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Three-dimension path planning for UCAV using hybrid meta-heuristic ACO-DE algorithm

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ABSTRACT

Three-dimension path planning of uninhabited combat air vehicle (UCAV) is a complicated optimal problem, which mainly focuses on optimizing the flight route considering the different types of constrains under complicated combating environments. A new hybrid meta-heuristic ant colony optimization (ACO) and differential evolution (DE) algorithm is proposed to solve the UCAV three-dimension path planning problem. DE is applied to optimize the pheromone trail of the improved ACO model during the process of ant pheromone updating. Then, the UCAV can find the safe path by connecting the chosen nodes of the three-dimensional mesh while avoiding the threats area and costing minimum fuel. This new approach can accelerate the global convergence speed while preserving the strong robustness of the basic ACO. The realization procedure for this hybrid meta-heuristic approach is also presented in detail. In order to make the optimized UCAV path more feasible, the κ-trajectory is adopted for smoothing the path. Finally, series experimental comparison results demonstrate that this proposed hybrid meta-heuristic method is more effective and feasible in UCAV three-dimension path planning than the basic ACO model.

1. Introduction

Uninhabited combat aerial vehicle (UCAV) is one of inevitable trends of the modern aerial weapon equipments which develop in the direction of unmanned attendance and intelligence [1]. Research on UCAV directly affects battle effectiveness of the air force and is fatal and fundamental research related to safeness of a nation. Path planning is to generate a space path between an initial location and the desired destination that has an optimal or near-optimal performance under specific constraint conditions, and it is an imperative task required in the design of UCAV. There are several considerations for an ideal path planner including: optimality, completeness and computational complexity, which are also the most important requirements since path planning has to occur quickly due to fast vehicle dynamics. The flight path planning in a large mission area is a typical large scale optimization problem, a series of algorithms have been proposed to solve this complicated multi-constrained optimization problem, such as the A^* algorithm, evolutionary computation [1], genetic algorithm [2] and ant colony algorithm [3]. However, those methods can hardly solve the contradiction between the global optimization and excessive information. Furthermore, the current work mainly focuses on UCAV path planning in two dimensions.

Ant colony optimization (ACO) algorithm was originally presented under the inspiration during collective behavior study results on real ant system [4]. The inspiring source of ACO is the foraging behavior of real ants which enables them to find shortest paths between nest and food sources. The promising ant colony algorithm is a relatively new optimization technique, which is also a model-based approach for solving complicated combinatorial optimization problems. It has been

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applied extensively to benchmark problems such as the traveling salesman problem (TSP), the job-shop scheduling problem (JSP), the vehicle routing problem (VRP), the quadratic assignment problem (QAP), and so on [5–7].

In 1995, Storn and Price firstly proposed a novel evolutionary algorithm: differential evolution (DE) [11,12], which is a new heuristic approach for minimizing possibly nonlinear and non-differentiable continuous space functions. It converges faster and with more certainty than many other acclaimed global optimization methods [13]. This new method requires few control variables, which makes DE more robust, easy to use, and lends itself very well to parallel computation.

Combining the basic model of ACO with DE algorithm, a novel three-dimension path planning approach for UCAV has been proposed in our former work [14], which published in the "2008 Asia Simulation Conference – Seventh International Conference on System Simulation and Scientific Computing" in October, 2008. This work is the extension our former work. In this paper, our approach overcomes the deficiencies of existing path planning algorithms for UCAV, which is the contradiction between the global optimization and excessive information. The main characteristic of our proposed algorithm is that the DE forms the new pheromone updating strategy, then an improved ACO is used to search the optimal path with complicated multi-constraints. A smooth path is essential for a real UCAV, because non-smooth path can't satisfy the turning constraint. In the UAV community, most researchers apply the Dubins algorithm to generate a smooth path [15,16]. In this paper, we used a computationally efficient path smoothing method called κ-trajectory [17], and more new experiments are conducted to verify the feasibility and effectiveness of our proposed approach. The series experiments conducted under complicated combating environment illustrate that our hybrid meta-heuristic approach with κ-trajectory path smoothing can generate a feasible optimal three-dimension path of UCAV more quickly than the basic ACO algorithm.

The remainder of this paper is organized as follows. Section 2 introduces the threat resources in UCAV three-dimension path planning. Subsequently, the principle of the basic ACO is explained in Section 3. Then, in Section 4, we propose an improved ACO approach to UCAV path planning, then the hybrid meta-heuristic ACO and DE algorithm for UCAV three-dimension path planning is presented in Section 5, and the detailed realization procedure is also presented in this Section. Subsequently, a smoothing method for UCAV path is described in section 6. The series simulation comparison results are given in Section 7. Our concluding remarks are contained in Section 8.

2. Threat resources modeling in UCAV three-dimension path planning

Modeling of the threat sources is the key task in UCAV optimal three-dimension path planning [18,19]. In order to simplify the UCAV three-dimension path planning problem, the UCAV task region can be divided into three-dimensional mesh, thus forming a three-dimensional network diagram connecting the starting point and goal point. In this way, the problem of UCAV optimal three-dimension path planning is the general path optimization problem in essence. The typical UCAV battle field model in three-dimension can be shown in Fig. 1.

In Fig. 1, suppose the flight task for UCAV is from node B to node A. There are some threatening areas in the task region. We divide the space into m sub-cubes equally, so there are n nodes in the area, which can be labelled with $L_1, L_2, \ldots, L_n$. Let L_i (x_i, y_i, z_i) be the ith node. It is obvious that there are 26 candidate nodes could be chosen at most by the UCAV in each step. Because the nodes in the vertical direction of current point are unaccepted, the number of the candidate nodes decline to 24. Then, all the selected nodes could be connected one by one as the step going on until getting the target. In this way, the path from the starting node to the target node can be described as follows:

$$\text{Path} = \{B, L_1(x_1, y_1, y_{k1}), L_2(x_2, y_2, y_{k2}), \ldots, L_{m-1}(x_{m-1}, y_{m-1}, y_{k(m-1)}), A\} \tag{1}$$

A computationally more efficient and acceptably accurate approximation to the exact solution is to calculate the threat cost at several locations along an edge and take the length of the edge into account. In this work, the threat cost was calculated at five points along each edge, as shown in Fig. 2.

The threat cost associated with the ith edge is given by the expression [8,9]

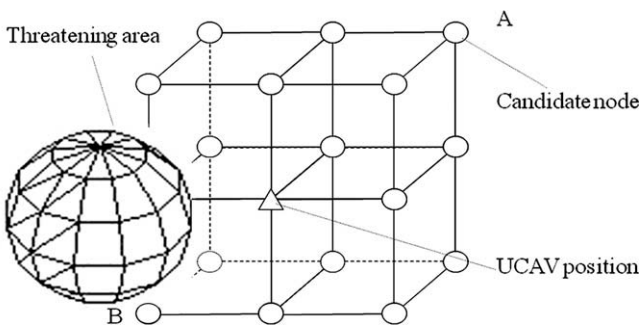

Fig. 1. Typical UCAV battle field model in three-dimension.

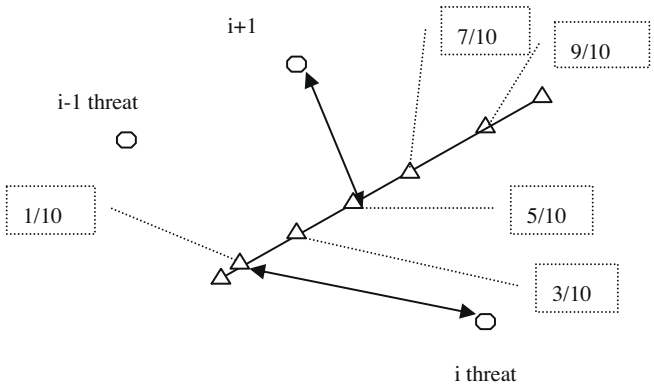

Fig. 2. Modeling of the UCAV threat cost.

$$w_{t,i} = L_i \sum_{j=1}^{N} \left(\frac{1}{d^4_{0.1,i,j}} + \frac{1}{d^4_{0.3,i,j}} + \frac{1}{d^4_{0.5,i,j}} + \frac{1}{d^4_{0.7,i,j}} + \frac{1}{d^4_{0.9,i,j}} \right) \tag{2}$$

where $d^4_{0.1,i,j}$ is the distance from the 1/10 point on the ith edge to the jth threat, L_i is the ith sub-path length, N is the number of the radars, the missiles and other threats. Moreover, it can simply consider the fuel cost w_f equals to L, then $w_{f,i}$ equals to L_i and the height cost $w_{h,i}$ equals to H which is the flight height of the UCAV when the speed is a constant. The total cost for traveling along ith edge comes from a weighted sum of the threat and fuel costs:

$$w_i = k_1 \cdot w_{t,i} + k_2 w_{f,i} + (1 - k_1 - k_2) w_{h,i} (0 \le k_1, k_2 \le 1) \tag{3}$$

The choices of k_1 and k_2 all between 0 and 1 give the designer certain flexibility to dispose relations among the threat exposition degree, the fuel consumption and the height information. When k_1 is more approaching 1, more attention is paid to the radar's exposed threat, and it requires avoiding the threat as far as possible with the cost of sacrifice the trajectory length and flight height. Similarly, when k_2 is more approaching 0, a shorter path is needed to be planned regardless of the cost of other two factors.

3. Principles of basic ACO algorithm

The natural metaphor on which basic ACO algorithm is based is that of ant colonies. Real ants are capable of finding the shortest path from a food source to their nest, without using visual cues by exploiting pheromone information. While walking, ants deposit pheromone on the ground, and follow, in probability, pheromone previously deposited by other ants [10]. With the positive feedback mechanism, all ants will choose the shorter path in the end. A way ants exploit pheromone to find a shortest path between two points is shown in Fig. 3.

The above behavior of real ants has inspired ACO algorithm, in which a set of artificial ants cooperate together for the solution of a problem by exchanging information via pheromone deposited on graph edges. This optimization algorithm can provide a possible new way for UCAV three-dimension path planning in complicated combating environments.

4. Improved ACO model for UCAV three-dimension path planning

The parallel mechanism of ACO model mainly contains two basic processes: adaption and cooperation. In adaption process, the candidate solutions continue to readjust their structures on the basis of information accumulating. While in the cooperation stage, the candidate solutions exchange information to produce better solutions [7]. The basic mathematical model of ACO has firstly been applied to the TSP. The aim of the TSP is to find the shortest path that traverses all nodes in the problem exactly once, returning to the starting city. While the UCAV path planning is to work out the optimal or sub-optimal safe flight trajectory in the proper time, along which UCAV is able to accomplish the prearranged task and avoid the hostile threats. There are some common points between TSP and UCAV three-dimension path planning, and ACO is a feasible way in solving UCAV three-dimension path planning problem under complicated combat field environments.

Let n ants be in the starting node, the ants will choose the next nodes in the grid network diagram according to the transition rule. An ant left pheromone which can be felt by the next ant as a signal to affect its action, and the pheromone that the following one left will enhance the original pheromone. Thus, the more ants a UCAV path is passed by, the bigger possibility that a path can be selected by the other ants. This process can guarantee nearly all ants walk along the shortest UCAV path in the end.

We define the transition probability $P_k(r,s)$ from node r to node s for the kth ant as follows [8]

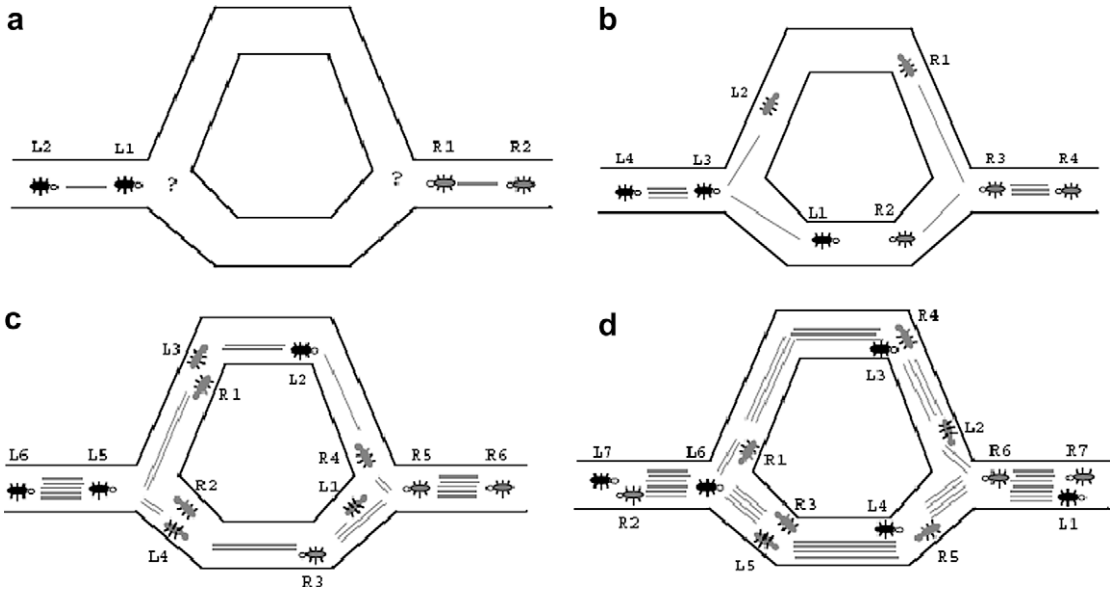

Fig. 3. How real ants find a shortest path.

$$P_k(r,s) = \begin{cases} \frac{\tau(r,s)^{\alpha}\eta(r,s)^{\beta}}{\sum_{s\in j_k(r)}\tau(r,s)^{\alpha}\eta(r,s)^{\beta}}, & \text{if} \quad S \in J_k(r) \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

where $\tau(r,s)$ represents the accumulated the amount of pheromone trail on edge (r,s). α and β are parameters that control the relative importance of trail versus visibility, $\eta(r,s)$ is the heuristic desirability, and $\eta(r,s) = 1/C_{r,s}$. where $C_{r,s}$ represents the threat cost between the node r and the node s. $J_k(r)$ denotes the feasible domain of the kth ant at the node r.

When the ants move between nodes, the pheromone level on the selected edge (r,s) is updated according to the local updating rules in Eqs. (5) and (6). In this way, ants will make better use of their pheromone trail information; without local updating, all ants will search in a narrow neighborhood of the best previous tour.

$$\tau(r,s) = (1-\rho)\cdot\tau(r,s) + \rho\cdot[\Delta\tau(r,s) + e\cdot\Delta\tau^{e}(r,s)] \tag{5}$$

$$\Delta\tau(r,s) = \sum_{k=1}^{m}\Delta\tau^{k}(r,s) \tag{6}$$

where m denotes the number of ants, ρ is the pheromone decay parameter, and $\rho \subset [0,1]$. e is a small constant, $0 < e < 1$. $\Delta\tau_k(a,b)$ is the quantity of the length per unit of pheromone trail laid on edge (r,s) by the kth ant at time t, it can be given by

$$\Delta\tau^{k}(r,s) = \begin{cases} Q/w_k, & \text{if } (r,s) \text{ is } k\text{th ant's candidate edge} \\ 0, & \text{otherwsie} \end{cases} \tag{7}$$

$$\Delta\tau^{e}(r,s) = \begin{cases} Q/w_e, & \text{is best current candidate edge} \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

where Q is a constant, W_k is the generalized path cost for the kth ant, and W_e is the smallest path cost in this iteration.

5. Hybrid meta-heuristic ACO-DE approach to UCAV three-dimension path planning

DE is an excellent global optimization algorithm, which is originally proposed as a method for the global continuous optimization. Similar to GA, DE algorithm also contains three basic strategies, namely mutation, crossover, and selection. Firstly, DE randomly generates some initial solutions in the searching space. Then, DE adds the difference vector between two population vectors. In this way, it generates a mutated trial individual. Subsequently, DE combines the mutated trial individual and the original target individual to generate another new individual. If the new individual has a better fitness than the original target one, it will be accepted and replace the original individual in the next generation [11]. DE is a very simple population-based stochastic function minimizer, and DE can be better than GA in terms of efficiency, i.e., capability of finding the global optimum, and number of function evaluations. The crucial idea behind DE is a scheme for generating trial parameter vectors. Figs. 4 and 5 show the mutation and crossover strategies in DE.

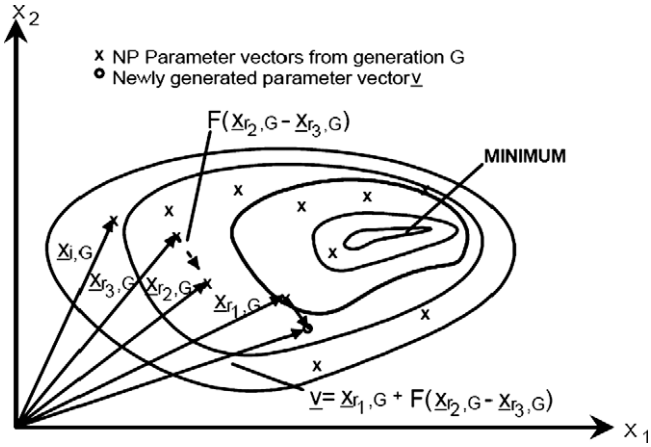

Fig. 4. DE mutation strategy.

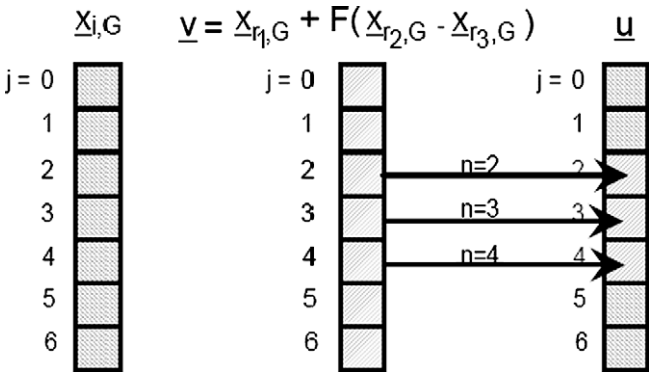

Fig. 5. DE crossover strategy.

The ACO pheromone plays a very important role in the path exploration and exploitation. A reasonable distribution of the pheromone trial can directly affect ants to explore their optimal paths. In view of this, we propose a hybrid meta-heuristic ACO and DE model. DE is used to make some random deviation disturbance in the ACO pheromone trail. Thorough this kind of random disturbance, we intend to realize that the pheromone trail between two neighboring nodes left by ant colony can reach a more reasonable distribution, which can lead ants to find out the optimal path.

In our proposed hybrid meta-heuristic ACO and DE algorithm model, we set the pheromone on the path left by ants in ACO as the object of the mutation, crossover and selection in DE [13]. In solving the UCAV three-dimension path planning problem, the objective function of the pheromone on all sub-paths between two neighboring nodes is the length of the best tour found by ants, which can be obtained according to the pheromone trail.

Some slightly adjustments are added to the basic ACO model: we divide the entire ant colony into several independent ant teams, and the team number is denoted with *Team*, which is a restriction of the total ant number *m*. For each ant-team, the pheromone amount left on the links between each two neighboring nodes are named as $\tau = \{\tau_i\}$, $i = 1, \ldots, Team$. Obviously, τ_i is a $n \times n$ matrix. As to the current pheromone of each ant-team, DE mutation operation takes effect, and the new trial pheromone trail distribution is generated by the following equation:

$$\tau_{1_i} = \tau_{r_1} + F \times (\tau_{r_2} - \tau_{r_3}), \quad i = 1, 2, \ldots, Team \tag{9}$$

where r_1, r_2 and r_3 are integers, which can be chosen randomly from the interval $[1, Team]$; τ_{r_1}, τ_{r_2}, τ_{r_3} are three pheromone trail individuals, which are selected randomly among all ant-team units, and $r_1 \neq r_2 \neq r_3 \neq i$. F is a real and constant factor, and $F \subset [0, 2]$, which is named *constant of mutation* [11], and this constant factor can control the amplification of the differential variation $(\tau_{r_2} - \tau_{r_3})$. Obviously, the smaller the differential variation between two individuals, the weaker the disturbance which it brings about. It signifies that when the pheromone of each ant-team converges to the vicinity of a kind of reasonable pheromone distribution, the disturbance generated through mutation will become weaker automatically.

In our proposed hybrid meta-heuristic ACO and DE algorithm, in order to improve the diversification of pheromone trail between nodes, we can take advantage of the DE crossover operation to make the new trial pheromone trail τ_{1_i}, which is generated through mutation, combined with the current target pheromone τ_i.

The proposed hybrid meta-heuristic ACO and DE algorithm generates a new pheromone matrix $\tau_{2_i} = \begin{bmatrix} \tau_{2_i}^{1,1} & \cdot & \cdot & \tau_{2_i}^{1,n} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \tau_{2_i}^{n,1} & \cdot & \cdot & \tau_{2_i}^{n,n} \end{bmatrix}$, $i = 1, \ldots, Team$, which can be expressed as follows:

$$\tau_{2_i}^{j,k} = \begin{cases} \tau_i^{j,k}, & \text{if } randb \le CR \text{ or } rand_k = k, \\ \tau_{l_i}, & \text{if } randb > CR \text{ or } rand_k \neq k, \end{cases} \tag{10}$$

where $\tau_i^{j,k}$ denotes the amount of pheromone between city j and k of ith ant-team, $\tau_{1i}^{j,k}$ denotes the trial pheromone trail between city j and k of the ith ant-team after the mutation operation, $\tau_{2i}^{j,k}$ denotes the ith ant-team' pheromone trail between city j and k, after the crossover operation towards $\tau_i^{j,k}$ and $\tau_{1i}^{j,k}$. *randb* is a random positive number between [0,1]. *CR* is a constant between [0,1], which is known as *constant of crossover*; the larger it is, the greater possibility the crossover operation happens; $CR = 0$ represents that no DE crossover occurs. $rand_k$ is a integer number selected randomly from [1,n]. It is obvious that the new generated pheromone matrix τ_{2_i} will surely get at least one element from that mutation trial pheromone τ_{1_i}. Otherwise, it is possible that the pheromone trail will not change at all, which can weaken the pheromone exchange between different ant-teams.

In the UCAV three-dimension path planning, ants in each team construct their paths by the transition probability $p_{j,k}$, which can be calculated by their pheromone matrix τ_i. L_best_i denotes the length of the shortest path among all paths obtained by ants, which is the objective function of the pheromone trail τ_i at the same time. Toward the newly generated pheromone trails, and the path explorations of ant colony based on them, should we accept them or not? We need compare the objective function value of both the original target pheromone τ_i and the new τ_{2_i}.

After that, we select one solution by so-called "*Greedy*" selection model. If and only if the new pheromone trail individual τ_{2_i} has a better objective function value than the original one, it can be accepted and reserved into the pheromone trail matrix of the next generation; otherwise, the original target pheromone τ_i will remain in the pheromone trail between nodes of each ant-team. Thus, we can express the crossover operation to pheromone trail as follows:

$$\tau'_{i,t} = \begin{cases} \tau_{2_i,t}, \text{ if } & L\_best_{2_i} < L\_best_{0_i}, \\ \tau_{i,t}, \text{ if } & L\_best_{2_i} \le L\_best_{0_i}, \end{cases} \tag{11}$$

where $\tau_{i,t}$ denotes the original pheromone trail left by the ith ant-team, when the number of iteration is t; $\tau_{2i,t}$ denotes, at the tth iteration, the new pheromone trail of the ith ant-team after DE mutation and crossover operation; $\tau'_{i,t}$ is equal to the pheromone matrix which has high objective function value between $\tau_{i,t}$ and $\tau_{2i,t}$. $L\_best_{0_i}$ represents the length of the optimal route gained by $\tau_{i,t}$, which is the objective value of the original pheromone $\tau_{i,t}$; ant-team, while $L\_best_{2_i}$ represents the length of the optimal route gained by $\tau_{2i,t}$, which is also the objective value of the new pheromone $\tau_{2i,t}$ of the ith ant-team.

After the selection operation, the ith ant-team which have generated their tours by the pheromone trail $\tau'_{i,t}$ or $\tau_{2i,t}$, release their own pheromone regarding the length of tours they each covered, and update the selected pheromone trail $\tau'_{i,t}$ to gain the new pheromone trail $\tau_{i,t+1}$. Then pass the new pheromone of each ant-team on to next iteration to continue path exploration and exploitation or stop.

The process of our proposed hybrid meta-heuristic ACO and DE algorithm for solving UCAV three-dimension path planning can be described as follows:

Step 1. Initialization of parameters: set the current number of iteration $Nc = 1$. Set the maximum number of iteration as *Nc_max*; set the number of ants as m, and the number of ant-team as *Team*; set the initial amount of pheromone trail on each link between two path nodes $\tau^{j,k} = const$, where *const* is a positive constant number.

Step 2. Initialization of the ant colony: divide the whole ant colony into different ant-teams, the numbers of ant in each ant-team are recorded in the matrix T_m, $(1 \times Team)$; For the ith ant-team, the number of ant individuals is $T\_m(i)$; then put ants in each ant-teams on the starting node. Set other parameters of ACO and DE: α, β, ρ, Q, F, e, CR.

Step 3. Set $Nc = 1$, $i = 1$, the $T\_m(i)$ ants in the ith ant-team select the path nodes k and go forward as the transition probability $p_{j,k}$ calculated by Eq. (4), until the whole ant colony arrives at the target point; then update the pheromone trail left on the paths according to Eqs. (5)–(7), to generate $\tau_{i,2}$; set $i = i + 1$, return to Step 3 until $i > Team$.

Step 4. $Nc = Nc + 1$, take mutation and crossover operation to the original pheromone trail τ_i of each ant-team passed from the former iteration by Eqs. (9) and (11), and generates the new pheromone trail τ_{2_i}; set $i = i + 1$, return to Step 4 until $i > Team$.

Step 5. Set $i = 1$.

Step 6. Each individual ant of the ith ant-team finally arrives the target point to construct their tours according to the pheromone trail τ_i by the following equation:

$$p_{j,k} = \begin{cases} \dfrac{[\tau_i^{j,k}]^\alpha [\eta_{j,k}]^\beta}{\sum_{s \in allowed_{t-m(i)}} [\tau_i^{j,k}]^\alpha [\eta_{j,k}]^\beta} & k \in allowed_{T-m(i)} \\ 0 & \text{otherwsie} \end{cases} \tag{12}$$

Then calculate length of tours gained by each ant, choose the shortest one, and record it as $L\_best_{0_i}$.

Step 7. Each individual ant of the ith ant-team visits the whole nodes in the three-dimension paths to gain their tours by the pheromone trail τ_{2i} as follows:

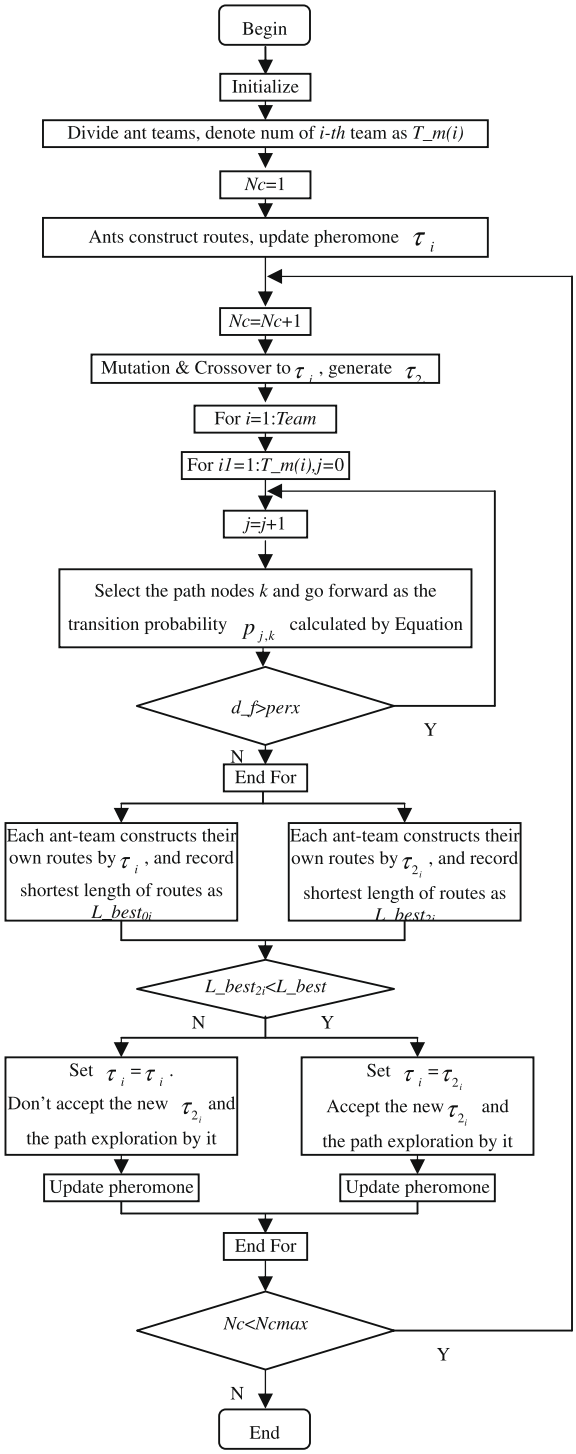

Fig. 6. Flow chart of the proposed hybrid meta-heuristic ACO and DE algorithm.

$$p_{j,k} = \begin{cases} \frac{[\tau_{2i}^{j,k}]^{\alpha}[\eta_{j,k}]^{\beta}}{\sum_{s \in allowed_{t-m(i)}} [\tau_{2i}^{j,k}]^{\alpha}[\eta_{j,k}]^{\beta}} & if\ k \in\ allowed_{T-m(i)} \\ 0 & \text{otherwise} \end{cases}$$

Then calculate the tour length gained by each ant, choose the shortest one, and denote it with L_best_{2i}

Step 8. Compare L_best_{0i} and L_best_{2i}, take the DE selection operation by Eq. (12), set the τ_i' as τ_i or τ_{2i} .
Step 9. Update the current pheromone τ_i' to gain τ_i of next iteration as follows:

$$\Delta\tau_{T-m(i)}^{j,k} = \begin{cases} \frac{Q}{W_{k\{T-m(i)\}}}, if & T\_m(i)th\ antpassed\ (j,k) \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

$$\Delta\tau_i = \sum_{s=1}^{T\_m(i)} \Delta\tau_s^{j,k} \tag{14}$$

$$\tau_i = (1-\rho)\cdot\tau_i' + \rho\cdot\Delta\tau_i \tag{15}$$

If select τ_i as τ_i' in Step 8, use the tours gained by ants in Step 6 to update the pheromone; if $\tau_i' = \tau_{2i}$ after selection operation, choose the tours gained in Step 7 to update the pheromone.

Step 10. Set $i = i + 1$; return to Step 6, until $i > Team$.
Step 11. Return to Step 4 until $Nc \geqslant Nc\_{max}$.
Step 12. The proposed hybrid meta-heuristic ACO and DE algorithm terminates and outputs the best path in three-dimension space.

The above-mentioned flow chart of the hybrid meta-heuristic ACO and DE algorithm process can also be described in Fig. 6.

6. Path smoothing strategies

The generated UCAV optimal path using the proposed hybrid meta-heuristic method is usually hard for exact flying. There are some turning points on the optimized path [20,21]. In this section, we adopt a class of dynamically feasible trajectory smooth strategy called κ-trajectories [17]. Consider the turning point path defined by the three waypoints w_{i-1}, w_i and w_{i+1}, and let

$$q_i = (w_i - w_{i-1})/\|w_i - w_{i-1}\| \tag{16}$$
$$q_{i+1} = (w_{i+1} - w_i)/\|w_{i+1} - w_i\| \tag{17}$$

denote the unit vectors along the corresponding path segments, which can be shown in Fig. 7.Let β represent the angle between q_i and q_{i+1} we can get $\beta = \arccos(-q_{i+1} \bullet q_i)$. As shown in Fig. 7, let $\overline{C}$ be a circle of radius

$$R = 0.5\min\{\|w_i - w_{i-1}\|, \|w_{i+1} - w_i\|\}\tan\frac{\beta}{2} \tag{18}$$

where center C_i lies on the bisector of the angle formed by the three waypoints, such that the circle intersects both the lines $\overline{w_{i-1}w_i}$ and $\overline{w_iw_{i+1}}$ at exactly one point each. The bisector of β will intersect $\overline{C}$ at two locations. So the center C_i is given by

$$C_i = w_i + \left(R/\sin\frac{\beta}{2}\right)(q_{i+1} - q_i)/||q_{i+1} - q_i|| \tag{19}$$

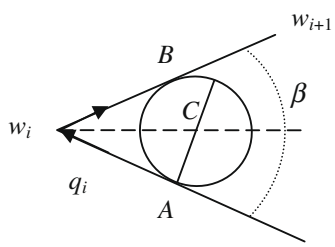

Fig. 7. Feasible sub-path of UCAV.

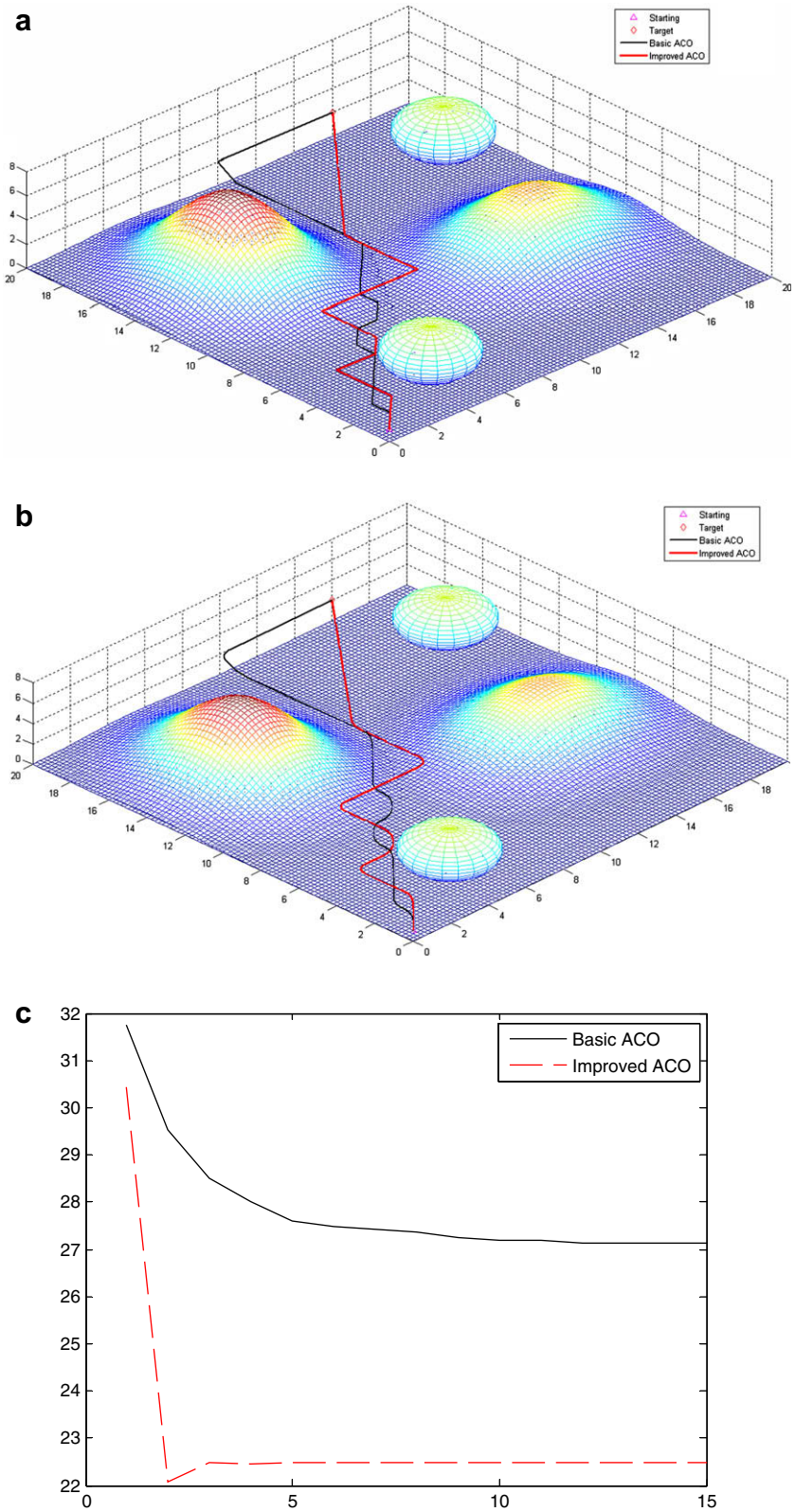

Fig. 8. Parameter values were $m = 10$, *Team* = 5. (a) Path planning original results comparison between basic ACO and improved ACO. (b) Route comparison after using the smoothing strategy. (c) Evolution curves comparison between the basic ACO and the improved ACO.

After this process, the original path $\overline{w_{i-1}w_i} \rightarrow \overline{w_i w_{i+1}}$ could be replaced by. $\overline{w_{i-1}A} \rightarrow \overset{\frown}{A}\,\overset{\frown}{C}\,\overset{\frown}{B} \rightarrow \overline{Bw_{i+1}}$. In this way, the optimized path can be smoothed for feasible flying. This trajectory smoothing algorithm has a small computational load and can be run in real-time.

7. Experimental results

In order to investigate the feasibility and effectiveness of the proposed hybrid meta-heuristic ACO and DE approach to UCAV three-dimension path planning, a series of experiments have been conducted under complex combat field environment.

The hybrid meta-heuristic ACO and DE algorithm was implemented in a Matlab 7.2 programming environment on an Intel Core 2 PC running Windows XP SP2. No commercial ACO tools or DE tools were used. In all experiments, the same set of ACO algorithm parameter values were $\alpha = 2$, $\beta = 3$, $\rho = 0.7$, $Q = 100$, Ncmax = 15.

Fig. 8 shows the UCAV path planning results comparison between basic ACO and the proposed hybrid meta-heuristic ACO and DE algorithm in three-dimension space with $m = 10$ and *Team* = 5, and the curve path comparison by the smooth algorithm, and also the evolution curves comparison. Fig. 9 shows the UCAV path planning results comparison and the evolution curves comparison between basic ACO and improved ACO with $m = 20$ and *Team* = 5. The symbol "△" denotes the starting

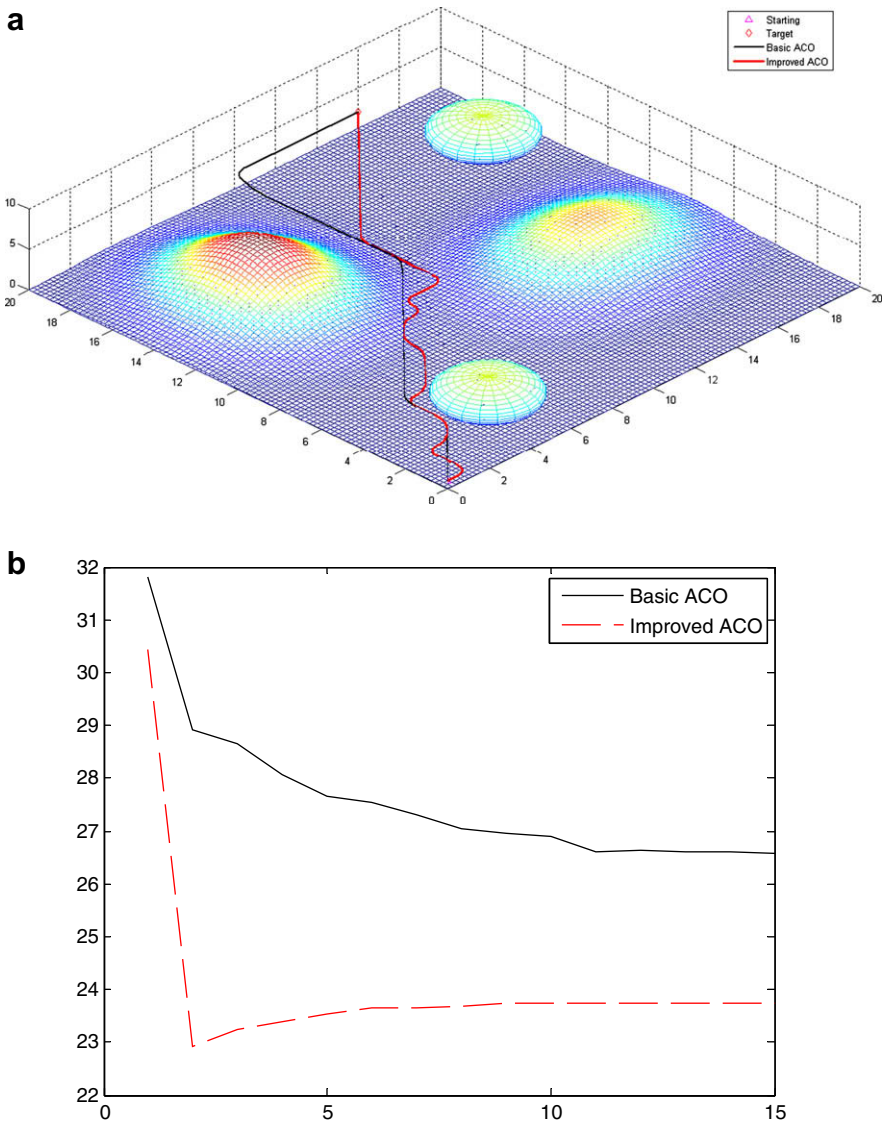

Fig. 9. Parameter values were $m = 20$, *Team* = 5. (a) Path planning results comparison between basic ACO and improved ACO. (b) Evolution curves comparison between the basic ACO and the improved ACO.

Table 1
Shortest length comparison between the basic ACO and the improved ACO.

	Basic ACO	Improved ACO
Optimal length ($m = 10$)	27.1421	21.2426
Optimal length ($m = 20$)	26.5563	21.6569

point, the sphere denotes the threaten area, while the symbol "◇" denotes the target point. And the thin line is the path generated by the basic ACO while the thick one is generated by the improved ACO.

The values of each optimal solution searched by the different algorithm could be given by the value of the "shortest length", which can be shown in Table 1.

From the experimental results presented in Figs. 8 and 9 and Table 1, it is obvious that the proposed hybrid meta-heuristic ACO and DE method can find feasible and optimal three-dimension path for the UCAV very quickly, and can effectively solve the three-dimension path planning of UCAV in complicated combating environments. The results also show that the more different ant-teams we dividing the whole ant colony, the better the solution is. This method provides a new way for three-dimension path planning of UCAV in real application.

8. Conclusions

This paper presented a hybrid meta-heuristic ACO and DE algorithm approach for UCAV three-dimension path planning in complicated combat field environment. A novel type of ACO model has been described for single UCAV three-dimension path planning, and DE is applied to optimize the pheromone trail of the improved ACO model during the process of ant pheromone updating. Then, the UCAV can find the safe path by connecting the chosen nodes of the three-dimensional mesh while avoiding the threats area and costing minimum fuel. This new approach can accelerate the global convergence speed while preserving the strong robustness of the basic ACO. The realization procedure for this hybrid meta-heuristic approach is also presented in detail. In order to make the optimized UCAV path more feasible, the κ-trajectory is adopted for smoothing the path, and this trajectory smoothing algorithm has a small computational load and can be run in real-time. The simulation experiments show that this hybrid method is a feasible and effective way in UCAV three-dimension path planning. It is also flexible, in that dynamic environments and pop-up threats are easily incorporated. Our future work will focus on the exact application of our proposed method in UCAV three-dimension path planning and re-planning.

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