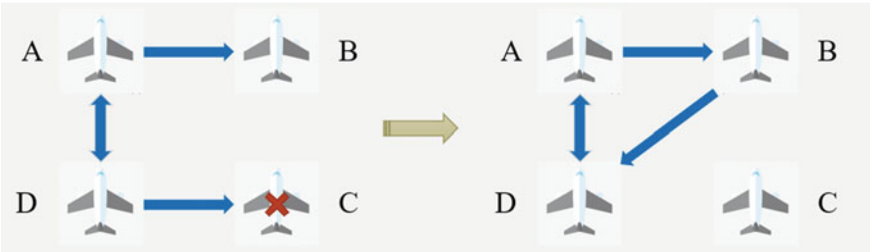

Fig. 8 Formation topological reconstruction under single UAV damage

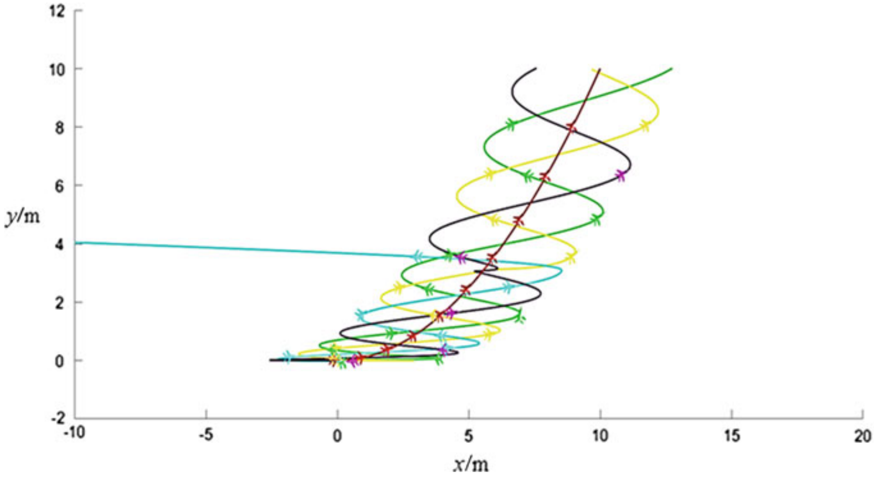

Fig. 9 Trajectory under the damage of single UAV in formation

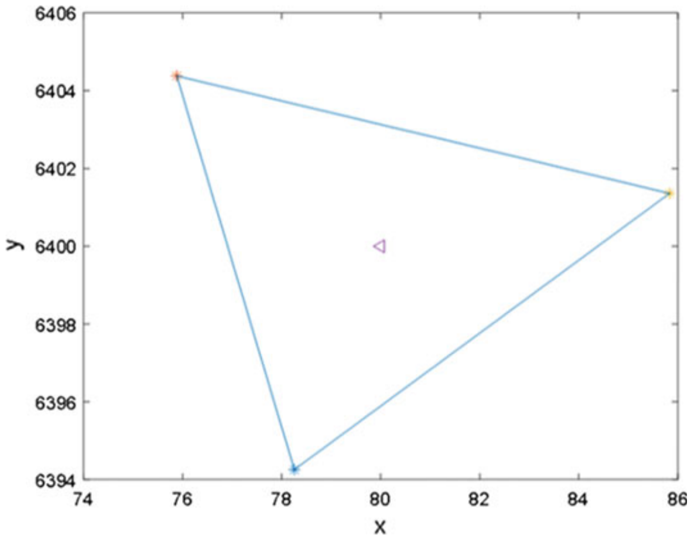

Fig. 10 Diagram of formation after damage and reconstruction

3.3 Fault Reconstruction Based on DE

The problem of UAV formation reconstruction needs to be calculated. Generally, it is necessary to solve the decision variable values that meet the minimum cost of reconstruction and the highest ability of task execution within a limited calculation time [17].

As mentioned before, there are two decision-making methods of formation reconstruction: topology reconstruction and formation reconstruction. Here, Differential Evolution (DE) is introduced to calculate the problem. Firstly, the decision variables need to be coded by computer language. Then the decision variables are treated as chromosomes and the genetic screening operation is carried out. For the progeny generated in evolution, the survival of the fittest is achieved through the fitness function and the outstanding progeny are selected to continue iteration eventually, thereby continuing to update the population [18, 19].

For optimization problem:

$$\begin{aligned} &\min f(x_1, x_2, \nu x_D) \\ &s.t\, x_j^L \le x_j \le x_j^U,\ j = 1, 2, \nu, D, \end{aligned} \tag{7}$$

where D is the dimension of solution space; x_j^L and x_j^U represent the upper and lower bounds of value range of the $j-th$ component x_j.

The detailed description of this process is as follows:

1. Initialization of population.
The primary population $\{x_i(0)|x_{j,i}^L \le x_{j,i}(0) \le x_{j,i}^U, i = 1, 2, \nu, NP; j = 1, 2, \nu, D\}$ is often generated by random generation, from which DE starts to screen and reproduce and its expression is as follows:

$$x_{j,i}(0) = x_{j,i}^L + rand(0, 1) \times (x_{j,i}^U - x_{j,i}^L) \tag{8}$$

where $x_i(0)$ represents jth chromosome(individual) of the $0th$ generation in population; $x_{j,i}(0)$ represents nth gene on jth chromosome of the $0th$ generation in population; NP represents the population size and $rand(0, 1)$ represents a random number uniformly distributed in the interval (0, 1).

2. Variation
DE are made to one or several genes of a chromosome to generate individuals that synthesize at least three genetic information of the previous generation, which is achieved by the introduction of Hamming distance as follows:

$$v_{i,j}^g = x_{r1,j}^g + F(x_{r2,j}^g - x_{r3,j}^g) \tag{9}$$

where $v_{i,j}^g$ represents the variation individuals and F refers to control differential step size.

3. Crossing
The process of crossing and displacing some local information of two chromosomes (individuals) to generate new individuals. The expression is as follows:

$$u_{i,j}^{g} = \begin{cases} v_{i,j}^{g}\ if\ r \le CR\ or\ j = j_{rand} \\ x_{i,j}^{g}\ otherwise \end{cases} \tag{10}$$

where CR refers to crossing probability with the value range from 0 to 1 and j_{rand} is a random integer in [1, 2, ν, D].

4. Selection

During the selection, the greedy selection function is used to keep the number of individuals in the population fixed. Its optimal meaning is the best fitness which is shown as follows:

$$x_i(g+1) = \begin{cases} u_i(g+1),\ if\ f(u_i(g+1) \le f(x_i(g)) \\ x_i(g),\ othersize \end{cases} \tag{11}$$

5.Termination

Termination condition usually refers to reaching the predicted fitness or reaching the predefined evolution generations. If the termination condition is reached, the optimization process is stopped, which means the algorithm is finished, or the fitness assessment of the new population will continue and the population will enter the next evolution.

4 Simulation Experiments

4.1 Experimental Analysis of DE

In this paper, differential evolution algorithm is proposed to solve the decision-making problem of reconstruction instructions. The convergence of population fitness can be judged and analyzed by observing the fitness changes of each generation after DE. Here, the numerical changes of these two parameters are plotted as a curve to observe and analyze whether the population has improved fitness in differential evolution, and whether the fitness can be optimized at the end of evolution.

1. Algorithm parameter

The parameters of DE used in this paper are set as follows [14]:

a. Generation: 4000
b. Population: 50
c. Initialization: Random number method
d. Crossing: Combination of uniform crossing and single point crossing
e. Variation: Difference variation based on Hamming distance
f. Elite individuals: 5

2. Fitness changes

It can be seen from the figure that the average fitness of the whole population decreases in a fluctuating way. This is because each generation has individuals with their own fitness lower than the optimal individual fitness, but after differential evolution and screening, the individuals with the worst fitness in each generation are screened out. Thus, the average fitness of the population will gradually increase to the optimal (Fig. 4).

4.2 Simulation of Reconstruction

According to the two scenario designs mentioned in the second section, the simulation research is carried out respectively: the decision-making process of instruction reconstruction is substituted into the designed control system to verify whether the whole system can complete the active fault reconstruction control under the communication fault after combination.

Reconstruction and Adjustment under Link Fault. Each agent in the multi-agent formation is functioning normally, but a communication link communication is interrupted due to terrain occlusion and other problems. At this moment, topology reconstruction and adjustments should be made to delete the link with low communication quality and connect the link with high communication quality. The specific scenario is shown as follows:

In the beginning, four aircrafts work normally. But the communication link between UAV C and UAV D is blocked midway, making UAV C unable to communicate with other UAVs in the formation (Fig. 5). At this moment, the communication topology is adjusted through the reconstruction decision as follows:

The simulation figures of the whole formation operation are as follows:

From the figure, it can be seen that UAV C will deviate from the formation after failure. However, it can quickly return to the formation after the communication topology is adjust. And the multi-agent formation composed of four UAVs will continue to complete the dynamic tracking operation (Figs. 6 and 7).

Reconstruction and Adjustment in Single UAV Fault. An agent in a multi-agent formation fails and flies to the wrong trajectory abruptly. At this moment, the agent should be abandoned to perform topology reconstruction and adjustment, maintaining the task execution capability of the formation. In the meanwhile, considering the reduction of the number of agents in the formation, the formation shape should be adjusted and the encircling circle should be contracted to achieve better encircling effect (Fig. 8). The specific scenario is shown as follows:

In the beginning, four aircrafts were working normally. But UAV C suddenly fails midway, which causes UAV C unable to participate in formation operations (Fig. 9). At this moment, the reconstruction decision is made to abandon the failed aircraft, shrink the formation and adjust the topology, which is shown as follows:

The simulation figures of the whole formation operation are as follows:

From the figure, it can be seen that UAV C will deviate from the formation after the failure, but the remaining three normal UAVs can still complete the task of dynamic target tracking, enclosing the target in the triangle geometry center after the reconstruction (Fig. 10). Thus, the feasibility and effectiveness of the active fault reconstruction control of multi-agent formation proposed in this paper is verified.

5 Conclusions

Aiming at the specific scenario of dynamic tracking of multi-UAV formations, this paper mainly studies the problem of fault reconstruction of multi-agent formations under fault conditions. Firstly, two specific scenarios of communication failure in dynamic tracking task is designed. Then, the overall framework of fault reconstruction is introduced, and the calculation methods of network communication quality and dynamic connectivity are explained in detail. Meanwhile, the implementation of differential evolution algorithm is described. Next, the differential evolution algorithm is introduced to adjust the control instructions according to the specific situation. Finally, the simulation cases of the whole active fault reconstruction control are given combining with the control system, which verifies the feasibility and effectiveness of the active fault reconstruction method in the paper. And it is worth mentioning that the cost of DE is large. Thus, how to guarantee the real-time performance is a future research direction.

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