

# A Flight Conflict Detection Method for eVTOLs

Haiyang Cui <sup>1, a</sup>, Yingying Huang <sup>1, d</sup>, Keyun Lan <sup>2, a</sup>, Xianyu Yue <sup>1, b</sup>, Yujia He <sup>1, c</sup>, Wanglong Yan <sup>1, e</sup>

<sup>1</sup> Guangzhou Civil Aviation Vocational and Technical College, Guangzhou Guangdong, 510403, China

<sup>2</sup> Guangdong Neusoft College, Foshan Guangdong, 528000, China

<sup>a</sup> 812329866@qq.com, <sup>b</sup> 1636558922@qq.com, <sup>c</sup> 2931635912@qq.com, <sup>d</sup> 2972175115@qq.com, <sup>e</sup> 1151042144@qq.com

**Abstract:** In the flight control process, ensuring the timely detection and effective resolution of flight conflicts is a core step in maintaining flight safety. We adopted a method that utilizes the binary classification function of the Support Vector Machine (SVM) technology to conduct deep learning on historical data of flight conflicts, thereby constructing an SVM model capable of accurately detecting flight conflicts. This model also incorporates the output results of the flight trend detection module, significantly enhancing the efficiency and accuracy of flight conflict detection. In practical operations, we carefully divided ADS-B (Broadcast Automatic Dependent Surveillance) data into training sets and validation sets. The training set was used to train the SVM model to enable classification capabilities; while the validation set was used to evaluate the classification performance of the SVM model. After multiple optimizations, we found the optimal parameters  $g$  and  $C$  for the SVM model, at which point the classification accuracy of the model reached 98%. This result strongly proves that by combining the flight trend detection module with the SVM and fully utilizing ADS-B information (including key data such as the longitude, latitude, altitude, speed, and heading of unmanned aircraft), we can achieve precise judgment of flight conflicts. This method not only improves the accuracy of flight conflict detection but also provides strong technical support for flight control work.

**Keywords:** Safety Engineering; Flight Conflict Detection; ADS-B Support Vector Machine; Cylindrical Protected Area.

## 1. Introduction

Flight conflict refers to the situation where a drone may collide with another drone or with terrain features such as mountains after flying for a certain period of time or covering a certain distance. To prevent the occurrence of flight conflicts, a certain safety interval is usually set between drones or between drones and obstacles. The core task of air traffic control is to ensure the safe operation of aircraft, and the main method to achieve this goal is to provide a safety interval between aircraft to avoid flight conflicts. The Automatic Dependent Surveillance Broadcast (ADS-B) system has the characteristics of large information transmission volume, high accuracy, wide application, and low cost. It is adopted by the United States as the main monitoring and communication method for the next-generation air traffic system. This paper mainly uses ADS-B information as the main data source.

In the evolution of drone conflict detection and collision avoidance technology, in 2013, Mullins et al. [1] based on the speed and performance characteristics of intruding drones, innovatively introduced a time threshold instead of a spatial distance threshold, thereby constructing a dynamic separation threshold drone conflict detection and collision avoidance model. Subsequently, in 2015, TOY et al. [2] conducted in-depth analysis of the trajectory operation in high-density flight areas (FRA), and pointed out that the workload of controllers has become a key factor restricting airspace capacity and overall operational performance improvement.

In 2017, Tony et al. [3] conducted a study revealing that the flight of multiple aircraft within low-altitude airspace is affected by multiple factors such as complex terrain, buildings, and meteorological conditions, resulting in an increase in the probability of flight conflicts. Traditional route conflict detection algorithms have limitations in such specific airspace. In the same year, V. D. Berdonosov [4] proposed using two or three track points obtained from the ADS-B

system to estimate the trajectory of unmanned aircraft and calculate the two extreme values that could lead to a collision, as well as the critical speed range.

In 2018, Thanh et al. [5] combined geometric constraints and dynamic equations to determine the collision angle by calculating the positional relationship between the multi-rotor eVTOL and the obstacle, thereby solving the collision avoidance problem of the multi-rotor eVTOL. In 2021, Cecen et al. [6] adopted a two-stage optimization method, constructed an aircraft conflict resolution model in the free flight route airspace, and solved it using an evolutionary heuristic algorithm.

In 2017, Guan Xiangmin et al. [8] constructed a conflict resolution model based on the satisfaction game theory. This model fully considered the influence of decision-makers' priorities on the operation of aircraft, and achieved real-time and efficient resolution of large-scale flight conflicts. In the same year, Wu Xueli et al. [9] improved the EVENT model and proposed the calculation methods for various parameters under ADS-B surveillance technology, thereby improving the detection accuracy of longitudinal collision risks of aircraft.

In 2018, Huang Yang et al. [10] pointed out that compared with manned aircraft, unmanned aircraft have the characteristics of smaller payload, stronger maneuverability, and more complex dynamic models, and they face higher uncertainty in threats. Therefore, solving the problem of conflict resolution for unmanned aircraft in the low-altitude integrated airspace is of great significance for the safe operation of unmanned aircraft. In 2021, Xu Jianfeng [11] combined the potential field theory with ADS-B technology and designed an unmanned aircraft trajectory planning algorithm based on ADS-B technology. By 2023, Xie Hua et al. [12] proposed a flight conflict classification detection and differential resolution method based on the improved speed barrier method, and designed an unmanned aircraft flight conflict resolution strategy and applicable conditions. This method can effectively detect potential flight conflicts in the

low-altitude airspace.

Summary of methods for detecting flight conflicts at home and abroad: 1) The method of calculating the probability of conflict by analyzing flight parameters, although it takes into account a wide range of factors, it has poor real-time performance and is difficult to meet the requirements of controllers' operations. 2) The method of further analyzing flight conflict situations by predicting flight trajectories and calculating the probability of flight conflict detection, although it has high accuracy, the calculation volume is too large. 3) Intelligent methods such as support vector machines have the advantages of strong real-time performance, high accuracy, small calculation volume, and comprehensive consideration of environmental factors. Therefore, this paper uses the identification number, latitude and longitude, speed and other information of ADS-B, combined with cylindrical flight protection areas and SVM to construct a model, achieving three-dimensional detection of flight conflicts. Compared with the existing elliptical protection areas, cylindrical protection areas are more suitable for the requirements of civil aviation flight separation. Based on the original ADS-B information processing method, a trend detection module is established, which can, on the basis of detecting conflicts, classify conflict levels and further accurately identify dangerous approaches during flight.

## 2. Establish a Cylindrical Flight Protection Zone

Flight conflict detection is carried out by using navigation equipment (such as radar, TCAS, etc.) based on a certain airspace condition, to detect aircraft within the airspace under its jurisdiction. By grasping the speed and position information of the aircraft in the air and combining with the flight plans of the aircraft, it is determined whether the distance between the aircraft complies with the requirements of the minimum safe interval. If any two aircraft violate the safety interval requirements, then these two aircraft are considered to have a potential conflict [17]. Considering the applicability of civil aviation regulations, this paper uses a cylindrical model to detect flight conflicts.

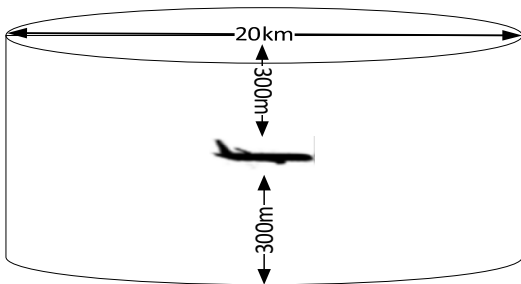


Fig 1. Cylindrical aircraft Bay protection area in control operation

The intervals of aircraft can be classified as longitudinal interval, lateral interval and vertical interval [17]. Among them, the longitudinal interval and lateral interval are also called horizontal interval. The horizontal interval is based on the idea of establishing a protected area around the aircraft. Each aircraft can form a cylindrical protected area in both the horizontal and vertical directions, and the size of the protected area depends on the minimum interval standard used. As shown in Figure 1, in the controlled operation, the minimum horizontal interval is 10 km and the vertical interval is 300 m, and the cylindrical protected area is shown. If another aircraft

invades this flight protected area, then the two aircraft will have a flight conflict.

## 3. Flight Conflict Detection Based on Support Vector Machine (SVM)

The flight conflict detection based on Support Vector Machine (SVM) described in this article can not only detect flight conflicts, but also distinguish the severity levels of flight conflicts and provide auxiliary support for resolving flight conflicts. The processing flow of the flight conflict detection system is shown in Figure 2. The steps are as follows:

- 1) The ADS-B receiving and demodulation equipment intercepts the ADS-B data of the loader and the surrounding drones.
- 2) The identification number, latitude and longitude, altitude, and heading information were extracted using the ADS-B message decoding system.
- 3) Perform preliminary calculations on the obtained data and convert it into a format that is compatible with the SVM and trend detection modules.
- 4) Using the support vector machine, we detect whether the unmanned aircraft has entered the cylindrical protected area, and at the same time, we use the trend detection module to detect the future movement trends of the two unmanned aircraft.
- 5) If two unmanned aircraft simultaneously engage in a flight conflict (with FLAG = 1) and the conflict level is 1 (D=1), a conflict alert will be issued.

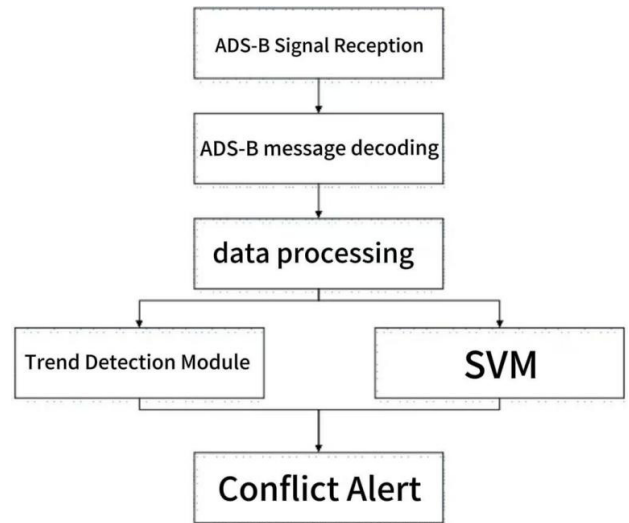


Fig 2. Processing flow chart of flight conflict detection system

### 3.1. Data Processing and Flight Trend Detection

The main purpose of data processing is to convert and filter the original ADS-B information to extract the longitude, latitude, altitude, speed, heading and identification number of the unmanned aircraft. Among them, the heading angle is  $\theta_i^a$  and  $\theta_i^b$ , Airspeed is  $V_i^a, V_i^b$ , The lifting speed is  $VU_i^a, VU_i^b$ . Convert the latitude, longitude and altitude information into the relative position vector and relative distance between the two drones.  $R_i^{ab}$ , relative altitude  $\Delta H_i^{ab}$ , determine flight conflicts. Calculate the relative position vector angle  $\Phi_i^{ab}$ , The relative height difference is  $\Delta H_i^{ab}$ , Radial relative

velocity difference  $\Delta V$  And classify the levels of flight conflicts. The specific process is as follows:

1) Construct the relative position vector of the two unmanned aircraft. Convert the longitude, latitude, and altitude into corresponding earth coordinates and represent them with x, y, and z. Arrange the identification numbers in a certain order and rename them as lowercase letters a, b, c... The position coordinates of unmanned aircraft a are expressed as  $P_i^a = (x_i^a, y_i^a, z_i^a)$ , Here, i represents the number of data groups, and the heading angle is  $\theta_i^a$ , The speed of drone A is  $V_i^a$ . The coordinates of drone B  $P_i^b = (x_i^b, y_i^b, z_i^b)$ , Course angle is  $\theta_i^b$ , The speed magnitude of drone B is  $V_i^b$ . Take the coordinate of drone A as the origin and make a vector pointing to the coordinate of drone B:  $\vec{a} = (x_i^b - x_i^a, y_i^b - y_i^a, z_i^b - z_i^a)$ , Its vector angle is  $\phi_i^{ab}$ , The calculation formula is 1, and the relative distance between drone A and drone B is  $R_i^{ab}$ , The calculation formula is 2. The relative altitude difference between the two drones is  $\Delta H_i^{ab}$ , The calculation formula is 3.

$$\phi_i^{ab} = \arctan\left(\frac{|x_i^b - x_i^a|}{|y_i^b - y_i^a|}\right) \quad (1)$$

$$R_i^{ab} = \sqrt{(x_i^b - x_i^a)^2 + (y_i^b - y_i^a)^2} \quad (2)$$

$$\Delta H_i^{ab} = z_i^a - z_i^b \quad (3)$$

From  $R_i^{ab}$  and  $\Delta H_i^{ab}$  Combined with the cylindrical protection zone model, determine whether the relative positions of drones pose potential risks of flight conflicts. When the target invades the protection zone, the parameter FLAG=1, When there is no invasion of the protection zone, the parameter FLAG=0, And comprehensively consider  $R_i^{ab}$ ,  $\Delta H_i^{ab}$ , The FLAG value serves as a piece of learning information for SVM (Support Vector Machine) learning.

2) Calculate the angle of the relative position vector  $\Phi_i^{ab}$ . Since the azimuth angles  $\theta_i^a$  and  $\theta_i^b$  start from the north direction, The angle of rotation in a clockwise direction based on the speed and direction as the terminal edge. In order to facilitate calculation, The direction angle  $\phi_i^{ab}$  of the direction vector needs to be converted into an angle  $\Phi_i^{ab}$ , which is the clockwise rotation angle from the north direction as the starting side to the direction of the position vector as the ending side. This angle is named the relative position angle. The formula for converting from  $\phi_i^{ab}$  to  $\Phi_i^{ab}$  is 4.

$$\Phi_i^{ab} = \begin{cases} \phi_i^{ab} & x_i^b - x_i^a > 0 \text{ and } y_i^b - y_i^a > 0 \\ \pi - \phi_i^{ab} & x_i^b - x_i^a > 0 \text{ and } y_i^b - y_i^a < 0 \\ \pi + \phi_i^{ab} & x_i^b - x_i^a < 0 \text{ and } y_i^b - y_i^a < 0 \\ 1.5\pi + \phi_i^{ab} & x_i^b - x_i^a < 0 \text{ and } y_i^b - y_i^a > 0 \end{cases} \quad (4)$$

By using  $\Phi_i^{ab}$ , heading angle  $\theta_i^a$  and  $\theta_i^b$ , airspeed

$V_i^a$  and  $V_i^b$ , as well as climb/descent speed  $VU_i^a$  and  $VU_i^b$ , the severity level of flight conflicts can be determined, If the two drones are approaching each other, the severity level of the conflict is indicated as 1. If the two drones are moving away from each other, the conflict level is indicated as 0. The absolute value of the difference between the relative position vector angle  $\Phi_i^{ab}$  and the heading angle  $\theta_i^a$  is represented by  $\gamma_a$  and  $\gamma_b$ , The calculation formulas are 5 and 6. The radial relative velocity difference between the two unmanned aircraft on the horizontal plane is denoted as  $\Delta V$ , and the calculation formula is 7. The relative velocity in the vertical direction is represented by  $\Delta VU$ , and the calculation formula is 8. The relative position in the vertical direction is represented by  $\Delta H_i^{ab}$ , and the calculation formula is 9.

$$\gamma_a = |\Phi_i^{ab} - \theta_i^a| \quad (5)$$

$$\gamma_b = |\Phi_i^{ab} - \theta_i^b| \quad (6)$$

$$\Delta V = V_i^a \times \cos \gamma_a - V_i^b \times \cos \gamma_b \quad (7)$$

$$\Delta VU = VU_i^a - VU_i^b \quad (8)$$

$$\Delta H_i^{ab} = z_i^a - z_i^b \quad (9)$$

$$D = \begin{cases} 0 & \Delta V < 0 \cap \Delta VU \bullet \Delta H_i^{ab} < 0 \\ 1 & \text{Other} \end{cases} \quad (10)$$

Therefore, we can conclude that when  $\Delta V > 0$  or  $\Delta VU \bullet \Delta H_i^{ab} > 0$  is present, it indicates that the two drones are approaching each other. According to formula 10, the determination factor D = 1, which means the severity level of the flight conflict output by the system is 1; otherwise, the severity level of the flight conflict is 0. When the severity level of the flight conflict is 0, the movement of the unmanned aircraft is shown in Figure 3.

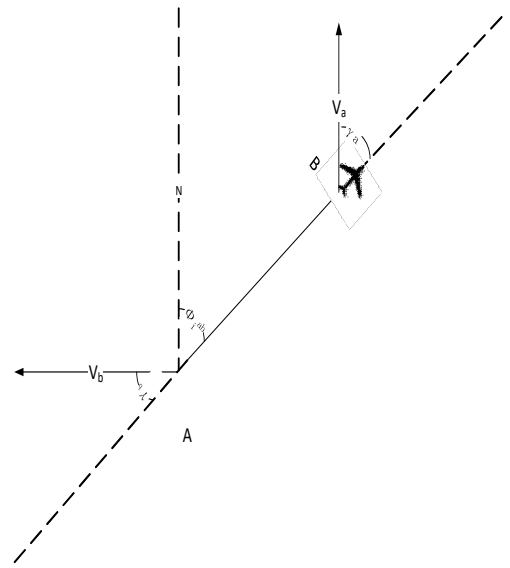


Fig 3. Schematic diagram of aircraft motion with severity level 0 of flight conflict

### 3.2. Support Vector Machine with Flight Conflict Detection Capability

The radial inner product kernel function selected in this paper is used as the kernel function of SVM. The cross-validation method is employed to optimize the parameters  $C$  and  $g$ , where  $C$  [11] is the penalty factor within the function and  $g$  [11] is the reciprocal of the width of the radial basis function.

The specific learning method of the support vector machine is shown in Figure 4. The specific process is as follows: 1) Use eVTOL A as the system's carrier platform,

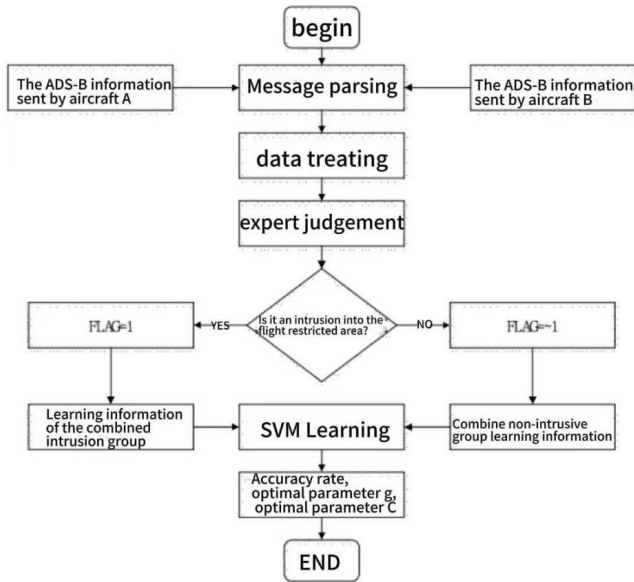


Fig 4. Operation flow chart of flight conflict detection system

eVTOL B is the target being detected. It simultaneously receives the ADS-B information from both eVTOL and, by parsing the ADS-B messages, obtains the respective identification numbers, latitude and longitude, altitude, heading, etc. of the two eVTOL. 2) Experts use the data to make a judgment on whether a flight conflict has occurred, and combine the data information with the corresponding FLAG value of the judgment result into a data module to support the learning of the support vector machine. 3) After the SVM learning, the optimal parameter  $g$  and the optimal parameter  $C$  are selected, and the accuracy rate is obtained.

### 4. Case Analysis

The data in this article is mainly received by the SBS-3 receiver. This receiver can receive ADS-B messages within 300 kilometers. The message information is shown in Figure 5. By using one SBS-3 receiver, one GPS timing device and one computer, a remote ground station can be formed to receive ADS-B messages. After parsing the ADS-B messages and constructing a database, all the longitude, latitude, altitude, heading, east-west speed, north-south speed, etc. of the unmanned aircraft with ADS-B OUT system installed within the receiver's working range can be conveniently extracted.

400 pieces of data were selected from the database to form the training group, including 200 pieces of feature data for conflict drones and 200 pieces for non-conflict drones, as well

as 100 pieces for the validation group, including 50 pieces of feature data for protected areas that were invaded and 50 pieces for protected areas that were not invaded. The data content included the longitude, latitude, altitude and heading information of each drone A and drone B. The longitude and latitude coordinates of the drones were converted into geodetic coordinates, and  $R_i^{ab}$  was obtained by formula 3-2 and  $\Delta H_i^{ab}$  was obtained by formula 3-3. Based on expert judgment, the corresponding parameter FLAG values were obtained. The absolute values of FLAG values,  $R_i^{ab}$  and  $\Delta H_i^{ab}$  were combined to form a learning module. Thus, 400 sets of training group data corresponding to this learning module were obtained and input into the support vector machine for learning. Some of the learning modules corresponded to Table 1. In this paper, the SVM used the RBF radial inner product kernel function, and the training parameters were optimized using the cross-validation method. The SVM learned from the information to obtain the optimal penalty factor  $C$  and parameter  $g$ , thereby making judgments on future unknown data.

Table 1. Information for SVM learning

| serial number | distance | High absolute difference | FLAG |
|---------------|----------|--------------------------|------|
| 1             | 10030    | 312                      | -1   |
| 2             | 9012     | 594                      | -1   |
| 3             | 9820     | 230                      | 1    |
| 4             | 9860     | 300                      | 1    |
| 5             | 9900     | 290                      | 1    |

The training parameters were optimized using the cross-validation method. Firstly, the data was divided into a training group and a validation group. The training group was further divided into 5 groups. Under different penalty factors  $C$  and parameters  $g$ , the 5 groups of data were input into the SVM for learning, and the accuracy rates of learning for each group of data were obtained. Thus, the group with the highest accuracy rate was selected, corresponding to the penalty factor  $C$  and parameter  $g$ . Different penalty factors  $C$  and parameters  $g$  were taken as independent variables, and accuracy was taken as the dependent variable. The three-dimensional image of the corresponding parameters was obtained. From the graph and program output parameters, it can be seen that when the penalty factor  $C = 1$  and the parameter  $g = 0.0039063$ , the accuracy rate was the highest at 94.1667%. Further, using the support vector machine with the penalty factor  $C = 1$  and the parameter  $g = 0.0039063$ , the data of the validation group was classified and judged, and the final recognition rate was obtained. The experiment shows that when classifying 100 sets of data from the validation group, there were 50 sets of feature data indicating the invasion of the protected area and 50 sets of data indicating that the protected area was not invaded. The classification accuracy rate reached 98%, that is, the conflict detection rate of the support vector machine model with flight conflict detection capability described in this paper is 98%, with a false alarm rate of 2% and a missed detection rate of 0%.

**Table 2.** Conflict level judgment table

| i | $\Phi_i^{ab}$ | $\theta_i^a$ | $\theta_i^b$ | $\gamma_a$ | $\gamma_b$ | $V_i^a$ | $V_i^b$ | $\Delta V$ | $VU_i^a$ | $VU_i^b$ | $\Delta UV$ | $\Delta H_i^{ab}$ | FLAG | D |
|---|---------------|--------------|--------------|------------|------------|---------|---------|------------|----------|----------|-------------|-------------------|------|---|
| 1 | 306           | 281          | 242          | 25         | 64         | 283     | 297     | 125        | 2        | -3       | 5           | -312              | -1   | 1 |
| 2 | 280           | 301          | 109          | 21         | 171        | 271     | 273     | 522        | 1        | 0        | 2           | -594              | -1   | 1 |
| 3 | 20            | 309          | 337          | 290        | 317        | 268     | 274     | -111       | 2        | 3        | -1          | 230               | 1    | 0 |
| 4 | 157           | 4            | 88           | 152        | 68         | 291     | 291     | -365       | -3       | 3        | -5          | 300               | 1    | 0 |
| 5 | 342           | 232          | 235          | 110        | 106        | 264     | 259     | -17        | 2        | -2       | 4           | 290               | 1    | 1 |

Extract the heading and speed information corresponding to each eVTOL from the database. Further calculate the azimuth angle  $\Phi_i$ , the absolute difference between the direction angle and heading angle of eVTOL A,  $\gamma_a, \gamma_b$ , the radial velocity difference on the horizontal plane  $\Delta V$ , the vertical velocity difference  $\Delta VU$ , and the vertical position difference  $\Delta H_i^{ab}$ . The final judgment of flight conflict levels is shown in Table 2. For the first group of data  $\Delta V > 0$ ,  $D=1$  and the conflict level are 1. Meanwhile, if the SVM module returns FLAG=1, a flight conflict occurs between the two eVTOL. For the fourth group of data  $\Delta VU \times \Delta H_i^{ab} < 0$  and  $\Delta V < 0$ ,  $D=0$  (conflict level is 0). The corresponding FLAG=1 indicates that although the eVTOL protection zone is intruded, since the radial velocity directions of the two eVTOL are opposite or the radial velocity of the intruding eVTOL is less than that of the host eVTOL, no flight conflict will occur after a period of time. For the fifth group of data  $\Delta VU \times \Delta H_i^{ab} > 0$ , the conflict level is 1 ( $D=1$ ), and its corresponding FLAG=1 indicates that when the eVTOL's protection zone is intruded, the two eVTOL are still approaching each other, which may lead to flight conflicts or even collisions in the future. Therefore, a conflict alarm is issued, pending conflict resolution.

## 5. Conclusion

This paper presents a flight conflict detection system that integrates the longitude, latitude, altitude and heading information of eVTOLs. It uses SVM and the flight trend detection module to detect flight conflicts.

1)The information from ADS-B is processed to extract and convert it into parameters such as  $\gamma$ ,  $\Delta H_i^{ab}$ ,  $\Delta V$  and  $\Delta VU$ , which are input into the flight trend detection module to obtain the value of the decision factor D. When the decision factor  $D=0$ , the severity level of flight conflict is 0, indicating that the two eVTOL are moving away from each other. When  $D=1$ , the severity level of flight conflict is 1, indicating that the two eVTOL are approaching each other.

2)The processed information is extracted and converted into values of  $\Delta H_i^{ab}$  and  $R_i^{ab}$ , which are input into the SVM module. The SVM is trained using a parameter optimization method with cross-validation to obtain the optimal penalty factor  $C=1$  and parameter  $g=0.0039063$ . Finally, the SVM is used to determine whether there is an intrusion into the flight protection zone of the two eVTOL: FLAG=1 if the target intrudes into the protection zone, otherwise FLAG=0.

3)Based on the severity level of the flight conflict and the

SVM determination result, the flight conflict is detected. When FLAG = 1 and D = 1, a flight conflict occurs; otherwise, it indicates that no flight conflict exists. When a flight conflict occurs, a conflict alert is issued and the next step of flight conflict resolution is awaited.

## References

- [1] MULLINS M, HOLMAN M, FOERSTER K, et al. Dynamic separation thresholds for a small air-borne sense and avoid system:AIAA-2013-5148[R]. Boston:A I A A, 2013.
- [2] TOY J. Complexity metric comparison study for controller workload prediction in 4Dtrajectory management environments [D]. Delft: Delft University of Technology, 2015.
- [3] TONY L A,GHOSE D,CHAKRAVARTHY A. Avoidance maps:a new concept in eVTOL collision avoidance[C]//2017 International Conference on Unmanned Aircraft Systems, Miami, 2017:1483-1492.
- [4] BERDONOSOV V D. Speed approach for eVTOL collision avoidance[J]. Journal of Physics:Conference Series,2018, 1015 (5):052002.
- [5] THANH H L N N,PHI N N ,HONG S K. Simple nonlinear control of quadcopter for collision avoidance based on geometric approach in static environment[J]. International Journal of Advanced Robotic Systems,2018, 15(2): 17298814 1876757.
- [6] CECEN R K,SARAÇ T,CETEK C. Meta-heuristic algorithm for aircraft pre-tactical conflict resolution with altitude and heading angle change maneuvers[J]. TOP,2021,29(3):629-647.
- [7] TONY L A, GHOSE D, CHAKRAVARTHY A. Correlated-equilibrium-based eVTOL conflict resolution[J]. Journal of Aerospace Information Systems, 2022, 19(4):283-304.
- [8] GUAN X M,LYU R L. Conflict resolution method of complex low-altitude flight based on satisfactory game theory [J]. Acta Aeronautica et Astronautica Sinica,2017,38(Sup 1):721475(in Chinese).
- [9] Wu Xueli, Huo Jiannan, Zhang Jianhua. Research on the Minimum Longitudinal Separation of Aircraft Based on ADS-B Monitoring Technology [J]. Journal of Hebei University of Science and Technology, 2017, 38(1): 52-58.
- [10] HUANG Y, TANG J, LAO S Y.eVTOL flight conflict resolution algorithm based on complex network[J].Acta Aeronautica et Astronautica Sinica,2018,39(12):32222.
- [11] Xu Jianfeng's Track Planning Algorithm Based on ADS-B in eVTOL Flight Management [J]. Modern Radar2021, 43(1): 34-41.
- [12] Xie Hua, Su Fangzheng, Yin Jiannan, et al. Research on Classification Detection and Differential Resolution Methods for Low-altitude eVTOL Flight Conflicts [J]. Journal of Safety and Environment, 2023, 23(9): 3131-3142.