Research on Capability Optimization of High Maneuvering Combat Force Based on Mission Completion Quality

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Abstract. In order to optimize the capability of high maneuvering combat force, considering the non-measurability of capability, a capability optimization method based on mission completion quality is proposed in this paper. In this method, the capability optimization objective is replaced by the mission completion quality, and the quality is measured by the mission completion success rate and the mission completion cost. The optimal solution set which is the path with highest success rate and lowest cost is obtained based on the improved NSGA-II. In light of the cost value of each path in this solution set, the solution has various optimization directions. Based on the actual requirements of mission, decision maker can select one from optimal solution set. Thus, the capability of high maneuvering combat force is optimized.

1. Introduction

In the information warfare, high maneuvering combat force realizes rapid reconnaissance, rapid decision-making, and quick strike by utilizing its high mobility, thereby forming capability advantages compared with the traditional combat force. The key element of high maneuvering combat force is maneuver capability. Therefore, maneuver capability optimization is essential for high maneuvering combat force. The unmanned aerial vehicle (UAV), which is a typical representative of high maneuvering combat force, can quickly penetrate into the enemy's deep area to execute reconnaissance and strike missions [1]. UAV's maneuver capability is affected by internal and external factors such as the battlefield environment, enemy threats during the execution of the maneuver mission [2]. Therefore, the problem of capability optimization of UAV is the single-objective optimization problem under multi-constraint conditions. In view of the difficulty in measurement and calculation of maneuver capability, the optimization model is difficult to establish. The paper replaces the capability optimization objective with other optimization objectives, and the capability optimization problem is transformed into a multi-objective optimization problem.

At present, multi-objective optimization methods mainly include MOGA [3], NPGA [4], PAES [5], SPEA-II [6] and NSGA-II [7-8], among which the most representative algorithm is NSGA-II. According to the traditional genetic algorithm, NSGA-II crosses and mutates the initial population to produce the next generation population with the same number as the initial population size, and then adopts the non-dominated layer sorting method to combine the initial population and the next generation population to select the high quality individuals [7-8]. Compared with other multi-objective evolutionary algorithms, NSGA-II is characterized by non-dominated sorting, elite strategy and congestion degree calculation, which reduces the complexity of traditional genetic algorithm, and has
the advantages of fast running speed and good convergence [7]. Therefore, this paper uses the improved NSGA-II algorithm as the capability optimization algorithm for UAV.

2. Multi-Objective Optimization Model

In fact that capability of the UAV is difficult to measure, this paper substitutes the capability by the quality of the UAV accomplishing mission. And the quality is determined by the mission success rate and the mission completion cost, regardless of the influence of the aircraft’s own factors. As shown below:

\[
C_i \propto Q_i = f(P_{i,success}, S_{i,con})
\]

(1)

\(C_i\) is the capability of UAV in the completion of mission \(i\), \(Q\) denotes the completion quality of mission \(i\), \(P_{i,success}\) denotes the success rate of mission \(i\), \(S_{i,con}\) is the completion cost of mission \(i\).

2.1. Basic assumption

On the basis of simplifying the model, in order to highlight the negative impact of enemy threats on the mission completion quality, the following assumptions were made:

1) Considering the influence of external environmental factors, \(P_{i,success}\) only relevant to enemy threats.

2) Enemy threats are the reconnaissance sensors deployed in the battlefield airspace. The sensor needs to track for a long time from discovery target to capture target, and the time limit is \(T\). If the aircraft is continuously tracked for more than \(T\), the reconnaissance sensor successfully captures the UAV to indicate that the UAV is destroyed, and the mission completion success rate is zero.

3) Several reconnaissance blind nodes exist in the battlefield space, and the UAV at the blind node will not be discovered by the enemy sensor. If the UAV enters the reconnaissance blind node in the tracked state, it needs a minimum stay time to ensure that the reconnaissance sensor loses the UAV location information, and the time is \(t\).

4) The mission completion cost only includes the distance cost and the time cost.

5) The UAV is regarded as a mass point, ignoring its size, and the speed is constant.

6) The UAV is limited by the structure and control system, cannot change direction abruptly.

7) The UAV can turn at any corner of the space at a minimum turning radius at any time.

2.2. Optimization Objective

Based on the above basic assumptions, the capability optimization model of the UAV is based on the highest mission success rate and the minimum mission completion cost. Mission completion cost requires the maneuver distance is as small as possible and the maneuver time is as short as possible. Mission success rate requires the UAV should be continuously tracked by the enemy reconnaissance sensor for no more than \(t\). Therefore, the UAV must pass a number of reconnaissance blind nodes during the maneuver process. The mission success rate optimization objective can be transformed into a constraint on the distance between two reconnaissance blind nodes that pass continuously in the maneuver path.

The mission completion cost objective can be converted into the distance cost objective and the time cost objective, and the optimization objective function is as follows:

\[
\begin{aligned}
S_{j,\text{costLength}} &= (\text{Distance} - \text{Len}(M_{\text{start}}, M_{\text{end}}))/\text{Len}(M_{\text{start}}, M_{\text{end}}) \\
S_{j,\text{costTime}} &= (\text{Time} - \text{Len}(M_{\text{start}}, M_{\text{end}})/v)/\text{Len}(M_{\text{start}}, M_{\text{end}})/v \\
\text{Distance} &= \min_{\text{in path}(k)} \sum_{i \in \text{in path}(k)} \text{Dist}(M_i, M_{\text{ref}}) \\
\text{Time} &= \min_{\text{in path}(k)} \left( \text{Distance(path(k))}/v + (n(path(k)) - 2) \times t \right)
\end{aligned}
\]

(2)

\(S_{j,\text{costLength}}\) denotes the distance cost for performing mission \(j\), \(S_{j,\text{costTime}}\) denotes the time cost for performing mission \(j\), \(m\) is maneuver path size, \(\text{path}(k)\) indicates the \(k\)th maneuver path, \(M_{\text{start}}\) and
$M_{\text{end}}$ is the starting node and the ending node, $\text{Len}(M_{\text{start}}, M_{\text{end}})$ indicates the straight line distance between the starting node and the ending node, $\text{Dist}(M_i, M_{i+1})$ is the path distance of $M_i$ and $M_{i+1}$, $\text{Distance}$ indicates the shortest distance, $\text{Time}$ indicates the shortest time, $\text{Distance}(\text{path}(k))$ indicates the path distance of the $k$th maneuver path, $n(\text{path}(k))$ is the number of passing nodes in the $k$th maneuver path, $v$ is the maneuver speed, $t$ is the minimum time that the UAV stays in reconnaissance blind nodes to dodge reconnaissance.

2.3. Constraints
Any one of the maneuver paths must meet the following constraint: The maneuvering time of UAV between any two consecutive nodes must be no more than the continuous tracking time of the sensor; the turning radius of the UAV at any turning point must be bigger than the minimum turning radius of the UAV.

$$\begin{align*}
\text{Dist}(M_i, M_{i+1}) & \leq v \times T \\
R & = \frac{l_{BC}}{2\cos \theta} \geq r
\end{align*}$$

$T$ indicates the minimum time that the UAV is continuously tracked by the reconnaissance sensor, $R$ indicates the turning radius of the UAV from node $B$ to node $C$, $r$ indicates the minimum turning radius of the UAV. The turning radius of UAV from node $B$ to node $C$ is shown in Figure 1 below.

![Figure 1. Schematic diagram of the turning radius](image_url)

3. Model Solutions

3.1. NSGA-II Algorithm Process
The basic idea of NSGA-II algorithm: generate an initial population of size $m$, each individual in the population is a feasible solution for the model, iterate through the crossover, mutation, and pruning after sorting by non-dominated layer, until the end condition is met. The specific process is shown in Figure 2 below.

![Figure 2. NSGA-II algorithm process](image_url)
3.2. Individual Coding and Initial Solution Generation

The feasible solution of the capability optimization model is a maneuver path of the UAV that meets the above-mentioned constraints and arrives at the ending node after a number of reconnaissance blind nodes from the starting node. The feasible solution can be represented by the serial number of the nodes in turn. Therefore, the node number can be directly used as the code of chromosome. Assuming that the number of nodes of the maneuver path is $N$, the number of reconnaissance blind nodes in the path is $N-2$, and the length of the chromosome is $N$. The chromosome structure is as follows.

\[
P_{mon} \quad P_1 \quad \cdots \quad \cdots \quad P_{N-2} \quad P_{end}
\]

Considering that the searching space is large and the constraints are harsh, it is difficult to obtain an effective initial solution by randomly generating chromosomes. Therefore, the paper employs the distance constraint to ensure the feasibility of the solution. Based on the conditions, the random searching space is limited and a feasible initial solution set is generated as quickly as possible.

3.3. Fitness Calculation

In this paper, the fitness value is described by the optimization objective function value. The maneuver time calculation is based on the maneuver distance. Since the UAV cannot make an immediate turn, the maneuver path of the UAV will consist of line segments and arc lines. In the three-dimensional space, the length of the line segment can be obtained by the distance formula between two nodes, and the calculation process of the length of the arc line is as follows. The schematic diagram is shown in Figure 3 below.

Step 1: determine the centre coordinates of the circle where the arc line is located. Taking node $B$ as the starting node, taking the normal vector perpendicular to the $ABC$ plane and line $AB$ as the direction, intercept the line with the length of minimum turning radius $r$, and judge the centre of the circle based on the distance between $CO_1$ and $CO_2$. 

Step 2: determine the coordinates of the tangent node $D$. Take the coordinate origin as the centre, establish the scatter circle with radius $r$, and determine the total number of scatter points as $Sum$. According to the pitch angle, azimuth angle of plane $ABC$ and the centre coordinates $O_1$, rotate and translate the scattered point circle to obtain circle $O_1$, obtain the position information of node $B$ on circle $O_1$. According to the coordinates of node $C$ and $O_1$, the length of radius $r$, the length of tangent $CD$ and $CD'$ are determined, and the position information of node $D$ and $D'$ are obtained, which is $LocD$ and $LocD'$. Compare the size of angle $DBA$ and angle $DBC$, if $\angle DBA > \pi/2$ and $\angle DBC < \pi/2$, then delete the tangent node $D'$, and keep the tangent node $D$ as the end node of the shortest turning path.

Step 3: calculate the length of the arc line $BD$. According to the position information of node $B$ and node $D$ in circle $O_1$, $Nodenumber$ which is the total number of scattered points between two nodes is determined. The length of the circular arc line $BD$ is as follows.

\[
BD = 2\pi r \times \left(\frac{Nodenumber}{Sum}\right)
\] (4)

![Figure 3. Calculation diagram of the length of arc line BD](image)
3.4. Population Crossover

For any two feasible solutions, if each node is randomly selected for cross-splicing, the distance between the two nodes may not satisfy the distance constraint. To ensure that the progeny chromosomes produced by the crossover satisfy the constraints, the crossover nodes of the two chromosomes should be reasonably chosen.

The first crossover strategy is to use the same node as the crossover point in addition to the starting node or ending node of two chromosomes, as shown in Figure 4(a). The second crossover strategy is to select the two closest nodes as the crossover nodes if there are no same nodes except the starting node or ending node in the two chromosomes, as shown in Figure 4(b). In the figure, the node that code is 2 of chromosome 1 is the closest to the node that code is 3 of chromosome 2, so they are regarded as crossover nodes. In order to ensure the diversity of the populations, a distance threshold can also be set. The node pairs whose distance between two nodes in two chromosomes is less than the threshold can be regarded as the crossover node pairs, forming the crossover node pair set, taking the distance between the node pairs as the weight, using roulette to randomly select a node pair for crossover.

![Figure 4. Schematic diagram of chromosome crossover](image)

3.5. Population Mutation

Population mutation is to search for the global optimal solution, which can be random variation or in accordance with the direction of the optimization objective. Aiming at the two optimization objectives of distance cost and time cost, two mutation strategies are set up in this paper. Each mutation strategy is selected randomly. The first mutation strategy is to randomly select any node on the path except the starting node and the ending node, and exchange the node with the node within the range of 2 hops on the path. If the maneuver path still meets the constraints after replacement, the chromosome of the mutation offspring will be output. The second mutation strategy is to randomly delete any node on the maneuver path except the starting node and ending node. If the maneuver path still meets the constraints after deletion, the chromosome of the mutation offspring will be output.

3.6. Population Pruning

Population pruning is to eliminate the individuals with low fitness from the parent population and the offspring population generated by crossover and mutation, keep the best individuals, and ensure that the population size is consistent with the parent population. Due to the existence of multiple optimization objectives, it is difficult to determine the merits and demerits among individuals, so the non-dominated layer sorting and congestion degree calculation are used to determine the excellent individuals. The ranking of non-dominated layer is a process to determine the non-dominated order value of all individuals in the population. The individuals with low order value are better. Therefore, the non-dominated order values are placed in the next generation population in descending order. If all individuals with non-dominated order values of \( i \) are placed in the next generation population, the population size exceeds the parent population size. Then we calculate the congestion degree of all individuals non-dominated order values is \( i \), and individuals with high congestion degree are preferentially placed in the next generation population.
4. Simulation Analysis

The simulation experiment in this paper uses MATLAB (R2015a) as the software platform for programming. The experimental environment: operating system is Windows 10, processor Inter(R) Core(TM) i7-8750 CPU @ 2.20GHz 2.21GHz, memory 16GB. The specific parameters are set as follows:

Basic parameters: speed \( V = 200m/s \), minimum turning radius \( r = 200m \), continuous tracking time limit when the sensor is locked \( T = 60s \), the time limit for reconnaissance blind node residing when getting rid of tracking \( t = 20s \).

Mission airspace parameters: X-axis coordinate interval \([0,100000]\), Y-axis coordinate interval \([0,10000]\), Z-axis coordinate interval \([0,10000]\), the starting node coordinate \((0,50000,5000)\), the ending node coordinate \((100000,60000,5000)\), unit is meter, the number of reconnaissance blind nodes is 611, scouting blind node coordinate parameters.

NSGA-II parameters: initial population size is 1000, the number of iterations is 30, the proportion of crossover quantity is 0.8, the proportion of mutation quantity is 0.4.

After multi-objective optimization, there are two Pareto optimal solution sets with dominant layer 1, as shown in the following Figure 5. The blue nodes in the figure are the reconnaissance blind nodes in the space. The star-shaped red nodes are the starting node and the ending node. The black path is the UAV straight flight path, red path is the UAV turn path.

![Figure 5. Schematic diagram of two optimal paths for UAV](image)

The distance of the first path is 110.665km, the time is 773.325s, the distance cost is 0.1011, and the time cost is 0.1673. In second path, the distance is 111.566km, and the time is 757.832s, the distance cost is 0.1101 and the time cost is 0.1439, the detailed path sequence is as shown in Table 1 below.

| Serial Number | Maneuver Path Sequence | Distance(km) | Time(s) |
|---------------|------------------------|--------------|---------|
| 1             | 1-72-579-65-367-16-541-251-173-215-426-303-613 | 110.665 | 773.325 |
| 2             | 1-72-579-65-367-16-541-251-404-595-502-613 | 111.566 | 757.832 |

This model corresponds to two optimization directions: one is to ensure when the distance cost is guaranteed to be minimal, the time cost is as small as possible; the other is to ensure when the time cost is guaranteed to be minimal, the distance cost is as small as possible. The decision maker can select the best one according to the actual requirements of the mission, and then optimize the quality of the completion mission.

For more in-depth analysis of capability optimization, the paper conducted four experiments by adjusting the relevant variables, and obtained the relationship between distance cost, time cost and the number of iterations, as shown in Figure 6. It can be seen from the results that the NSGA-II algorithm converges quickly, the distance cost and the time cost are optimized at 10 to 15 generations. And when
the speed is increased by 25%, as shown in Figure 6(b), the optimal value of the distance cost and time cost is the lowest, which is 26.9% and 33.8% lower than the initial situation. The increasing of speed can significantly enhance the maneuver capability. When the enemy's continuous tracking lock time is shortened by 25%, as shown in Figure 6(c), the optimal value of distance cost and time cost is the highest, which is 82.9% and 66.3% higher than the initial situation. The increasing of enemy reconnaissance capability can significantly weaken the maneuver capability. When the number of battlefield reconnaissance blind nodes is reduced by 50%, as shown in Figure 6(d), the optimal value of distance cost and time cost is increased by 72.8% and 34.1%.

When the UAV performs a maneuver mission, if the speed and the reconnaissance capability of enemy have been determined, it is necessary to grasp as much as possible the number of blind nodes to achieve the optimization of the maneuver capability.

![Figure 6](image)

**Figure 6.** Distance cost and time cost as a function of the number of iterations, (a) initial situation, (b) speed increased by 25%, (c) continuous tracking time reduced by 25%, (d) the number of reconnaissance blind nodes reduced by 50%

5. Conclusions
Based on the non-measurability of UAV's capability, this paper maps the capability optimization problem to the mission completion quality optimization problem. By introducing the factors such as mission success rate and mission completion cost, a maneuver mission completion quality optimization model is established, which takes mission completion success rate as constraint, mission completion distance cost and mission completion time cost as optimization objectives, and is solved by the improved NSGA-II multi-objective optimization algorithm. Finally, the optimal solution that satisfies the two optimization objectives is obtained, and the quality of the completion mission is optimized, and the capability optimization is realized.

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