Air Route Network Planning Based on Improved Cellular Automata Algorithm

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Abstract: In order to optimize airspace resources and reduce operational costs, this paper investigates the air route network planning problem considering the avoidance of prohibited, restricted, and danger zones (PRDs). Firstly, the airspace is discretized using the grid method, and the airspace information is binarized to enable the avoidance of these three zones. Then, a mathematical model is established with the objective of minimizing the total route length, considering factors such as nonlinear coefficient and flow constraints. The pathfinding process incorporates distance priority coefficients and collision risk coefficients, and the cellular automata algorithm is employed to solve the problem. Additionally, the results are further smoothed to obtain the shortest path. Finally, a case study is conducted using the air route network planning of Guangzhou FIR for verification. The results demonstrate that, compared to the current routes, the proposed approach effectively reduces the route length, decreases the number of waypoints, and lowers the nonlinear coefficient of the routes. These findings highlight the effectiveness of the improved cellular automata algorithm, which has important implications for real-world air route network planning.

Key words: air traffic management; airspace management; air route network planning; "PRDs" avoidance; cellular automata

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0 Introduction

With the continuous development of the civil aviation industry, air traffic flow has been steadily increasing. Despite the recent slowdown in the industry due to the impact of the pandemic, the civil aviation industry is now regaining its vitality as the situation improves. The air route network planning is a crucial aspect of airspace planning and plays a vital role in optimizing airspace resources, enhancing airspace capacity, and alleviating air traffic congestion. The rationality of air route network planning is of paramount importance to the operational efficiency and effectiveness of the civil aviation transportation system.

Currently, there are three main methods for air route planning: Global route planning, local route planning, and high-speed route planning. Global route planning involves completely abandoning the current route network within a country or region and designing a new layout based on top-down planning principles. Local route planning optimizes certain or all waypoints in the existing route using optimization algorithms or heuristic methods without completely reconstructing the current routes. High-speed route planning aims to establish "highways" in the sky. Considering the fragmented airspace in China, local route planning is the most suitable method for air route planning in our country.

China has numerous prohibited, restricted, and danger zones (PRDs). According to data statistics, more than 80% of traffic control in the central and southern regions is due to military activities. Avoiding these "PRDs" in route planning can signif-

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icantly reduce the risk of traffic control. Therefore, considering the restrictions of these zones in route planning is of great practical research significance.

Currently, the most commonly used and effective method to avoid PRDs is the combination of grid modeling and path planning algorithms. Common path optimization algorithms include Dijkstra's algorithm, A* algorithm, cellular automata algorithm, and genetic algorithm. Dijkstra's algorithm often has efficiency issues when dealing with large-scale path planning problems, while heuristic algorithms like genetic algorithm and A* algorithm may easily fall into local optima. In complex network environments, cellular automata have unique advantages due to their discrete nature, which simplifies many complex problems. Additionally, the updated rules of cellular automata models do not rely on specific mathematical functions, making them more intuitive and straightforward to express. In 2014, Wang et al.[1] proposed a method for optimizing the air route network while satisfying the restrictions of "PRDs". They used a local optimization approach and constructed an optimization model based on grid modeling. They also used cellular automata (CA) theory to formulate solving rules. However, the optimized air route network resulted in compromises in terms of both economic efficiency and accessibility. In the same year, Wang and Gong[2] conducted optimization research on the PRD-based air route network using CA modeling. They established an optimization model with the objective of minimizing the total operational cost to improve the economic efficiency and safety of the route network within segmented airspace. However, this came at the cost of increased total route length. In 2015, Gong[3] combined CA to obtain the optimal solution for the air route network optimization model on a global scale. He validated the model using five representative routes in the Beijing Flight Information Region. However, this model only supported the optimization of single routes. In 2017, Wang et al.[4] proposed an optimization model for the air route network with the objective of minimizing the total operational cost. The model included constraints such as airspace restrictions, route network capacity, and non-linear coefficient. They used CA for solving. But there is still room for improvement in terms of algorithm efficiency. In 2020, Shi[5] compared and summarized the advantages and disadvantages of BFS algorithm, Dijkstra's algorithm, A* algorithm, and cellular automata algorithm in air route optimization based on the "PRDs" restrictions. They made improvements to the A* algorithm by optimizing the straight-line path, but the accuracy of the solution may be affected by the heuristic function. In 2022, Zhang et al.[6] proposed an optimization strategy that can significantly reduce the time consumption of robot path planning by simplifying the kernel and improving the greedy strategy-based cellular automata.

Although many researchers have applied the cellular automaton algorithm to path planning problems, there are still some limitations when it comes to handling diagonal obstacles. This paper proposes improvements to address this issue. Additionally, distance priority coefficients and collision risk coefficients are introduced to enhance the efficiency of the algorithm and obtain safer routes. Finally, the optimized paths are further smoothed.

1 Problem Description

1.1 Environment modeling

The process of environmental modeling also involves rasterizing airspace information. Rasterization is the process of converting airspace information into binary data that can be recognized by computers, which is then used for route planning. The steps involved in rasterization are as follows.

Step 1 Obtain the latitude and longitude coordinates of the boundary points of the planned airspace, as well as the coordinates of the waypoints and the location information of "PRDs". Use this information to create a CAD representation of the airspace map.

Step 2 Determine the appropriate grid size based on the actual airspace environment and divide the two-dimensional space into grids. To ensure flight safety, the grid size should not be smaller than the vertical interval of the aircraft. Set the maximum length of the environment as L, the maximum width as W, and the scale of the grid cube as a. The total number of grids can be calculated as $(L/a)*(W/a)$.

Step 3 Determine the attributes of each grid and utilize MATLAB to generate a binary image and a binary matrix. The binary image consists of 0s and 1s, where 0 represents the barrier-free area, and 1 the barrier area or "PRDs". This is done by assigning a raster attribute value of 1 to the corresponding grid cells

Step 4 Represent each grid using a two-dimensional array to denote its location, completing the construction of the grid map. The 2D array $A(x, y)$ represents the rows and columns in the raster map.

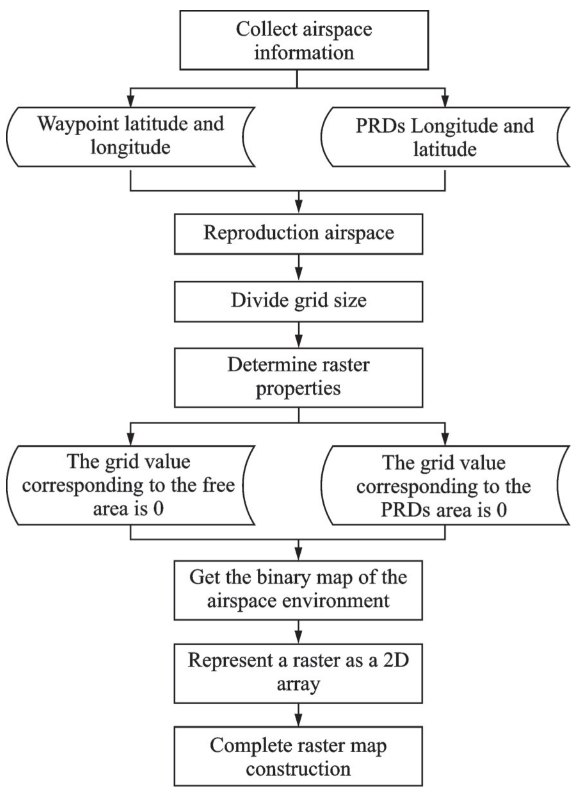


Fig.1 Information rasterization flowchart

1.2 Assumptions

In the established air route network planning model, the following assumptions are made to simplify the problem and facilitate the optimization process.

(1) All aircraft fly along the center of the route at a constant speed, regardless of any differences in aircraft type. This assumption allows for a uniform representation of aircraft movement and simplifies the optimization calculations;

(2) The air route network is treated as a two-dimensional plane, without considering altitude information. This simplification allows for easier visualization and analysis of the air route network, but it neglects the impact of altitude on route planning and safety considerations;

(3) The "PRDs" are considered as impenetrable areas, meaning that aircraft cannot pass through these areas. However, the boundaries of the PRDs are considered safe areas;

(4) Airports are treated as fixed waypoints, meaning they do not move. Additionally, the radio stations named after the airports, which serve as waypoints for navigation, are considered movable waypoints. This distinction allows for more flexibility in route planning;

(5) The model only considers the cruise phase of the aircraft and does not take into account the climb and descent phases. This simplification allows for a focus on optimizing the main phase of flight and avoids the added complexity of considering altitude changes.

1.3 Mathematical model

Suppose N represents the air route network planning model, in which the meaning of each parameter is shown in Eqs.(1)—(7).

$$N=\{V, D, I, F, U, B, C\} \tag{1}$$

(1) Waypoint constraints

$V(N)$ represents the set of waypoints, the waypoints are divided into fixed waypoints and movable waypoints, and the number of fixed waypoints and non-fixed waypoints are represented by m and n, respectively. When $i \leqslant m$, V_i represents a fixed waypoint, that is, an airport point. And when $m+1 \leqslant i \leqslant m+n$, it represents a non-fixed waypoint, that is, a navigation station.

$$V=\{V_1, V_2, \cdots, V_m, V_{m+1}, V_{m+2}, \cdots, V_{m+n}\} \tag{2}$$

(2) Non-linear coefficient constraints

$D(N)$ represents a collection of distances d_{ij} between waypoints, d_{ij} the actual distance between V_i and V_j, $I(N)$ the collection of nonlinear coefficients, I_{ij} the nonlinear coefficient between V_i and V_j, and $I_{\max}$ the maximum value of the acceptable nonlinear coefficient, which can be used to measure the convenience of the entire route network, the cost of the route network, and the airspace utilization. O_{ij} represents the Euclidean distance between V_i and V_j.

$$d_{ij}=\begin{cases}\sqrt{(x_i-x_j)^2+(y_i-y_j)^2} & \text{There is a route between } V_i \text{ and } V_j\\ 0 & \text{Else}\end{cases} \tag{3}$$

$$I_{ij}=\frac{\sum_{i=1}^{m}\sum_{j=1}^{m}d_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{m}O_{ij}}\leqslant I_{\max}\qquad i\neq j \tag{4}$$

(3) Flow constraints

$F(N)$ represents the flow collection between the waypoints, and f_{ij} the flight flow between V_i and V_j, which should be less than the capacity G_{ij} between two nodes.

$$\sum_{i=1}^{m+n}\sum_{j=1}^{m+n}f_{ij}\leqslant G_{ij}\qquad i\neq j \tag{5}$$

(4) "Three zones" constraints

$U(N)$ indicates the "PRDs" in the air travel network, and line (V_i, V_j) represents the route between V_i and V_j, which cannot pass through the "PRDs".

$$\text{line}(V_i,V_j)\cap U=\varnothing\quad i\neq j,i\geqslant 0,j\leqslant m+n \tag{6}$$

(5) Air route network boundary constraints

$B(N)$ indicates the boundary constraint of the air route network node, and the air route network node must be located in the planning area.

$$x_{\min}\leqslant x_i\leqslant x_{\max},y_{\min}\leqslant y_i\leqslant y_{\max} \tag{7}$$

$C(N)$ represents the total length of the route, and the air route network planning model can be expressed by the following formula. Taking the shortest total route length as the goal, the objective function can be expressed by Eq.(8). Nonlinear coefficient constraints, flow constraints, and waypoint boundary constraints are respectively shown as Eqs.(8)—(12).

$$\min C=\sum_{i=1}^{m+n}d_{ij} \tag{8}$$

$$\text{s. t. line}(V_i,V_j)\cap U=\varnothing \tag{9}$$

$$I_{ij}\leqslant I_{\max} \tag{10}$$

$$\sum_{i=1}^{m+n}\sum_{j=1}^{m+n}f_{ij}\leqslant G_{ij} \tag{11}$$

$$x_{\min}\leqslant x_i\leqslant x_{\max},y_{\min}\leqslant y_i\leqslant y_{\max} \tag{12}$$

2 Path Search

2.1 Introduction to cellular automata algorithms

CA, initially proposed by John von Neumann in 1950 to simulate the self-replication of biological cells, has now found widespread applications in various fields such as physics simulation, biological modeling, and path planning.

There are three types of grid structures in cellular automata: Triangular grids, square grids, and hexagonal grids, as shown in Fig.2. Square grids are intuitively simple and can be cleverly integrated with grid-based modeling in geographic environments. Therefore, this paper adopts square grids for the evolution of cellular automata.

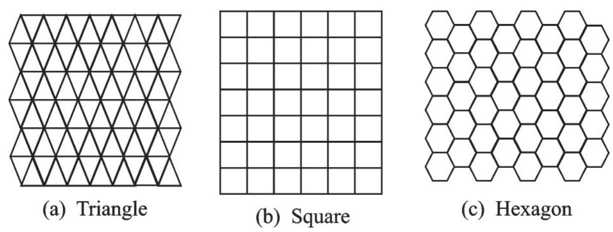


Fig.2 Grid type diagram

Cellular automata consist of four key elements: Cells, cell space, neighbors, and state transition rules, as represented by

$$C_{\mathrm{A}}=\{R,L_{\mathrm{D}},J,g\} \tag{13}$$

where C_{A} represents the cellular automaton system, R the set of cell states, L_{D} the cell space, J the state of all adjacent cells to the current cell, and g the state transition rule of the cellular automaton, which determines the evolution of the state based on the current state of the cell and the states of its neighbors.

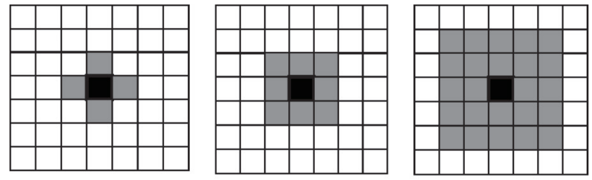
$$R=\{R_{x,y}\in\{0,1\}\} \tag{14}$$

where 0 and 1 represent the working state and the sleep state, respectively.

The working process of the cellular automaton model involves traversing each cell in the space according to the evolutionary rules. The evolution starts from the cell near the endpoint and progresses towards the starting point. The evolution process terminates when the state values of the neighboring cells around the starting point change. This process ensures that the evolution propagates throughout the system[7].

2.2 Evolutionary rules

There are typically three neighbor models for square grid cellular automata: Von-Neumann, Moore, and extended Moore models[8], as shown in Fig.3. In Fig.3, the central grid represents the current cell, and the gray grids represent the neighboring cells that can be moved to.



(a) Von-Neuman (b) Moore (c) Extended Moore

Fig.3 Three neighborhood models for cellular automata square grids

In this study, the cells are divided into intermediate cells and boundary cells based on their positions. The Moore neighbor model is adopted, which considers the eight nearest neighbor cells of the current cell as reachable cells.

The evolution rule is as follows: Let (c, t) represent the state value of the intermediate cell c at time t, and let (n, t) represent the state value of any neighbor of the intermediate cell c. If the current state value of the cell is 0 or greater than 3, and there is a neighbor cell with a value greater than 3, then the neighbor cell with the smallest value greater than 3 is selected, and 1 is added to its value. As expressed in Eq.(15), this process is repeated until all cells no longer meet the evolutionary conditions, resulting in the optimal solution for path planning.

$$(c,t+1)=\begin{cases}\min\left[(n,t)\geqslant 3\right]+1 & \left[(c,t)=0 \text{ or } (c,t)\geqslant 3\right] \text{ and } \exists (n,t)\geqslant 3\\ (c,t) & \text{Else}\end{cases} \tag{15}$$

2.3 Algorithm improvement

In the given Fig.4, the central cell represents the current cell, and the black grid represents an unreachable obstacle cell. Based on the evolution rules of cellular automata, the current cell can move in eight directions: due north, due east, northeast, northwest, southwest, southeast, due west, and due south.

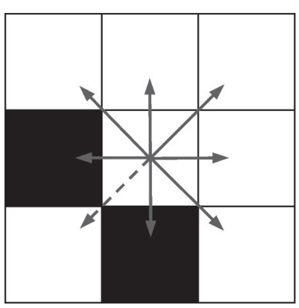


Fig.4 Movable direction of the target cell

However, in real-world scenarios, there are cases where certain directions are blocked by obstacles, making it impossible for the aircraft to pass through them. To address this, constraints can be added to the evolution rules. For example, if there are two diagonally adjacent obstacle cells, the corner cells included within the adjacent obstacle cells are considered unreachable.

By incorporating these constraints, the results obtained from the cellular automata model become more realistic and meaningful.

To enhance the algorithm's efficiency, an optimization process incorporates a priority coefficient comprising two components: The distance priority coefficient and the collision risk coefficient. In Fig.5, the target cell is located northeast of the current cell. Based on the distance advantage, the reachable cells in the northeast, due east, due north, northwest, southeast, due west, due south, and southwest directions are prioritized sequentially. The corresponding coefficients assigned to these directions are 8, 6, 6, 4, 4, 2, 2, and 1, respectively. The collision risk coefficient is determined by the number of obstacle cells in the neighbors of each reachable cell. Let α denote the distance priority coefficient of the reachable cell, β the number of obstacle cells in the neighbors of the reachable cell, and $(8-\beta)$ indicate the collision risk coefficient of the reachable cell. The priority coefficient of the reachable cell can be calculated by

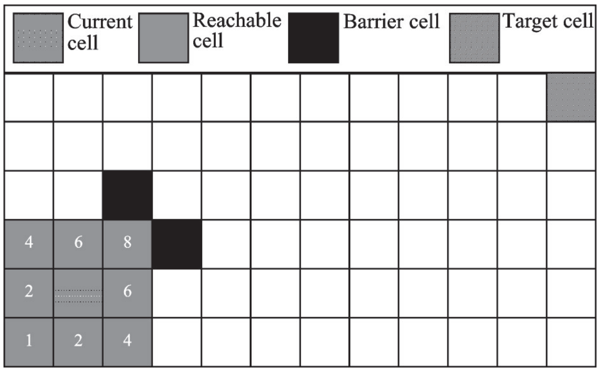


Fig.5 Schematic diagram of improvement rules

$$\gamma=\alpha+(8-\beta) \tag{16}$$

In the given scenario, we can start by assigning the following initial state values to the cells: 1 for the cells containing the "PRDs", 0 for the free cells, 2 for the origin cell, and 3 for the destination cell. The evolution process starts from time $t=0$ and continues until the last iteration, denoted as $t=n$. During each iteration, the state values of the cells are updated based on those of their neighboring cells. The goal is to determine the shortest path from the origin to the destination. After the last evolution, when $t=n$, we can calculate the distance from each cell to the destination by subtracting 3 from their state value. The resulting value represents the distance of each cell from the destination, except for the starting point cell. To find the optimal path between the origin and the destination, we can trace back the evolution path of the cell with the smallest distance value. This path, followed through each iteration, represents the shortest path from the origin to the destination.

In the improved CA algorithm, the process of smoothing the path by straight line optimization is a crucial step. In the initial algorithm, the path has more turning points, which results in insufficiently smooth trajectories. To solve this problem, we introduce the straight line optimization method. The process is as follows: First, the three neighboring points are checked in the path. If the line between the first point and the third point does not cross an obstacle, the middle point can be removed from the path. This helps to straighten the path, reduce the number of turning points and achieve a smoother trajectory.

3 Case Study

The Guangzhou Flight Information Region (FIR) is one of the busiest airspace areas in China. As air traffic continues to grow, the route network within the Guangzhou FIR has encountered issues such as longer detour distances and incomplete one-way routes. In this study, we focus on several busy routes within the Guangzhou FIR, including A461, A599, R343, and W19. Our objective is to plan, model, and solve these routes to validate the feasibility of the proposed approach.

Fig. 6 illustrates the airspace environment map of the Guangzhou FIR. The black areas represent the inaccessible "PRDs" regions. The macro binary map in Fig.6 (a) provides an overview of the airspace environment, while the detailed binary map in Fig. 6 (b) corresponds to the numerical values and the "PRDs" areas. This division allows us to categorize the airspace of the Guangzhou FIR into reachable and unreachable regions, facilitating the avoidance of the "PRDs" areas during the route network planning process.

(a) Macro binary plot (b) Detail binary plot

Fig.6 Airspace environment binarization

We select six routes for the optimization experiment. We compare the original CA algorithm, Dijkstra's algorithm, and the A* algorithm. The evaluation of the optimization results is based on three indicators: Route length, non-linearity coefficient, and number of turning points. The optimized routes are shown in Fig.7.

The results of different algorithms are presented in Table 1. The A* algorithm's performance is less stable due to the accuracy of the heuristic function. Dijkstra's algorithm and the original CA algorithm demonstrate advantages in terms of route

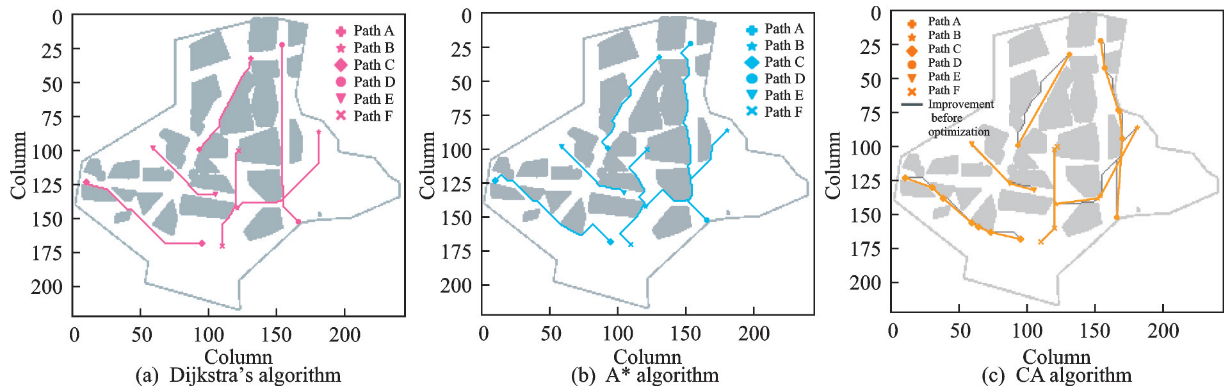


Fig.7 Optimization results of different algorithms

Table 1 Comparison of optimization results of different algorithms

Parameter	Algorithm	Air route					
		A	B	C	D	E	F
Length/km	Dijkstra	372.33	435.02	466.38	607.37	273.02	337.37
	A*	398.43	468.54	511.11	678.20	273.02	423.09
	CA	372.33	435.02	466.38	622.26	273.02	337.37
	Improved CA	346.64	409.10	442.80	596.03	265.46	337.37
Number of waypoints	Dijkstra	41	7	13	5	5	13
	A*	18	23	40	40	10	26
	CA	19	13	19	21	9	4
	Improved CA	2	4	7	6	3	4
Coefficient	Dijkstra	1.08	1.18	1.08	1.03	1.06	1.06
	A*	1.15	1.27	1.18	1.15	1.06	1.32
	CA	1.08	1.18	1.08	1.06	1.06	1.06
	Improved CA	1.00	1.11	1.02	1.01	1.03	1.06

length and non-linearity coefficient. However, they tend to have more turning points, resulting in less smooth paths. Additionally, the CA algorithm exhibits higher efficiency in handling large-scale maps compared to Dijkstra's algorithm. The improved CA algorithm not only offers higher efficiency but also effectively reduces the route length and non-linearity coefficient without crossing the "PRDs" regions. The optimization ratios range from approximately 10% to 44%. Furthermore, the optimized paths generated by the improved CA algorithm are smoother.

Since the optimization results may be affected by the grid size, this paper selects the grid size of 10 km, 5 km and 3 km for example optimization, and compares and verifies the route length, nonlinear coefficient and number of waypoints of the optimized route.

According to the data in Tables 2—4, the route planned by the improved cellular automata algorithm can not only effectively avoid the "PRDs", but also can effectively shorten the length of the route. The reduction ratio is about 19%—44 %, and the nonlinear coefficient is also reduced in the same proportion. This is of great significance for airlines to shorten the flight range, reduce flight time, reduce flight costs, and improve the core competitiveness of airlines. At the same time, the number of waypoints has also been reduced to a certain extent.

As shown in Fig.7, the figure shows the average optimization ratio of each indicator under different grid sizes. The grid size is different, the optimization effect is different. In general, the smaller the grid size, the more accurate the identification of obstacles, the better the optimization effect, but the slower the optimization speed.

Table 2 Comparison of route length after optimization for different grid sizes

Air route	Before optimization/km	Grid size/km					
		10		5		3	
		After optimization/km	Reduction ratio/%	After optimization/km	Reduction ratio/%	After optimization/km	Reduction ratio/%
A	467.96	380.52	18.69	346.64	25.93	346.20	26.02
B	729.74	432.36	40.75	409.10	43.94	406.20	44.34
C	772.73	472.77	38.82	442.80	42.70	441.60	42.85
D	814.37	627.93	22.89	596.03	26.81	595.92	26.82
E	340.19	266.67	21.61	265.46	21.97	260.67	23.38
F	461.49	344.79	25.29	337.37	26.90	333.87	27.65

Table 3 Comparison of nonlinear coefficients after optimization for different grid sizes

Air route	Before optimization	Grid size/km					
		10		5		3	
		After optimization	Reduction ratio/%	After optimization	Reduction ratio/%	After optimization/km	Reduction ratio/%
A	1.35	1.07	20.74	1.00	25.93	1.00	25.93
B	1.98	1.17	40.91	1.11	43.94	1.11	43.94
C	1.78	1.08	39.33	1.02	42.70	1.02	42.70
D	1.38	1.07	22.46	1.01	26.81	1.02	26.09
E	1.32	1.06	19.70	1.03	21.97	1.03	21.97
F	1.45	1.08	25.52	1.06	26.90	1.04	28.28

Table 4 Comparison of the number of waypoints after route optimization for different grid sizes

Air route	Before optimization	Grid size/km					
		10		5		3	
		After optimization	Reduction ratio /%	After optimization	Reduction ratio /%	After optimization/km	Reduction ratio/%
A	9	3	66.67	2	77.78	2	77.78
B	9	5	44.44	4	55.56	4	55.56
C	6	6	0	7	−16.67	6	0
D	9	5	44.44	6	33.33	6	33.33
E	8	4	50.00	3	62.50	3	62.50
F	7	4	42.86	4	42.86	5	28.57

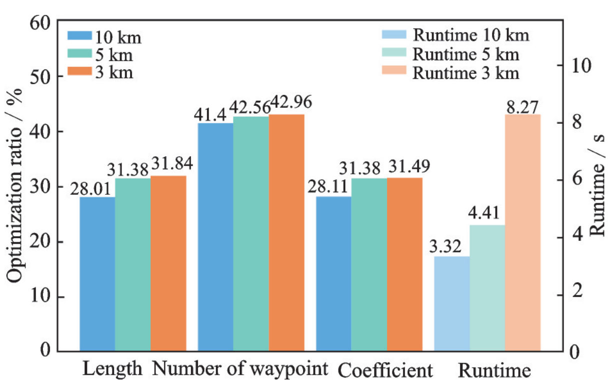


Fig.8 Comparison of optimization results for different grid sizes

4 Conclusions

This study primarily focuses on improving CA algorithm by addressing its limitations in obstacle avoidance. By introducing a priority coefficient and implementing straight-line optimization, the algorithm's path optimization speed is accelerated, and the optimized paths are smoothed.

Comparisons with different algorithms demonstrat that the improved CA algorithm outperforms others in terms of route length, non-linearity coefficient, and number of turning points. Additionally, the comparison of algorithm efficiency at different grid resolutions reveals that as the grid size decreases, the algorithm's accuracy improves, although the improvement rate diminishes. It suggests that pursuing accuracy blindly is not necessary, as a balance between accuracy and efficiency can be achieved.

In conclusion, this research contributes to the field of flight route optimization by providing a reliable and efficient algorithm that generates shorter, smoother, and more optimized flight paths. Although classical algorithms can compute the shortest path efficiently, in future research, neuronal cellular automata models can be introduced to adapt to more complex and intractable tasks and enhance the generalization ability of models[9].

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Author contributions Ms. **NIU Kexin** designed the study, complied the models, conducted the analysis, interpreted the results and wrote the manuscript. Prof. **LI Guifang** contributed to the discussion and background of the study. Ms. **HUANG Xiao** contributed to data and model components for the sequencing model. Prof. **TIAN Yong** contributed to data for the analysis of Guangzhou FIR. All authors commented on the manuscript draft and approved the submission.

Competing interests The authors declare no competing interests.

(Production Editor: WANG Jing)

基于改进元胞自动机算法的航路网络规划研究

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摘要:为优化空域资源、提升空域容量、缓解空中交通拥堵,本文研究了"三区"规避情况下的航路网络规划问题。首先通过栅格法进行空域离散化建模,将空域信息二值化,以此实现"三区"规避;接着以航路总长度最小为目标,考虑非直线系数、流量约束等建立数学模型,在寻路过程中添加距离优先系数和碰撞风险系数,利用元胞自动机算法求解,并在此基础上增加了路径平滑过程;最后以广州飞行情报区航路网络规划为实例进行验证。结果表明,相比于现行航路,航路长度有效缩短、航路点个数减少且航路的非直线系数也有所降低,验证了改进的元胞自动机算法的有效性,对现实的航路网络规划具有重要的参考意义。

关键词:空中交通管理;空域管理;航路网络规划;"三区"规避;元胞自动机算法