Training Airspace Dynamic Programming in Stages Using Improved Particle Swarm Optimization

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Abstract: Dynamic planning of training airspace is of great significance for improving airspace utilization, improving troop training efficiency, and alleviating the conflicts between military and civilian air use. In this paper, the dynamic planning problem in the airspace is processed in stages, and the improved genetic-particle swarm algorithm is used in the calculation examples, and the total occupancy time is minimized by seeking the optimal solution at each stage, and the feasibility and effectiveness are verified through simulation.

1. Introduction

The training airspace is an important carrier to enhance military combat effectiveness and national defense capability. In recent years, with the upgrading of weapons and the combat transformation of the air force, the demand of daily training for airspace is increasing rapidly. At the same time, the airspace demand of civil aviation is also sharply increased. The conflict between military and civil aviation is becoming more and more prominent. Therefore, the dynamic programming of training airspace plays a positive role in improving the utilization rate of airspace resources and the flexible use of airspace. At the same time, it can also alleviate the conflict between military and civil aviation.

As for the dynamic programming of airspace, foreign researches started earlier. In 2005, Alexander Klein et al. improved the regular hexagon segmentation method and used radar historical data to divide airspace on the basis of the existing segmentation method [1]. In 2009, Sabhnani et al. used geometric algorithms to dynamically recombine sectors according to the historical data of air traffic density within each sector [2]. In 2012, Dr.Krishan Kumar et al. used ART1 neural network and combined with the workload of the sector controller to redivide the sector, which improved the air traffic control capacity while reducing pressure for the controller [3]. In Germany, the flexible use of airspace also provides a strong support for the coordinated development of civil and military aviation. It claims that the reserved airspace for military training should be given to other users during periods when there is no military training. However, due to the particularity of military activities, it is impossible to completely copy foreign methods. Domestic researches on airspace planning are mostly aimed at civil aviation [4]. Studies on dynamic utilization of airspace are mainly conducted from a qualitative perspective [5][6]. At present, the dynamic planning of the training airspace mainly relies on the experience of staff and lacks of quantitative analysis. So far, it has not formed a set of efficient planning procedures for the troops.

The dynamic planning of tactical training airspace is actually a broad combination optimization problem, which requires the premise of meeting the space constraint, arranging the starting node and the end node of all the training tasks, so that they can shorten the airspace utilization time as much as possible. In theory, the problem is similar to the problem of resource scheduling [7][8], which has been widely studied, with genetic algorithms and integer programming algorithms that dominate the

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main status. The main problems facing the planning process are: 1. Because of the different kinds of training subjects, and the size of the airspace required by each subject, the utilization of the airspace is not guaranteed.2. Due to the burden of training and the limitation of the airspace resources, it is necessary to carry out the implementation in batches, and to determine the time and space of each subject is the hard part.

Based on the characteristics of the dynamic planning problem of the training space, this article divides it into several stages of mutual independence and interaction. Then enter a stage after each stage to make the optimal decision, so that the overall decision of the whole process is optimal. For each stage, this article is dispose training space into disperse, and the optimal decision is obtained by the genetic particle swarm algorithm. Compared with the traditional particle swarm algorithm, the novel of this article are: 1. Using the cross and variation ideas in genetic algorithm to improve the convergence rate of the algorithm. 2. Introduced adaptive cross and mutation operator, improved search breadth and depth, and ensure the diversity of population.

2. Problem description

The training airspace is the range designed to ensure the flying team's regular training. The size of the airspace required is not the same because of the different methods of the implementation of each subject. The dynamic planning of tactical training airspace is to arrange the training tasks of each batch properly within the airspace of the airport, shorten the total training time required while ensuring space utilization. The constraint is:

1)Once each training task begins, it must continue to be the end of the service.

2) All training tasks must be completed.

3) All training tasks must be completed within the airspace of the airport and shall not exceed the airspace boundary.

4) The task of the training task is 10 minutes per unit.

5) The airspace of each training mission shall not overlap.

6) In case of actual situation, when the required airspace is arranged for each task, it needs to be parallel to the coordinate axis, but it can rotate 90 degrees.

For each stage of the airspace plan, it refers to the arrangement of training subjects as much as possible on the basis of ensuring the utilization of the airspace. That is, in the process of implementation, the utilization of airspace in the entire period is the largest. Its objective function is:

$$\max \quad E = n + \sum_{i=1}^{n} (l_i \times w_i) / S \tag{1}$$

In the form, S is the area of the operational area. l_i is the length of the airspace required for a training course; w_i is the width of the airspace required for a training course; n refers to the total number of subjects in the course of the period, and $1 \le i \le n$.

In the planning process, it needs to follow the following constraints:

1) Due to fighters are not allowed to exceed the airspace boundary, each subject must be carried out in the combat area.

2) There is a need for a certain distance between the subjects and not overlapping.

3) The training airspace of each subject needs to be parallel to the axes, but it can be rotated. The formula is as follows:

$$E_{xy} + B_i^{xy} \le 1, \forall i \in \{1, 2, \cdots, m\} \tag{2}$$

$$B_i^{xy} + B_j^{xy} \le 1, \forall i, j \in \{1, 2, \cdots, m\} \tag{3}$$

$$\begin{cases} l_{xi}+l_{yi}=1 \\ w_{xi}+w_{yi}=1 \\ l_{xi}+w_{xi}=1 \\ l_{yi}+w_{yi}=1 \end{cases} \quad \forall i\in\{1,2,\cdots,m\} \tag{4}$$

In the formula, (x,y) means the coordinates of the airspace, E_{xy} and B_i^{xy} are all variables of 0 or 1. The former means whether the airspace in (x,y) is occupied, the latter indicates whether the airspace in (x,y) is occupied by the i training subject. If it is occupied, the value is 1 and the other is 0. l_{xi} and l_{yi} are variables evaluated as 0 or 1, indicating whether the long sides of the training subject i are parallel. If it parallels to the X-axis, l_{xi} equals to 1; w_{xi} and w_{yi} are variables evaluated as 0 or 1, indicating whether the broad edge of training subject i is parallel to the axis. If it parallels to the Y-axis, w_{yi} equals to 1.

3. Method of training space dynamic programming

The dynamic planning of the training airspace refers to the reasonable arrangement of training subjects in the airspace of the airport, allowing it to shorten the time as much as possible while ensuring space utilization. Due to the limitation of the airspace, the training of all subjects cannot be completed at the same time, so this problem is regarded as a double constraint problem of timing and space. In this paper, the problem of the sequence constraint is solved by the method of phase processing, and the spatial constraint problem is solved by genetic particle swarm algorithm.

3.1 Phase processing model

Assuming there are m independent training tasks, $j_1, j_2, \cdots, j_m$ need to be completed in the airspace of the airport, but because of the limited airspace resources, they cannot complete m training tasks at the same time. We divide it into n separate and interconnected phases, each of which requires the appropriate decision making. Each phase is usually divided in chronological order (after the subject is completed and entered into the next stage), the stage variable is represented by k. T_{ks} and T_{ke} represent the starting time and the end time of the phase, and $T_k(i)$ indicates that the time is required for the task in this phase. Assuming that there is a training task at some point, so $T_{ke}=T_{ks}+\min\{T_k(1),T_k(2),\cdots,T_k(a)\}$,and $T_{(k-1)e}=T_{ks}$. Through multi-stage processing until all the training tasks have been completed. Then using the genetic and discrete particle swarm algorithm to calculate the time of different solutions, and the shortest one is selected as the final planning scheme on the premise of ensuring the airspace utilization rate.

3.2 Spatial planning using Genetic discrete particle swarm optimization algorithm

Particle Swarm Optimization (PSO) algorithm focuses on solving some continuous and unconstrained problems. There is still a large research space for discrete, discontinuous and constrained problems such as airspace planning. In this paper, transformators and transformational sequences are proposed to solve discrete programming problems. In addition, crossover and mutation in Genetic Algorithm (GA) are introduced to improve the ability of discrete PSO algorithm for getting rid of the local optimal solution and improve the convergence speed and accuracy of the algorithm. A new position in solution space is created by cross-varying the current solution with the individual optimal solution and the global optimal solution. At the same time, in order to ensure the diversity of population and the adaptability of individuals, the crossover rate and mutation rate are controlled by adaptive hierarchical algorithm.

4. Simulation

To evaluate the effectiveness of the proposed method in solving the problem of tactical training airspace dynamic programming, the following example simulation is carried out. It is assumed that a certain part needs to complete 3 tactical training tasks on a certain day, and each task has 4 batches (m=12). The duration and required airspace size of the training task are shown in Table 1 below.

Table 1 Airspace size required for training tasks

Sequence	Long/ Kilometer	Width/ Kilometer	Duration/ Minutes	Sequence	Long/ Kilometers	Width/ Kilometers	Duration/ Minutes
1	6	16	50	2	12	10	40
3	6	6	30	4	8	16	50
5	12	10	40	6	6	6	30
7	8	16	50	8	12	10	40
9	6	6	30	10	8	16	50
11	12	10	40	12	6	6	30

By applying the above algorithm to solve this problem, it can be obtained through calculation that the above training task needs to be divided into 6 stages. The airspace planning diagram of each stage is shown in Figure 1~6 below.

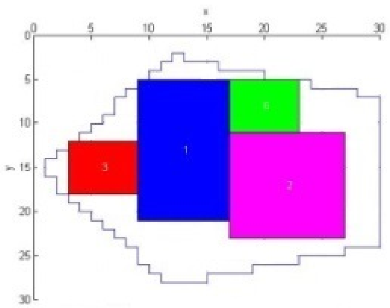

Fig. 1 Airspace diagram at the first stage

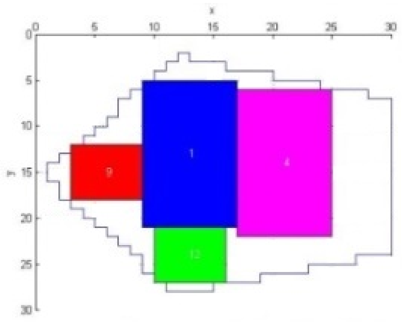

Fig. 2 Airspace diagram at the second stage

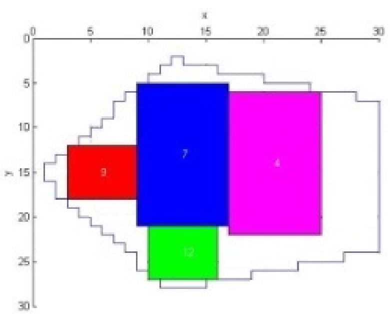

Fig. 3 Airspace diagram at the third stage

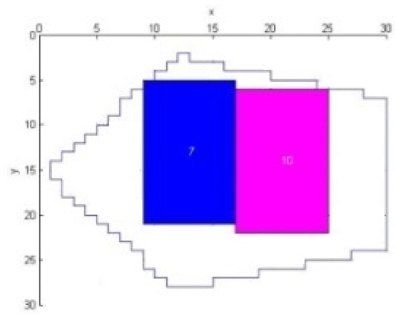

Fig. 4 Airspace diagram at the fourth stage

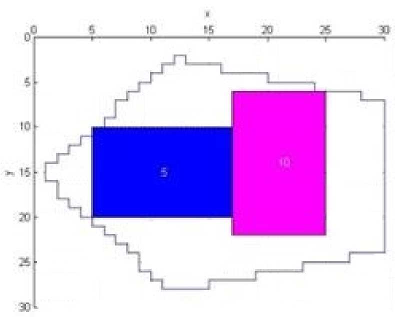

Fig. 5 Airspace diagram at the fifth stage

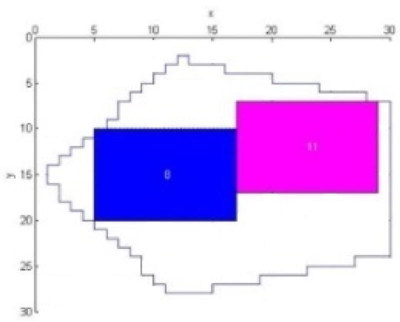

Fig. 6 Airspace diagram at the sixth stage

Fig. 1~ Fig. 6 shows that the established training task can be completed in six stages. In the first stage, task 1 (blue), 2 (purple), 3 (red) and 6 (green) can be executed. In the second phase, task 1 (blue), 4 (purple), 9 (red) and 12 (green) will be executed. In the third stage, execute 4 (purple), 7 (blue), 9 (red) and 12 (green);The fourth stage is to execute tasks 7 (Blue) and 10 (purple);The fifth stage is to execute tasks 5 (Blue) and 10 (purple);Phase six, mission 8 (Blue), 11 (purple).

5. Conclusions

The training airspace planning problem is dealt with in stages. The proposed method can shorten the airspace occupancy time as much as possible while ensuring the airspace utilization. Compared with the current artificial planning method, the method can greatly shorten the time needed for training, improve flight efficiency and effectively alleviate the conflict between civil and military flights.

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