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Pre-planning model for complex low-altitude rescue trajectory based on ant colonyalgorithm

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ABSTRACT

To improve emergency rescue efficiency in the complex low-altitude dense flight environment, secure low-altitude flight, shorten total implementation time of a rescue mission, this paper establishes the pre-planning model for complex low-altitude rescue trajectory and designs the solution model of ant colony optimization algorithm based on the constrains such as restricted airspace, flight interval distance, turning point and secure interval and validates effectivity of this model and algorithm via the simulation experiment.

KEYWORDS

Air traffic control; Low-altitude rescue; Trajectory planning; Pre-planningtrajectory; Ant colony optimization algorithm.

INTRODUCTION

The air rescue features quickness, high efficiency and few restriction from geological airspace, so it is an effective means which is widely adopted by the aviation-developed countries in the world for the disaster fighting and rescue and emergency accident handling [1]. When the rescue aircraft flights under 3000m altitude during flight emergency rescue, it will face problems such as high risk, low-efficiency rescue and unreasonable implementation due to disturbance from the uncertain factors such as geological environment and dense flight. How to carry out secure, timely and efficient low-altitude emergency rescue in dense and complex low-altitude flight environment in future is an urgent and critical front subjects for research, which has an important theoretical value and realistic meaning for perfectness of flight emergency rescue system.

Trajectory planning for complex low-altitude rescue flight is critical in the flight emergency rescue and aims to find an optimal or feasible flight trajectory from the start point to the destination point under the constraints such as aircraft moving performance, ground collision probability and flight time[2-3]. The target function of the aircraft trajectory planning problem is very complex and involves processing of a large number of different information. Generally planning is divided into whole trajectory pre-planning and dynamic optimization of local trajectory[4].The whole trajectory pre-planning is performed on the ground prior to flight and the planned trajectory is also called as the reference trajectory. Planning involves global optimization, should avoid local optimization, and reduce computing workload. Dynamic optimization of the local trajectory should reduce computing workload as much as possible to ensure real-time performance.

Many trajectory planning algorithms are available and can be divided into trajectory optimization, path planning and analogy-based trajectory planning[5]. The trajectory planning problem is converted for solution based on the physical or biological concepts in the analogy-based trajectory planning, including artificial potential field method, generic algorithm, neutral network method, simulated annealing method and ant colony algorithm. The ant colony algorithm is a new bionic algorithm, which simulates the activity of ants [6]. As one random optimization method, this method absorbs the behavioral features of ants, is free of the constraints of the search airspace constraint assumptions, and does not require assumptions such as continuity, derivative existence and single peak, and realizes better application effect in combined optimization solution. To effectively utilize the advantage of this algorithm, the hybrid algorithm[7-9] becomes the development trend of the trajectory planning algorithm. Generally not only single trajectory planning algorithm is used in practicable application, different planning algorithms are used in different stages, so the hybrid algorithm can effectively utilize the advantages of different algorithms[10-11], it can ensure optimal performance of the whole trajectory for certain performance indicator, and realize practicable planning under complex environment. This paper will study how to establish the pre-planning model for complex low-altitude rescue trajectory, design the heuristic ant colony optimization algorithm based on the features of the complex low-altitude flight, and realize practicability and reasonability of the pre-planning of whole trajectory for the complex low-altitude rescue.

THEORETICAL ANALYSIS

Pre-planning modelling for complex low-rescue trajectory

This model aims to minimize the total implementation time of the rescue mission, reasonably schedule the flight mission of the rescue aircraft, optimize the trajectories of different missions, reduce rescue waiting time, and efficiently complete rescue mission based on the location of the rescue base and rescue site, geological and weather conditions of rescue area, airspace environment, rescue fleet scale and conditions of waiting rescue personnel. To simplify the model, the following reasonable assumptions are taken:

(1) The departure and return trajectory of a rescue aircraft is consistent, namely the trajectory of each aircraft in each flight mission is only planned once to reduce the model dimension and ensure operability in practice.

(2) The capacity of the departure site and rescue site of the rescue aircraft is not restricted, namely different rescue aircrafts can take off or land simultaneously for rescue.

(3) The type of aircrafts and corresponding average flight speed is known. The boarding time of different persons can be ignored.

(4) Generally the change of the flight direction should not be over 90°, which can be set according to the actual conditions. To simplify the model, the change of the flight direction can be set as 45°.

The following symbols are defined:

O: set of the departure site,O=$\{o_1,o_2,\ldots,o_m\}$, namely the number of departure site is m ;

D: set of therescue site, D=$\{d_1, d_2,\ldots, d_n\}$, namely the number of rescue site is n ;

F: set of rescue airplanes, F=$\{f_1,f_2,\ldots,f_m\}$, for $\forall f_m \in F$, h_m airplanes are available.

t_m: rescue waiting time of personnel, $f_m \in F$, $t_m = a_m + g_m$,a_m indicates the air flight time, g_i is the ground waiting time. To simplify the model, set g_m as0.The air flight time is determined by the flight distance and airplane type:

$$t_m = S_{O\text{-}D} / v_m \quad (1)$$

The waiting rescue person is carried by the rescue airplane f_m.$v_m$is the average flight speed of the rescue airplane $f_m$and $S_{O\text{-}D}$ is the length of the planned trajectory O-D of the rescue airplanef_m:

$$s_{\text{O-D}} = \sum_{l=1}^{L-1} d\left(q_l, q_{l+1}\right) \quad (2)$$

q_l is the trajectory point and L is the number of trajectory points.

To easily solve this model, the rescue flight airspace is divided into grids, namely the airspace is expressed as grids, shown as the figure 1. Each cell is a square and the edge (cell length) depends on the actual conditions. The gray area indicates the flight-restricted airspace. The trajectory points are the acmes of the cells. The solid line indicates the planned trajectory in this figure. If a benchmark is set, the positions of different trajectory points can be easily expressed. If the coordinates of the trajectory points are identified, the trajectory O-D can be identified. Assume that q_1 indicates the start point, namely the departure site-O of the rescue airplane, $q_L$is the destination point, namely the rescue site-D.

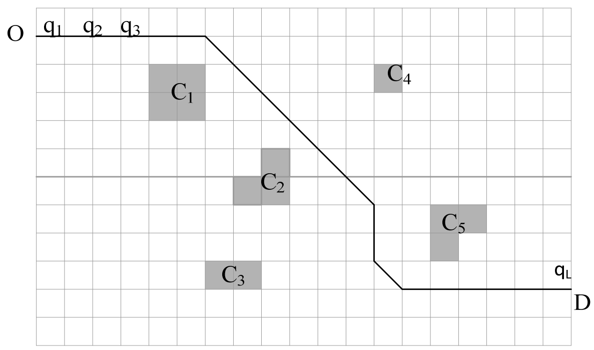

Figure 1Airspace grids of rescue flight

$S(f_x, f_y)$: aircraft interval and horizontal line distance between aircraft f_x and f_y

S: secure interval, for simplicity, the secure interval between aircrafts and between aircrafts and obstacles is set as a constant.

C_p: restricted airspace, two-dimensional diagram can be easily solved, so the altitude-restricted airspace can be converted to two-dimensional restricted airspace by section. Generally the altitude change is smaller in flight. Assume that the restricted airspace includes the secure interval, namely the trajectory can be the boundary of the restricted airspace.

D: Minimal flight segment distance, namely the minimal distance between two turning points, which should ensure that an aircraft can continuously complete turning twice. Generally it is regarded as a constant.

A: maximum size of rescue flight airspace.

With the shortest total rescue time as the optimization target, the target function can be expressed as follows:

$$\min \sum_{i=1}^{N} t_i$$

Constraints:

$$q_l q_{l+1} \cap C_p = \Phi, 1 \le l \le L, 1 \le p \le P \quad (3)$$

$$d\left(q_l, q_{l+1}\right) \ge D, 1 \le l \le L \quad (4)$$

$$q_l \le A/20, 1 \le l \le L, d\left(q_{l-1}, q_l\right) \ne d\left(q_l, q_{l+1}\right) \quad (5)$$

$$S\left(f_x, f_y\right) \le S, f_x, f_y \in F \quad (6)$$

The constraint (3) indicates the constraint on the restricted airspace and indicates that any flight segment should not cross the restricted airspace, namely it can not pass through the restricted airspace. The constraint (4) is the constraint on the flight segment distance and indicates that the length of any flight segment can not be less than the set minimal flight segment distance. The constraint (5) is the constraint on the turning points and indicates that the number of the turning points should not be over the limit to ensure flight operability and meet actual operation. The constraint (6) is the constraint on the aircraft's secure interval and indicates that the aircrafts performing the rescue mission simultaneously should keep the secure interval in flight.

Heuristic ant colony optimization algorithm

The ant colony algorithm is an adaptive global probability search algorithm, which simulates the behaviors of the ant colony such as food finding and mission allocation and features distributed computing, information positive feedback and heuristic search[12-14]. As one search optimization algorithm, the ant colony algorithm can start with the initial ant colony and repeatedly perform iterative calculations by certain rule till the optimal value is obtained or approached. The ant colony algorithm is a preliminary heuristic algorithm and guide the potential heuristic methods associated with the problem to search the airspace with possible high-quality solutions [15-16]. The heuristic ant path search procedure is designed and the information element update and evaporation mechanism is established according to the trajectory planning model for complex low-altitude rescue.

Heuristic path search procedure

When the ant searches a path, it can only "see" three direction at the stop point due to turning constraint (the turning direction is not over 45°), namely left 45°, straight and right 45°. We respectively express them with the flight direction code "0", "1" and "2". When the ant searches the path in each step, it will be expressed by connecting the nodes in the cell, so we can get the search path of the ant in the airspace grids.

The grid information taboo table (tabu1) is designed as the initial information table, which includes the coordinates of the grid boundary node (except exit point q_L) and restricted airspace C_1–C_5 boundary points and enables ants to avoid obstacles and meet the restricted airspace constraints. When the ants search paths, they should select next node at certain probability to establish a local solution and multiple local solutions compose a complete solution. The choice probability depends on the size of the information element concentration between optional nodes. When the k_{th} $(k=1,2,3,\dots,m)$ ant is located at the node i in case of the step t, it selects the node j as the next destination node at the probability as follows:

$$P_{ij}^{k}(t)=\begin{cases}\dfrac{w_{ij}\tau_{ij}^{\alpha}(t)\cdot\eta_{ij}^{\beta}(t)}{\sum_{h\in N_i^k} w_{ih}\tau_{ih}^{\alpha}(t)\cdot\eta_{ih}^{\beta}(t)}, & h\in N_i^k \\ 0, & \text{in the other cases}\end{cases} \quad (7)$$

Wherein N_i^k is the set of the optional adjacent nodes of the ant k at the node i (namely points in three advance directions of ants). The choice probability of ants for the next node is affected by the heuristic information η_{ij} and information element τ_{ij} and the influence degree is controlled by the parameter α and β. α and β respectively reflect the relative importance of the information element information and heuristic information in choice of ants. When ants simultaneously reach the step of the horizontal axis and vertical axis required by the grid, it indicates that the ants complete path search.

The heuristic information η_{ij} is computed as follows:

$$\eta_{ij}=a_{ij}b_{ij} \quad (8)$$

In this equation, a_{ij} indicates the absolute direction attraction coefficient of this adjacent node and b_{ij} indicates the relative direction attraction coefficient of this adjacent node. This paper designs bigger coefficient in the straight direction and positive direction of the relative exit.

ω_{ij} is the weight coefficient and can impose additional external information or constraints on the ant path selection. To impose the constraints on the flight segment distance (the distance between adjacent turning points is more than or equal to 20km) and ω_{ij} is 0 in non-straight direction. When the flight segment distance constraints are available, to prevent ant's search path from dead lock, the soft taboo table is set. When the current nodes of the ants are restricted and can not forward, ω_{ij} from the previous point of the ant's search path to this point is set as a smaller value.

Information element update and evaporation mechanism

True ants will release the information elements in advance. The artificial ants can determine the amount of the released information elements according to the path quality after a complete path search is completed and release it in the return path. Information elements are released instantaneously in this algorithm. When the information elements are updated, the artificial ant colony will also evaporate information elements like the true ant colony to balance accumulation of information elements, expand the search scope of the ants, prevent ants from concentrating in some paths earlier, and assist to get the optimal solution. The update and evaporation mechanism of the ant information elements are described as follows:

$$\tau_{ij}(t+1)=(1-\rho)\cdot\tau_{ij}(t)+\Delta\tau_{ij}(t) \quad (9)$$

Wherein $\Delta\tau_i(t)$ indicates total increment of information elements on the node i in this cycle and ρ indicates evaporation coefficient of the information elements.

The update rule of the information elements are described as follows:

$$\tau_{ij}(t+1)=(1-\rho)\cdot\tau_{ij}(t)+\Delta\tau_{ij}^{bs}(t),\quad \forall (i,j)\in T^{bs} \quad (10)$$

$$\tau_{ij}(t+1)=(1-\rho)\cdot\tau_{ij}(t),\quad \forall (i,j)\notin T^{bs} \quad (11)$$

$$\Delta\tau_{ij}=\frac{Q}{f(k^{best})},\quad \forall (i,j)\in T^{best} \quad (12)$$

Q indicates the strength of the information, T^{best} indicates the set of the past nodes of ants, $\Delta\tau_{ij}^{bs}(t)$ is the information element increment of optimal path, and $f(k^{best})$ indicates the value of the optimal solution in the equation (12).

The ant search process is constructed in parallel. All ants will simultaneously start to search like true ant system. Some solutions which do not comply with constraints will be punished in information element update to prevent these solutions from becoming optimal solutions and being counted as the update information. This mode can avoid too many constraints on ant's search and make some unfeasible solutions become the feasible solutions via mutation. The constraints of the turning points can be implemented via this mode. After the ants complete path search once, the value of the turning point in the path is over the set value, the target value is computed (fitness) and the punishment coefficient is increased to reduce fitness of this solution. When the information elements are updated, some solutions which do not comply with constraints will be punished to prevent these solutions from becoming the optimal solutions and being counted as the update information. The constraints on the turning points are implemented in this manner. After the ants complete path search one time and the number of the turning points is over the set value, the target value is computed (fitness) and the punishment coefficient is increased to reduce fitness of this solution.

The flow of the ant colony algorithm is shown as the figure2.

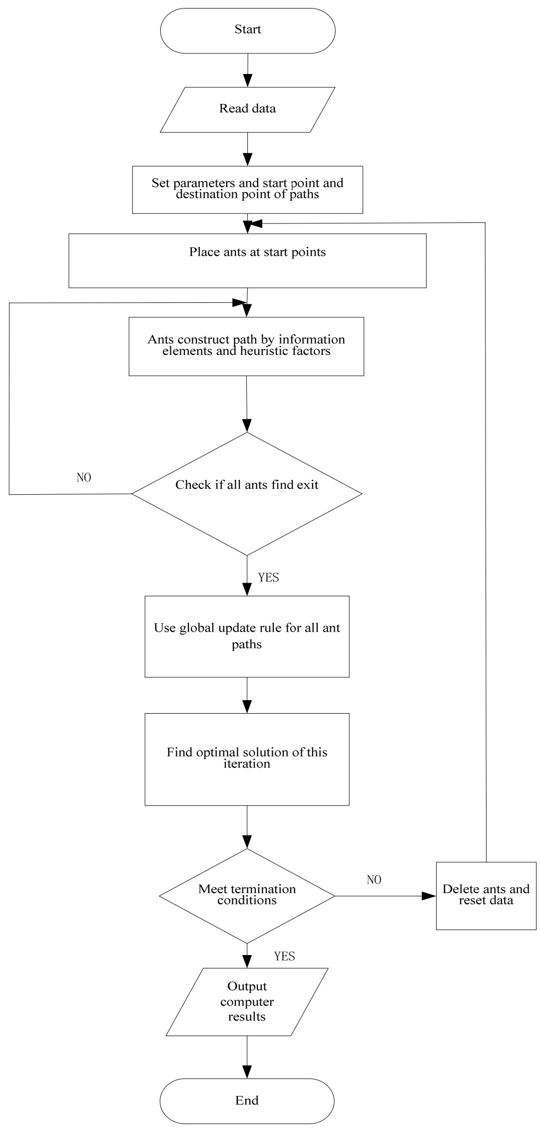

Figure 2 : The ant colony algorithm flow

SIMULATION EXPERIMENT

To verify the effectivity of this mode, a simulation experiment is performed. The airspace grids are shown as the figure 3. The upper boundary of the grids on the horizontal axis is 20, the upper limit of the grids on the vertical axis is 13, and the edge of the unit grid is 5km. The origin of the coordinate is located at the node at the left down corner of the grid. The coordinates of rescue departure site o_1, o_2 and o_3 are respectively (0,11), (0,8) and (0,5). The coordinate of the rescue destination d is (19,2). The restricted airspace is expressed with the grid obstacle C_1–C_5. To simplify computing, reduce model complexity and be generic, assume that three rescue airplanes are available, each aircraft is carried out ona rescue flight mission .

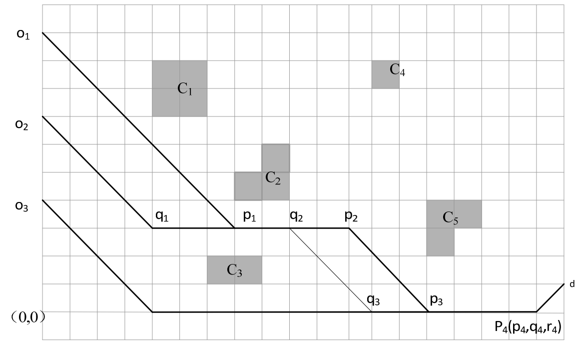

Figure 3 : Airspace grid and rescue airplane planned trajectory

The C language is programmed to implement this algorithm. The parameters in this algorithm are set as follows:*M=15,alpha=1.000,betra=2.000,ruo=0.05,Q=100.000*,RZ=*50,V=200, Limit=20*.

In the introduction to the above heuristic ant colony algorithm, M indicates the ant number m, alpha indicates the information element influence coefficient α , beta indicates the heuristic information influence coefficient β, ruo indicates the information element evaporation coefficient ρ, Qindicates the information element strength, *RZ* indicates the total iteration time of the algorithm , *V* indicates the average flight speed of airplanes (unit: km/hour) and Limit indicates the minimal flight segment distance constraints (unit: km).

RESULT AND DISSCUSS

To solve this model, we can get 339.7056 km as the minimal flight distance, 1.6988 minimal flight hours and 4, 4 and 2 turning points. The shortest path code is:2 1 1 1 1 1 1 0 1 1 1 2 1 1 0 1 1 1 0 3 2 1 1 1 0 1 1 1 1 2 1 1 0 1 1 1 1 1 0 3 2 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0. The code is divided into 3 segments. Each section is separated by "3" and respectively indicates the trajectory the aircrafts departing from the rescue departure site o_1,o_2 and o_3. After they are decoded by the flight direction coding rule, these codes can be recovered to the complex low-altitude planned trajectory, shown as the line from node o_1,o_2 and o_3 as the rescue departure sites to the rescue node d infigure 3:o_1-p_1- p_2- p_3- p_4-d;o_2-q_1-q_2-q_3-q_4-d;o_3-r_1-r_2-d. We find that the shortest paths are same when the total iteration time RZ of the algorithm is 11 and 50 in program-based solution. The optimal solution of the algorithm converges in case of 11^{th} generation and the algorithm features better convergence, shown as the figure 4.

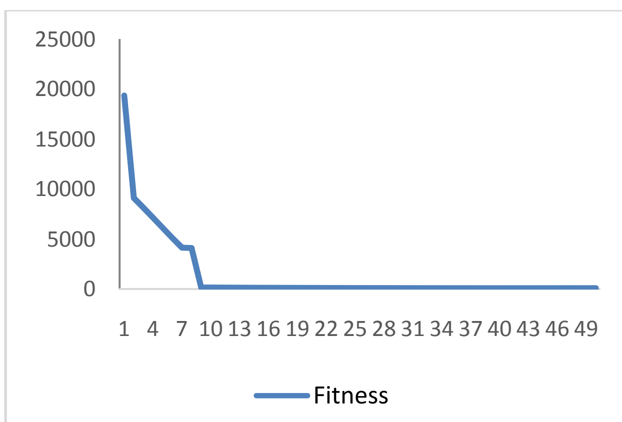

Figure4 Convergence effect of heuristic ant colony algorithm

Quick and effective convergence mechanism of the heuristic ant colony algorithm can ensure that the optimal solution of the advance planned trajectory for complex low-altitude rescue can be identified in a shorter time and is very meaningful for highly real-time rescue actions.

CONCLUSIONS

This paper establishes the pre-planning model for complex low-altitude rescuetrajectory,designs corresponding ant colony optimization method, and validates effect of the model and algorithm via the simulation experiment based on the current conditions and features of low-altitude air rescue in China.

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