Multivariate Combined Collision Detection for Multi-Unmanned Aircraft Systems

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ABSTRACT To mitigate the problem of multiple unmanned aircraft systems (MUAS) conflicts at low altitude and ensure the operational safety, this paper proposes a Multivariate Combined Conflict Detection (MCCD) method for MUAS by combining the characteristics of nominal and probabilistic trajectory method. Firstly, the structural framework of the MCCD method is established based on the concept of potential conflict pool, and a detection pattern is derived for MUAS. Secondly, a three-dimensional conflict fast detection model is constructed by velocity obstacle methods, which can rapidly detect potential conflict risks. Thirdly, a trajectory prediction model is constructed by using bidirectional long-short term memory (Bi-LSTM) network, and then a probability-based conflict detection model can be obtained by the expected value and error distribution of trajectory prediction, which can accurately calculate the collision probability of UAS pair. By fully integrating the above models, the fast and accurate detection of MUAS conflicts is achieved. Finally, multiple conflicting trajectories are constructed to analyze the effectiveness of MCCD method, the tests indicate that the average detection time of the proposed method is less than 15ms, the false positive rate is less than 0.01 and the false negative rate is less than 0.0035. The results show that the MCCD has the accuracy advantage and better real-time performance for MUAS conflict detection compared to the method of velocity trend extrapolation, single probabilistic conflict detection and probabilistic neural network.

INDEX TERMS Conflict detection, multi-unmanned aircraft systems, potential conflict, probability estimation.

I. INTRODUCTION

Recent years have witnessed the rapid development of unmanned aircraft systems (UAS), especially in urban environments, UAS has received widespread attention for their flexibility, convenience, and low cost. Now UAS is widely used in different livelihood fields such as traffic monitoring, aerial photography, geographic mapping and light transportation [1]. According to the statistics of the Civil Aviation Administration of China, by the end of 2020, there were 493,000 registered users of civil drones, 524,000 registered drones and 1,594,000 hours of drones operating activities. It is foreseeable that a large number of UAS will serve more

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Management (UTM) to ensure the safety of MUAS in low altitude airspace [3] and clarified its four development stages [4]. In 2016, Nanyang Technological University (NTU) proposed an Operating system of UTM to promote the safe and orderly integration of MUAS into urban air traffic systems [5]. Meanwhile, in 2017, NTU has identified “UAS conflict risk and severity” as one of the key research areas in air traffic systems [6]. However, the current research on urban air traffic only stays at the conceptual level, especially in the field of conflict detection and risk assessment, where there are still many technical blankness, there is still a lot of room for improvement in terms of detection accuracy and real-time detection.

This paper will propose a multivariate combined conflict detection (MCCD) method to achieve timely and accurate detection of collision risk and provide support for the safe operation of MUAS. The rest of the paper is organized as follows. In Section II, related work is summarized, including previous and current work. In Section III, we define the concept of potential conflict pool, based which the framework and working pattern of the MCCD method are proposed. In Section IV, in response to the structural framework of the previous section, a three-dimensional conflict fast detection model is constructed based on the ellipsoidal collision zone; a probability-based conflict detection model is constructed based on trajectory prediction and the prediction error. In Section V, the effectiveness of the method is verified by multiple conflicting trajectories. In Section VI, some conclusions and summaries are drawn.

II. LITERATURE REVIEW
Conflict detection is usually based on trajectory prediction or state propagation to determine whether a flight conflict will occur between aircraft, i.e. whether the aircraft spacing is less than the safety interval standard. Timely alerting if there is a conflict in order to reduce the incidence of safety incidents. There are three common types of methods that are widely used in UAS collision detection: the nominal trajectory method [7], [8], the probabilistic trajectory method [9], [10], and the worst-case range method [11].

A. THE NOMINAL TRAJECTORY METHOD
The nominal trajectory method is to detect the potential conflicts in the future period based on the current position and movement tendency of UAS before entering the collision zone, it can predict the time of conflict based on the distance between the conflicting UAS and the relative conflict point in the scene, regardless of other uncertainties (e.g. wind, air pressure, detection accuracy). Yin et al [12] developed a deterministic conflict detection model based on the fixed trajectory of the aircraft, by analyzing the minimum horizontal distance between two aircraft and the vertical distance during the time period when safety risks exist. Wang et al. [13] combined with the static protection zone principle and the sliding window polynomial fitting method, determined the invasion track of UAS in the short term, so as to timely carry out conflict warning.

Nominal trajectory method can make estimate of the UAS position based on the current state information, which has considerable accuracy in the case of very predictable UAS trajectories, and nominal trajectory method has features such as simple models and short detection periods, which meet the real-time requirements of MUAS conflict detection. However, the movement tendency of the UAS has a random nature, and the trajectory in the future period does not necessarily extend in the direction of the current velocity, so this method has obvious drawbacks in long-time conflict detection.

B. THE PROBABILISTIC TRAJECTORY METHOD
The probabilistic trajectory method models the uncertainty of the trajectory and characterizes the predicted position of the UAS in the form of probability distribution, in order to describe the potential changes in the trajectory of the UAS in the future time. This method generally derives the probability of conflict between two aircraft based on the expected value of trajectory prediction and the distribution of uncertainty error. Liu and wang et al. [14] established a four-dimensional trajectory prediction model with reference to Markov state transfer process and approximated the collision probability between UAS pair based on the cumulative distribution function of Gaussian random error. Pour et al. [15] calculated the conflict probability interval between UAS pair based on Gaussian distribution and improved the accuracy of conflict detection by refining the upper and lower bounds of the interval through constant verification.

The probabilistic trajectory method takes into account the detection errors due to random factors such as wind and air pressure, and allows for an objective assessment of current safety based on conflict probabilities, with a relatively high degree of accuracy in detection results [16]. However, the probabilistic trajectory method is generally combined with trajectory prediction, and its prediction accuracy depends heavily on the accuracy of the trajectory prediction. On the other hand, the relatively complex model of probabilistic conflict detection increases the detection time, especially in the low-altitude airspace with MUAS, which requires pairwise trajectory prediction and conflict probability calculation for MUAS, so the computational volume is relatively large and the conflict detection refresh interval is long, it is not conducive to realizing real-time conflict detection.

C. THE WORST-CASE RANGE METHOD
The worst-case range method can be considered as an extreme case of the nominal trajectory method, which assumes that the UAS can maneuver in any direction from its current position, so the UAS may be present in all locations within its maximum range [17]. The detection range of this method consists of all possible trajectories, which can be considered as the collision area of the UAS, and whenever the collision areas of two UAS overlap, it indicates the occurrence of a conflict. The worst-case range is too rigid and triggers conflict alerts
whenever there is a possibility of conflict, thus generating an excessive false alarm rate and leading to a serious waste of low-altitude airspace resources. Currently there are very few applications of worst-case range method in low-altitude MUAS detection.

D. CURRENT WORK

In the field of Air Traffic Management (ATM), the collision detection methods are mostly limited to two-dimensional geometric approaches. In the field of UAS Traffic Management (UTM), the collision detection methods only for the determination of conflicts between two UAS, and the detection means are relatively single. Considering the potential of UAS in smart cities, the focus of current work is to develop a method for multi-UAV conflict detection in 3D space.

As mentioned in Sections A and Sections B above, the current methods of UAS conflict detection mainly focus on two aspects: the nominal trajectory method and the probabilistic trajectory method. When facing the multi-UAS in urban scenes, these two methods have their own advantages and shortcomings in terms of real-time and accuracy. In order to ensure the accuracy of multi-UAS conflict detection, while meeting the demand for real-time detection, this paper aims to fuse the nominal and probabilistic trajectory method and proposes an efficient MCCD method, which can address the increasing risk of MUAS collisions in urban low altitude environments.

III. MULTIVARIATE COMBINED CONFLICT DETECTION MODEL

Facing the scenario of multiple UAS operating at low altitude, this section proposes the MCCD method. The basic framework of the MCCD method is established in Section A, the concept of potential conflict pool for UAS pair is described in Section B, and the MCCD detection pattern is summarized in Section C.

A. THE STRUCTURE OF COMBINATORIAL COLLISION DETECTION

Specifically for the conflict detection process of UAS pair, the nominal trajectory method uses the relationship between the velocity vector at the current moment and the collision zone of UAS pair to determine conflicts, the model is relatively simple and the detection period is short, so it can meet the real-time requirements of conflict detection under MUAS conditions, however, due to the mobility and flexibility of UAS, its velocity vector will change significantly in the free airspace as the detection time span increases, thus reducing the accuracy of the detection model [18]. The probabilistic trajectory method uses prediction error estimation and collision probability calculation to perfectly improve detection accuracy, however, due to the combination with trajectory prediction, its prediction time will increase compared to velocity obstacle method and may not achieve the expected results in terms of detection real time. This paper proposes two mathematical models suitable for MUAS conflict detection based on the nominal trajectory and probabilistic trajectory method, and combine the two to propose the MCCD method. The specific model is shown in Table 1.

| Type of method | Model |
|----------------|-------|
| Nominal trajectory method | Velocity obstacles-based three-dimensional conflict detection model (Subsection A of section IV) |
| Probabilistic trajectory method | Trajectory prediction-based probabilistic conflict detection model (Subsection B of section IV) |

The core idea of the MCCD method is: using the velocity obstacles-based three-dimensional conflict detection model to detect the UAS pair with potential conflict risk at a certain time, and this pair will be listed as a key target in the later process. Using the trajectory prediction-based probabilistic conflict detection model to further calculate the instantaneous collision probability of the UAS pair, and an algorithm is designed to convert it into a continuous collision probability during the encounter, which is combined with a probability threshold to determine whether the UAS pair is at risk of collision. The overall technical route is shown in Figure 1.

B. POTENTIAL CONFLICTS POOL

Based on the technical route of the MCCD method, the concept of potential conflicts pool of UAS pair is proposed as a node to connect the three-dimensional conflict detection model and the probabilistic conflict detection model (as shown in Fig. 2). The risky UAS pair detected by the three-dimensional conflict detection model are stored in the pool, i.e. the UASs in this pool are key targets for the next time period. And then their spatial position in the next time period will be predicted and the collision probability during the encounter will be calculated to obtain a more accurate detection result.
The potential conflicts pool saves detection time by avoiding trajectory prediction and collision probabilities estimation for all UASs in the airspace. In addition, the relationship between the relative velocity direction and the combined collision region affects the collision probability of UAS pair in the potential conflict pool. If relative velocity direction is tangential to the collision zone, then a slight adjustment between the UAS pair can avoid the conflict and the calculated collision probability is relatively small, and if relative velocity direction passes through the center of collision zone, then there will be a greater probability of collision. Therefore, the calculation of the collision probability can be considered as an extension of the velocity obstacle method. Once a mid-air collision accident occurs, it not only damages the aircraft but may also cause casualties and property losses on the ground, so it is necessary to focus on all cases where the velocity direction intersects the collision zone and calculate the collision probability of all UAS pairs within the potential conflicts pool one by one.

### C. DETECTION PATTERN

The MCCD method combined the concept of velocity obstacle method, potential conflict pool, trajectory prediction, and collision probability, based on the performance of different detection methods over different detection time spans, the detection pattern is as follows:

\[
\text{detection cycle} = \left\{ \begin{array}{l}
\text{Model}^1, \text{pool}^t_i, \text{Model}^2_{t+1}, \ldots, \\
\text{Model}^m, \text{pool}^m, \text{Model}^n_{t+1}, \ldots
\end{array} \right\}_{\text{Combined Model}}
\]

(1)

\[
\text{Potential UAS}^t_i \in \text{pool}^t_i
\]

(2)

\[
T_D = \{ t_i : t_1 < t_2 < \ldots < t_n, t_i + t' \leq t(i + 1) \}
\]

(3)

The detection pattern of MCCD method is described in equations (1), (2), (3). As shown in equation (1), each combined conflict detection model consists of three components: \text{Model}^t_i, \text{pool}^t_i, \text{Model}^2_{t+1}, a detection cycle consists of several circulations of the above detection model. \text{Model}^1_i is the velocity obstacles-based three-dimensional conflict detection model at time \(t_1\), \text{pool}^t_i is the potential conflicts pool at time \(t_1\), \text{Model}^2_{t+1} is the trajectory prediction-based probabilistic conflict detection model at time \(t_1\). \(T_D\) is the set of detection moments in a detection cycle and the time span of one conflict detection is \(t'\).

Assuming that the whole conflict detection starts at time \(t_1\) and ends at time \(t_n\), the specific process of MCCD method is as follows: Firstly, for all UASs in the airspace at time \(t_1\), use the model1 to detect the UAS pairs with potential conflicts. Secondly, store the UAS pairs detected at time \(t_1\) into the potential conflicts pool. Thirdly, define the time span of trajectory prediction as \(\Delta t\), and predict the spatial position of UAS in the potential conflict pool after \(\Delta t\). Fourthly, based on the expected value and error distribution, the instantaneous collision probability of one prediction can be obtained, and the total collision probability can be taken as the maximum value of the instantaneous probability. Fifthly, determine the conflicting UASs at moment \(t_1\) by comparing the collision probability with the threshold value, and turn to the conflict detection at time \(t_2\) (as shown in Fig. 3).

### IV. THE METHODOLOGY OF MULTIVARIATE COMBINED CONFLICT DETECTION

In this section, we divide the theoretical approach of MCCD method into two parts: Velocity obstacles-based three-dimensional conflict detection method and trajectory prediction-based probabilistic conflict detection method. Firstly, we define the boundary of the ellipsoidal collision zone for UAS and describe how to generate the parameters of collision zone. Secondly, we propose the pattern of the velocity obstacle method and construct the three-dimensional conflict fast detection model on this basis. Thirdly, we obtain the trajectory prediction expectation and error distribution through bidirectional long-short term memory (Bi-LSTM) network and formulate the definition of instantaneous collision probability for UAS pair by the triple integral. The integrand function is the Gaussian PDF whose parameters are determined by the combination of predicted position errors, and the integration region is the combined collision zone.

#### A. THREE-DIMENTIONAL CONFLICT DETECTION METHOD BASED ON VELOCITY OBSTACLE

1) COLLISION ZONE FOR UAS

The first step to build a UAS conflict detection model is to establish a suitable collision region. The selection of collision region is directly related to the complexity of the post-order model and the solving efficiency of the algorithm, so a simple and effective collision region model is important for conflict detection that emphasizes response time. The current
internationally accepted aircraft collision zone model is the Reich model proposed in the 1960s and 1970s [19], which assumes each aircraft as a cube. However, this model is not derivable at the connection of each surface, so it is easy to cause unstable collision probability calculation results at the corners. In the current research the spherical shape is usually used as the collision zone for UAS.

With the increasing tension of low-altitude airspace resources, the volume of the UAV collision area needs to be minimized under the premise of ensuring safety. Taking the DJI Matrice 600 model in the experiment of this paper as an example (section V), its form factor (L × W × H) was set to 1668 mm × 1668 mm × 759 mm, the longitudinal dimension is obviously smaller than the transverse dimension, using a spherical type as the collision area will inevitably take up more space, the comparison diagram is shown in Figure 4(a). So the ellipsoid is considered as the collision zone of UAS to reduce the space occupation in the vertical direction.

The equation of ellipsoidal collision zone is:

\[ V = \frac{4\pi}{3} HR^2 - 8a^2 h = \frac{8\pi a^2 H^3}{3(H^2 - h^2)} - 8a^2 h \]

(4)

The size of the minimum circumscribed ellipsoid can be computed by:

\[ \frac{dV}{dH} = \frac{8\pi a^2 (H^4 - 3H^2 h^2)}{3(H^2 - h^2)^2} = 0 \]

(5)

Thus, we get:

\[ H_b = \sqrt[3]{h R_b} = \sqrt[3]{a} \]

(6)

where \(H_b, R_b, R_b\) are the semi-axes of the ellipsoid, then the equation of ellipsoidal collision zone is:

\[ D = \{ r \in \mathbb{R}^3 : r^T A r \leq 1, A^{-1} = \text{diag}(3a^2, 3a^2, 3h^2) \} \]

(7)

2) THREE-DIMENSIONAL CONFLICT FAST DETECTION METHOD

The core idea of the three-dimensional conflict fast detection method is: neglecting the effect of UAS uncertainties and considering the maneuvering behavior (position, velocity, etc.) of UAS at the current moment. Then a relative velocity obstacle region is defined, and if the relative velocity of an UAS pair falls into this region, the UAS pair is considered to have a potential conflict in geometric space, and the moment of conflict can be predicted based on the distance between the UAS and the relative conflict point [20].

Let subscripts \(S\) and \(R\) designate the stochastic UAS and the reference UAS respectively in any UAS pair during the encounter. The collision region of the UAS is defined as ellipsoidal, \(P_R\) denotes the position of the reference UAS, \(P_S\) denotes the position of the stochastic UAS, and the velocities of the reference UAS and the stochastic UAS at the current moment are \(V_R, V_S\). In the process of modelling, the combined collision zone of the UAS pair is assigned to the reference UAS so that the stochastic UAS can be regarded as a particle. The parameters of combined collision region \(D\) are:

\[ H_D = 2H_b = 2\sqrt[3]{h} \quad R_D = 2R_b = 2\sqrt[3]{a} \]

(8)

Establish a 3D collision coordinate system with the origin fixed at the position of the reference UAS, the relative position and velocity of the UAS pair is: \(\Delta P = P_S - P_R\), \(\Delta V = V_S - V_R\). Define the conflict region \(CR\), which is the set of relative velocity extensions. If there is a potential conflict between UAS pair:

\[ CR = \{ \Delta l \cap D \neq \emptyset \} \]

(9)

In (9), \(\Delta l\) is the extension of the relative velocity.

With the above description, the following judgement can be made: when the intersection of relative velocity and conflict region \(CR\) is non-empty, i.e. \(\Delta l \cap D \neq \emptyset\), there is a potential conflict between the UAS pair, otherwise it can be considered temporarily safe. The schematic diagram of the 3D conflict fast detection model is shown in Figure 5.
The trajectory data of UAS should have basic information such as time, longitude, latitude, altitude, and velocity \( v_t \). The output of the track prediction is the predicted position after a fixed period of time, including the longitude, latitude and altitude. Therefore, the output data structure of the track prediction is:

\[
P_{it} = [x_{it}, y_{it}, z_{it}, v_{it}] \quad (13)
\]

In Equation (13), \( P_{it} \) is the trajectory parameter vector of UAS\(_i\) corresponding to time \( t \). \( v_{it} \) represents the UAS\(_i\) velocity (m/s) corresponding to \( t \).

The UAS position information under ADS-B is usually updated at a frequency of 1s, 5s, 10s and 20s. In general, the original UAS trajectory data are usually missing some time stamps, so the neural network model trained on this data has poor performance, in addition, the trajectory corresponding to the original data is a fold line, which does not match the real UAS movement. Therefore, the UAS trajectory needs to be smoothed and interpolated. In this paper, a third-order Bezier curve is used to smoothly interpolate the flight trajectory of UAS [22], and the trajectory smoothing algorithm is shown in equation (15):

\[
B_n(t) = \sum_{k=0}^{n-1} C_n^k t^k (1 - t)^{n-k} P_k \quad (15)
\]

In Equation (15), \( P_0, \ldots, P_k \) is the original trajectory data point \( (k \leq n, n = 3 \) for the third-order Bezier curve), \( t \) is the smoothing parameter, \( \forall t \in [0, 1] \). \( B_n(t) \) is the trajectory data point after smoothing.

In this paper, the trajectory prediction is modeled by Bi-LSTM network with smoothed trajectory data, which is divided into two parts: model training and model prediction. But the actual trajectory of most UAS has no obvious long-term trajectory characteristics. Therefore, the trajectory data of UAS should be reconstructed before model training.

The trajectory reconstruction process: Firstly, select a 4D trajectory data after smooth interpolation (the interval of the trajectory data is 1s). Secondly, start from the first trajectory point, combine this point with the next two adjacent trajectory points to form a time window. Thirdly, the operation is repeated until the n-th trajectory point, where n is the length of the selected UAS trajectory sample. The schematic is shown in Figure 6, and it is easy to see that the reconstructed UAS trajectory has a simpler data structure and is more suitable as the input for model training.

It is necessary to explain why two adjacent timespans (three trajectory points) were chosen to form a time window instead of other quantities.

The state vectors of the trajectory points include only the latitude, longitude and altitude \([x, y, z]\). The direction and magnitude of the velocity in Eq. (13) can be represented by the location feature, and they do not constitute a new vector space, only create a new dimension for training the machine learning model. Thus, the rank of the UAS motion Euclidean space is 3, \( R(\Omega) = 3 \).

If the number of trajectory points in the time window exceeds 3, according to the Markov property, there will be information that is not relevant to the future predicted state,
i.e., \( R(P_1, P_2, P_3, \ldots, P_n) = R(\Omega) = 3 \), it implies redundancy of vector information and increased computational complexity. If there are only two trajectory points in a time window, the following relationship remains: \( R(P_1, P_2) = 2 < R(\Omega) = 3 \). Therefore, it cannot reflect the full intent of the 6-DOF UAS, such as turning to climb, turning to descend, etc. The accuracy of the trajectory prediction model trained by such a time window will be significantly reduced. If there are three points in a time window, can just satisfy the equation: \( R(P_1, P_2, P_3) = R(\Omega) = 3 \).

The above completes smooth interpolation processing and trajectory reconstruction processing for UAS trajectory data, and obtains high-quality trajectory data suitable for the input of post-sequence prediction model. Next, a Bi-LSTM network-based trajectory prediction model is developed to obtain more accurate predicted positions of the UAS in a fixed time span.

Bi-LSTM neural network is a variation of the basic recurrent neural network, whose basic network structure relies on the LSTM. Compared with the traditional RNN, the Bi-LSTM model compensates for the problems of insufficient long-term memory and gradient disappearance by introducing three control gate units, i.e. forgetting gate, input gate and output gate, thus effectively optimizing the accuracy of the RNN prediction model [23].

Assumes that \( x_t \) is the current moment input, \( h_t \) is the current moment output, \( C_t \) represents the cell state, \( \tanh \) is the hyperbolic tangent activation function, \( \sigma \) is the Sigmoid activation function, \( f_t \) is the output of the forgetting gate, and \( o_t \) is the output of the outputs.

The specific process for a standard LSTM neural network is:

The forgetting gate determines the cell state \( C_t \) by looking at the output value \( h_{t-1} \) at the previous moment and the input value \( x_t \) at that moment:

\[
f_t = \sigma (W_f [h_{t-1}, x_t] + b_f) \quad (16)
\]

The input gate determines the value to be updated inside the cell, thus determining the cell status \( C_t \):

\[
C_t = \tanh (W_c [h_{t-1}, x_t] + b_c) \quad (17)
\]

Finally the output gate determines the result of the output:

\[
o_t = \sigma (W_o [h_{t-1}, x_t] + b_o) \quad (19)
\]

\[
h_t = o_t \tanh (C_t) \quad (20)
\]

In the training process of LSTM, the model tends to carry out extensive regularity analysis on the upstream information. The Bi-LSTM combines the downstream information with upstream information based on the LSTM. Its structure is shown in Figure 7. The output sequence \( h_t \) of the upstream layer is computed using the input sequence from time \( y-t \) to time \( y-1 \), and the output sequence \( h_t \) of the downstream layer is computed using the input sequence from time \( y + t \) to time \( y + 1 \), as shown in equations (16) to (20) [24, 25].

![FIGURE 6. UAS trajectory reconstruction.](image)

![FIGURE 7. Structure of Bi-LSTM.](image)

Similar to the LSTM layer, the final output of the Bi-LSTM layer can be represented as a vector. The output vector \( y_t \) is calculated as shown in equation (21), where the function \( \sigma \) can represent any method used to combine two output sequences such as averaging, summing, concatenating, etc.

\[
y_t = \sigma (h_t, h_t) \quad (21)
\]

The design concept of Bi-LSTM is to make the output vector obtained at moment \( t \) have both past and future information. Experimentally, this neural network structure has proved to have better efficiency and performance than single LSTM model for data information prediction.

In this paper, based on the Bi-LSTM model, 80% of the reconstructed UAS segment data are used as the training set for extracting segment features and training deep learning model, and the remaining 20% of the UAS segment data are used as the validation set to test the generalization ability of the trained model. Now, we complete the work of trajectory prediction in conflict detection.

2) POSITION DISTRIBUTION BASED ON TRAJECTORY ERROR

Due to the interference of wind, air pressure, navigation errors and other irresistible factors, the position points obtained from the track prediction in the previous section may have some deviations. In order to improve the accuracy of conflict...
FIGURE 8. Diagram of trajectory prediction error.

detection, a model of aircraft position distribution based on trajectory error estimation is constructed to represent the aircraft position during the detection time.

Assuming that the UAS trajectory error grows in the body coordinate system along the body axis direction respectively, and the three directional trajectory errors are independent of each other, \( \hat{P}_i \) is the predicted location of UAS \( S_i \) at moment \( t \), i.e. the nominal position of the UAS in the global coordinate system at moment \( t \). \( \hat{P}_i \) is the trajectory error in the position of the UAS in the airframe coordinate system, then we get \( \hat{P}_i \sim N_3(0, \Lambda) \), where \( \Lambda = \text{diag} (\sigma_1^2, \sigma_2^2, \sigma_3^2) \). \( \sigma_1^2, \sigma_2^2, \sigma_3^2 \) denotes the variance of the track error along the three directions of the airframe coordinate system, respectively. Therefore, the distribution of the UAS position in the global coordinate system is (subscript \( i \) and moment \( t \) are omitted below):

\[
r = \hat{R}p + \bar{P}
\]

In equation (22), \( R \) denotes the rotation matrix for the body coordinate system to global coordinate system transformation, which can be calculated from equation (23):

\[
R(\theta, \varphi) = \begin{bmatrix}
cos \varphi & -\sin \varphi & 0 \\
\sin \varphi & -\cos \varphi & 0 \\
0 & 0 & 1
\end{bmatrix} \begin{bmatrix}
cos \theta & 0 & -\sin \theta \\
0 & 1 & 0 \\
\sin \theta & 0 & \cos \theta
\end{bmatrix} = \begin{bmatrix}
cos \varphi \cos \theta & -\sin \varphi \cos \theta & \cos \varphi \sin \theta \\
\sin \varphi \cos \theta & -\cos \varphi \cos \theta & \sin \varphi \sin \theta \\
-\sin \theta & \cos \theta & 0
\end{bmatrix}
\]

In equation (23), \( \varphi \) is the UAS heading, \( \theta \) is the UAS climb angle. It should be noted that the amplitude of roll during the actual movement of the UAS is very small, and the roll angle in its track point data is very small (mostly 0). In order to simplify the complexity of the calculation, two rotation matrices, pitch and yaw, are considered in the process of performing the coordinate system conversion.

Thus, the position distribution of the UAS is \( r \sim N_3(\hat{P}, \bar{R}A\bar{R}^T) \), the diagram of the trajectory prediction error is shown in Figure 8.

3) COLLISION PROBABILITY FOR UAS PAIRS

Based on the definition of the collision region, it is clear that if there is an overlap between the collision regions of UAS, the UAS pair can be considered to be in an airborne collision. If the stochastic UAS is considered a particle and the combined collision area is superimposed on the reference UAS, this definition can also be translated as follows: if the stochastic UAS enters the combined collision area of the reference UAS, then a collision occurs in the UAS pair. During the flight of a short-term segment in free airspace, the UAS state is relatively stable and the uncertainty of UAS trajectory mainly comes from the influence of trajectory error, so this paper calculates the instantaneous collision probability of the UAS pair based on the prediction error of the trajectory.

If the combined position error of the UAS pair is assigned to the stochastic UAS, then the combined position distribution model of the stochastic UAS can be obtained. Similarly, let subscripts \( S \) and \( R \) designate the stochastic UAS and the reference UAS in any UAS pair during the encounter, the relative position of the two UASs:

\[
\Delta r = r_S - r_R = R_S P_S - R_R P_R + \Delta \bar{P} \tag{24}
\]

In equation (24), \( \Delta \bar{P} = \bar{P}_S - \bar{P}_R \), if the position errors of the two UASs are independent of each other, the relative positions is:

\[
\Delta r \sim N_3 (\Delta \bar{P}, R_S \Lambda_S R_S^T + R_R \Lambda_R R_R^T) \tag{25}
\]

Let \( \mu = \Delta \bar{P} \) and \( \Sigma = R_S \Lambda_S R_S^T + R_R \Lambda_R R_R^T \), we can get \( \Delta r \sim N_3 (\mu, \Sigma) \), let \( D \) denote the combined collision zone, then

\[
D = \left\{ r \in R^3 : r^T A r \leq 1, A^{-1} = \text{diag} \left( R_D^2, R_D^2, H_D^2 \right) \right\} \tag{26}
\]

Refer to equation (8), \( R_D \) is the radius of the combined collision zone, \( H_D \) is the half height of the combined collision zone. Therefore, the instantaneous probability of collision between the UAS pair at moment \( t \) is:

\[
P_{IC} (t) = \int \int \int_{\Delta r(t) \in D} N_3 (\Delta r (t) ; \mu (t), \Sigma (t)) d \Delta r (t) \tag{27}
\]

For UAS pairs with potential conflict in the potential conflict pool, we can use the instantaneous collision probability to calculate the collision probability during the encounter, which characterizes the likelihood of conflict occurrence. According to [26] the probability during the encounter can be defined as:

\[
P( C | T) = \max_{k \in M} P( C (k)) = \max_{k \in M} P (k T_S) \tag{28}
\]

In the equation (28), \( M = \{ k \in Z^+ : 1 \leq k \leq T/T_S \} \), \( T \) is the detection period, \( T_S \) is the sampling period, \( p (k T_S) \) is the instantaneous collision probability at the time \( k T_S \).

Then we define the collision threshold \( \delta \), if \( P (C | T) > \delta \), which can indicate the UAS pair is at a risk of conflict during the time period \( T \).
### TABLE 2. MCCD method brief pseudocode.

| Algorithm: Combined collision detection algorithm for multiple unmanned aircraft  
(Asume that the detection period and sampling period are both 1s) |
|---|---|
| **Input:** UAS trajectory parameters $X_r = [x, y, z, \nu]$, a certain ellipsoidal collision zone $D$, an alert threshold $\delta$, the relative predicted position $\Delta \bar{r}$, the covariance matrix of predicted position errors $\Sigma_v$, total number of UASs N. |
| **Output:** conflict UAS sets $C$. |

While $t \leq T$:

**V. EXPERIMENTS**

#### A. OVERVIEW OF DATA AND SCENARIES FOR CONFLICT DETECTION

To analyze the performance of the MUAS conflict detection method, this paper select DJI Matrice 600 as a case study, whose form factor $(L \times W \times H)$ is set to $1668 \times 1668 \times 759$ mm, and the probability threshold for conflict determination is 5% based on the validation in [27].

![Spatial distribution of UAS trajectories](image)

**FIGURE 9. Spatial distribution of UAS trajectories.**

We use the low-altitude airspace range in [28] as a simulation scenario for experiments, and 10 trajectories with multiple conflict points are constructed based on the real flight data with the reference to the coordinates of waypoints in [28], the main flight altitudes are 50-60m, the longitude range of trajectory data is [118.79, 118.81], the latitude range is [31.94, 31.95], and the important trajectory parameters are shown in TABLE 3.

Six trajectories in the dataset were selected for display, and the effect is shown in Figure 9.

#### B. CONFLICT DETECTION EXPERIMENT OF MCCD METHOD

The results of trajectory prediction are directly related to the accuracy of the probabilistic conflict detection model, so a well-performing Bi-LSTM neural network is an important part during the training of the conflict detection model. To visualize the trajectory prediction error, the Mercator projection is applied to convert the latitude and longitude into the form of plane coordinates as shown in equation (29).

$$
egin{align*}
    x &= K \ln [\tan (\frac{\pi}{4} + \frac{\phi}{2})] \\
    y &= K(\lambda_0 - \lambda_0) \\
    K &= \frac{a^2}{\sqrt{1 + e'^2 \cos^2(\phi_0)}} \times \cos \phi_0
\end{align*}
$$

In equation (29), $a$ denotes the long semi-axis of the IAG75 ellipsoid, $b$ denotes the short semi-axis of the IAG75 ellipsoid, $e$ denotes the first eccentricity, $e'$ denotes the second eccentricity [29].

For one of the trajectory data, the mean squared error (MSE) of prediction model varies with the training generations as shown in Figure 10, and the prediction accuracy of validation set is finally stabilized at $4 \times 10^{-6}$, indicating that the training model has good generalization performance.

To determine the more accurate prediction time span, we select all trajectory data and use the single-step bootstrap
TABLE 3. Data of conflict trajectory parameters.

| Type of trajectory | Starting point (lon, lat, alt(m)) | Terminal point (lon, lat, alt(m)) | Conflict point (lon, lat, alt(m)) | Number of points |
|--------------------|----------------------------------|----------------------------------|----------------------------------|-----------------|
| trajectory 1       | (118.791, 31.954, 52)           | (118.805, 31.942, 53)           | (118.802, 31.921, 50)           | 1006            |
| trajectory 2       | (118.792, 31.943, 56)           | (118.805, 31.946, 58)           | (118.802, 31.921, 50)           | 1027            |
| trajectory 3       | (118.793, 31.948, 56)           | (118.797, 31.946, 54)           | (118.794, 31.948, 56)           | 805             |
| trajectory 4       | (118.797, 31.945, 52)           | (118.793, 31.943, 51)           | (118.794, 31.943, 50)           | 604             |
| trajectory 5       | (118.802, 31.948, 52)           | (118.797, 31.944, 53)           | (118.797, 31.945, 53)           | 1027            |
| trajectory 6       | (118.800, 31.948, 53)           | (118.799, 31.944, 53)           | (118.800, 31.948, 53)           | 1006            |
| trajectory 7       | (118.800, 31.941, 55)           | (118.800, 31.945, 55)           | (118.796, 31.949, 55)           | 514             |
| trajectory 8       | (118.803, 31.949, 52)           | (118.801, 31.946, 54)           | (118.804, 31.943, 50)           | 321             |
| trajectory 9       | (118.796, 31.948, 56)           | (118.797, 31.945, 56)           | (118.797, 31.945, 53)           | 954             |
| trajectory 10      | (118.806, 31.951, 55)           | (118.802, 31.954, 52)           | (118.804, 31.944, 53)           | 689             |

FIGURE 10. Variation of cross entropy error of Bi-LSTM with epochs.

As we can see from Figure 11, for the data characteristics and prediction patterns in this paper, the Bi-LSTM model has a stable prediction effect in the prediction time span of 0-6s, and the mean and variance of MSE begin to increase sharply with the extension of the prediction time after 6s. Considering the correlation between detection time span and prediction accuracy, and leaving enough operation time for subsequent conflict resolution, the time span of UAS conflict detection is set to 6s in this paper.

Applying the above conflict trajectory data, combined with the MCCD method for simulation experiments, the results were obtained as shown in Figure 12.

From the figure, we can see that the UAS pairs with conflicts at any moment are in the potential conflict pool, indicating that the potential conflict set covers all possible risks. Moreover, the establishment of potential conflict pool effectively narrows the scope of conflict detection, which is more efficient than directly calculating the collision probability of all UAS pairs.
Figure 13 provides a more visual representation of the conflict situation in the airspace and the collision probability of an UAS pair in the form of a heat map.

Figure 13(a) shows the heat map of the conflict distribution of all UASs in the airspace at a certain moment. It can be clearly seen that 2 UAS pairs (UAS 4 with UAS 9 and UAS 4 with UAS 5) are in a risk of conflict, 5 UAS pairs are in potential conflict risk and the rest of the UASs are temporarily safe at this moment. Figure 13(b) shows the change of the collision probability between UAS 1 and UAS 3 in the time period 50s-200s. Since this UAS pair has the same take-off moment, the conflict only occurs at the diagonal position in the figure, and we can see that the collision possibility of the UAS pair is highest around 105s.

C. PERFORMANCE COMPARISON ANALYSIS

To further analyze the detection performance of MCCD method in this paper, we select velocity trend extrapolation (VTE), single probabilistic conflict detection (PCD) and probabilistic neural network (PNN) algorithms to conduct comparison test.

The VTE method uses trajectory point data to calculate the geometric relationship between the positions and velocities of the UAS combinations, combined with the defined collision zones to determine the conflict. The PCD method uses triple integration to calculate the probability of conflict between each UAS pair, combined with a probability threshold for the determination of conflict. The PNN method is a deep learning-based conflict detection method, which treats conflict detection as a pattern recognition problem, and uses key feature indicators of UAS trajectories to train a neural network classifier, so as to identify conflicts during UAS movement [30].

The false positive rate (FPR), false negative rate (FNR) and average conflict detection time were used as evaluation metrics to obtain the performance parameters of each method. The FPR is the probability of mistaking the safe range as a conflict point during the conflict detection process; the FNR is the probability that a conflict point is not detected; and the average conflict detection time is the average time taken by the algorithm to perform one conflict detection in each experiment. Refer to (30).

\[
\begin{align*}
FPR & = 1 - \frac{1}{n} \sum_{i=1}^{n} \frac{FT_{i}}{T_{i}} \\
FNR & = 1 - \frac{1}{n} \sum_{i=1}^{n} \frac{PN_{i}}{N_{i}} \\
\bar{t}_{det} & = \frac{1}{mn} \sum_{i=1}^{n} \sum_{j=1}^{m} t_{ij}
\end{align*}
\] (30)

In the equation (30), n is the number of experiments, during all detection periods in the i-th experiment, \(N_{i}\) is the number of times a conflict occurs, \(T_{i}\) is the number of times no conflict occurs, \(PN_{i}\) is the number in \(N_{i}\) that the algorithm incorrectly judges to be conflict-free, \(FT_{i}\) is the number in \(T_{i}\) that are incorrectly judged by the algorithm to be in conflict, \(m\) is the number of detection periods in an experiment, \(t_{ij}\) is the time of a particular detection.

Using trajectory data and data processing mode for a certain number of comparative experiments (this paper takes 1000 times). On this basis, the FPR, FNR and conflict detection time of MCCD, VTE, PCD and PNN are obtained, and the comparison of evaluation metrics is shown in Figure 14.

As we can see from the figure, the false positive rate of the MCCD method is basically maintained at about 0.9%, the performance of this aspect is significantly better than the remaining detection methods. Due to the high mobility of the UAS, a relatively flexible maneuvering behavior may occur in the detection period, so the VTE method will have a relatively high false positive rate (30.7% on average). In terms of the average one-step detection time, the VTE method has the shortest detection time due to the simple model, and the average difference between the MCCD method and the VTE method is only 9.3ms, which also has a good detection performance in this respect.

The FNR was obtained by conducting a fixed number of experiments on the basis of all trajectory data using the above four methods, and several of these groups were selected for comparison tests, as shown in Figure 15.

The consequences caused by conflicting misses during UAS operation are much more serious than conflicting false
alarms. As we can see in the above figure, the MCCD method in this paper has the lowest false negative rate, which is a great improvement compared with the VTE, PCD and PNN method (the average miss rate can be controlled below 0.35%) and can fully guarantee the safe operation of MUAS within the free airspace.

The specific performance data of the three detection methods are shown in TABLE 4.

From the specific data in the table, we can see that the MCCD method in this paper shows better performance than other methods in both false negative rate and false positive rate, and slightly inferior to the VTE method in conflict detection time, so the MCCD detection method is the best choice for MUAS conflict detection on the basis of guaranteed false negative rate and false positive rate.

VI. CONCLUSION

This paper combines the unique advantages and applicability of deterministic and probabilistic conflict detection methods, and proposes a multivariate combined conflict detection method for low-altitude multi-UAS.

(1) The ellipsoidal shape is selected as the collision region of UAS, and the three-dimensional conflict detection model based on the velocity barrier method and the probabilistic conflict detection model based on the trajectory prediction are constructed as the main theoretical framework of the method in this paper.

(2) The concept of potential conflict pool is proposed as an important node to connect the two modules of multivariate conflict detection. The risky UAS detected by 3D conflict fast detection method are stored in this pool, and we only calculate the collision probability of the UAS pairs in the pool, which ensures the accuracy and real-time of the conflict detection.

(3) From the experimental results of conflict detection, the method in this paper has significant advantages in terms of FPR and FNR, and is slightly inferior to the VTE method with simpler model in terms of average single-step detection time. To ensure the operational safety of urban air traffic, the accuracy of conflict detection must be strictly required, so the MCCD method is a better choice for MUAS conflict detection under comprehensive consideration.

REFERENCES

[1] R. Goyal. (2018). Urban Air Mobility (UAM) Market Study. [Online]. Available: https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/20190001472.pdf

[2] C. Yao and G. Xi, “Research progress and prospect of smart city in China,” Hum. Geogr., vol. 36, no. 5, pp. 15–23, Oct. 2021.

[3] P. Kopardekar, “Unmanned aerial system (UAS) traffic management (UTM),” Enabling Low-Altitude Airspace and UAS Operations, Lake Panasoffkee, FL, USA, Tech. Rep., TM-2014-218299, 2014.

[4] P. Kopardekar, I. Rios, T. Prevot, M. Johnson, J. Jung, and J. E. Robinson, “Unmanned aerial system traffic management (UTM) concept of operations,” in Proc. 16th AAA Aviation Technol., Integ., Oper. Conf., Reston, VA, USA, 2016, pp. 1–16.

[5] L. Pathiyil, K. H. Low, B. H. Soon, and S. Mao, “Enabling safe operations unmanned aircraft systems in an urban environment: A preliminary study,” in Proc. Int. Symp. Enhanced Solutions Aircr. Vehicle Survell. Appl. (ESAVS), Berlin, Germany, 2016, pp. 1–10.
[6] M. Mohamed and K. Low, “Concept of operation (ConOps) for traffic management of unmanned aircraft systems (TM-UAS) in urban environment,” in Proc. AIAA Inf. Syst.-AIAA Infotech@Aerosp., Reston, VA, USA, 2017, p. 0223.

[7] G. Bakker, H. Kremer, and H. A. P. Blom, “Geometric and probabilistic approaches towards LIct prediction,” Nat. Aerosp. Lab. NLR, Amsterdam, The Netherlands, Tech. Rep., 2001. [Online]. Available: https://www.researchgate.net/publication/22878884

[8] J. Tang, “Conflict detection and resolution for civil aviation: A literature survey,” IEEE Aerosp. Electron. Syst. Mag., vol. 34, no. 10, pp. 20–35, Oct. 2019.

[9] R. A. Paielli and H. Erzberger, “Conflict probability estimation for free flight,” J. Guid., Control Dyn., vol. 20, no. 3, pp. 585–596, Oct. 1997.

[10] B. Carpenter, J. Kuchar, B. Carpenter, and J. Kuchar, “Probability-based collision alerting logic for closely-spaced parallel approach,” in Proc. 35th Aerosp. Sci. Meeting Exhib., Reno, NV, USA, Jan. 1997, p. 222.

[11] J. K. Kuchar and L. C. Yang, “A review of conflict detection and resolution modeling methods,” IEEE Trans. Intell. Transp. Syst., vol. 1, no. 4, pp. 179–189, Dec. 2000.

[12] Y. C. Yin and A. S. Tan, “Flight conflict detection model based on flight path prediction of aircrafts,” Electron. Opt. Control, vol. 22, no. 22, p. 637, Dec. 2015.

[13] Q. Wang, “Research on detection and alarm of air threat situation for UAS collision avoidance,” Adv. Aeronaut. Sci. Eng., vol. 10, no. 6, pp. 794–801, 2019.

[14] W. Liu and I. Hwang, “Probabilistic trajectory prediction and conflict detection for air traffic control,” J. Guid., Control Dyn., vol. 34, no. 6, pp. 1779–1789, 2011.

[15] S. S. Pour, H. Nobahari, and M. Prandini, “Probability estimation in aircraft conflict detection: A simple and computationally effective method with accuracy certificates,” in Proc. 18th Eur. Control Conf. (ECC), Napoli, Italy, Jun. 2019, pp. 4319–4324.

[16] Y. Yang, J. Zhang, K.-Q. Cai, and M. Prandini, “Multi-aircraft conflict detection and resolution based on probabilistic reach sets,” IEEE Trans. Control Syst. Technol., vol. 25, no. 1, pp. 309–316, Jan. 2017.

[17] C. H. J. Wang, S. K. Tan, and K. H. Low, “Collision risk management for non-cooperative UAS traffic in airport-restricted airspace with alert zones based on probabilistic conflict map,” Transp. Res. C, Emerg. Technol., vol. 109, pp. 19–39, Dec. 2019.

[18] S. P. Wang and D. G. Cui, “Conflict detection algorithm for air traffic control,” J. Tsinghua Univ. Sci. Technol., vol. 44, no. 10, pp. 1368–1371, Oct. 2004.

[19] P. G. Reich, “Analysis of long-range air traffic systems: Separation standards—I,” J. Navigat., vol. 19, no. 1, pp. 88–98, Jul. 1966.

[20] W. Yang, “Three-dimensional deterministic collision detection model based on velocity obstacle method,” J. Xihua Univ., vol. 40, no. 6, pp. 1–6, Aug. 2021.

[21] J. Zhou, H. Zhang, W. Lyu, J. Wan, J. Zhang, and W. Song, “Hybrid 4-dimensional trajectory prediction model, based on the reconstruction of prediction time span for aircraft en route,” Sustainability, vol. 14, no. 7, p. 3862, Mar. 2022.

[22] Z. Yang, R. Tang, J. Bao, J. Lu, and Z. Zhang, “A real-time trajectory prediction method of small-scale quadrotors based on GPS data and neural network,” Sensors, vol. 20, no. 24, p. 7601, Dec. 2020.

[23] L. Lin, W. Li, H. Bi, and L. Qin, “Vehicle trajectory prediction using LSTMs with spatial–temporal attention mechanisms,” IEEE Intell. Transp. Syst. Mag., vol. 14, no. 2, pp. 197–208, Mar. 2022.

[24] X. Xu, H. Yang, H. Chen, Q. Hu, and H. Hu, “Long-term 4D trajectory prediction using generative adversarial networks,” Transp. Res. C, Emerg. Technol., vol. 136, Mar. 2022, Art. no. 103554.

[25] Z. Shi, M. Xu, Q. Pan, B. Yan, and H. Zhang, “LSTM-based flight trajectory prediction,” in Proc. Int. Joint Conf. Neural Netw. (IJCNN), Rio de Janeiro, Brazil, Jul. 2018, pp. 1–8.

[26] I. Hwang and C. E. Seah, “Intent-based probabilistic conflict detection for the next generation air transportation system,” Proc. IEEE, vol. 96, no. 12, pp. 2040–2059, Dec. 2008.

[27] Y. Zou, H. Zhang, G. Zhong, H. Liu, and D. Feng, “Collision probability estimation for small unmanned aircraft systems,” Rel. Eng. Syst. Saf., vol. 213, Sep. 2021, Art. no. 107619.

[28] S. Li, H. Zhang, Z. Li, and H. Liu, “An air route network planning model of logistics UAV terminal distribution in urban low altitude airspace,” Sustainability, vol. 13, no. 23, p. 13079, Nov. 2021.