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Machine Learning-Aided Trajectory Prediction and Conflict Detection for Internet of Aerial Vehicles

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Abstract—As exploitation of low and medium airspace for air traffic management (ATM) is gaining more attention, aerial vehicles' security issues pose a major challenge to the Air-Ground Integrated Vehicle Networks (AGIVN). Traditional surveillance technology lacks the capacity to support the intensive air traffic management (ATM) of the future. Therefore, an advanced automatic dependent surveillance-broadcast (ADS-B) technique is applied to track and monitor aerial vehicles in a more effective manner. In this paper, we propose a grouping-based conflict detection algorithm based on the preprocessed ADS-B dataset, and analyze the experimental results and visualize the detected conflicts. Then, in order to further improve flight safety and conflict detection, the trajectories of the aerial vehicles are predicted based on machine learning-based algorithms. The results are fed into the conflict detection algorithm to execute conflict prediction. It was shown that the trajectory prediction model using long short-term memory (LSTM) can achieve better prediction performance, especially when predicting the long-term trajectory of aerial vehicles. And the conflict detection results based on the trajectory prediction methods show that the proposed scheme can make it possible to detect whether there would be conflicts within seconds.

Index Terms—Conflict detection, automatic dependent surveillance-broadcast (ADS-B), trajectory prediction, machine learning, aerial vehicle.

I. INTRODUCTION

Future sixth-generation wireless network outlines a cellular-free multi-layer network that integrates space, air, ground and underwater communications [1]. Internet of aerial vehicles plays a role in air communications. Compared with space and underwater communications, it shows flexibility in

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deployment, scheduling and maintenance. Hence, Internet of aerial vehicles is an important part of future Internet of everything (IoE), and new applications of air-ground integrated vehicular networks (AGIVN) can provide golden opportunities for traditional and emerging enterprises.

With the opening of low-altitude airspace, AGIVN covering drones, helicopters, and unmanned free balloons are developing rapidly [2]–[4]. As a result, the low and medium airspaces are becoming crowded, and security pose higher requirements for the AGIVN. According to civil aviation administration of China, more than 90% of accidents have occurred at low altitudes since the 21st century. Therefore, new techniques need be utilized to reduce probability of aerial vehicles collisions [5].

Traditional surveillance technologies, such as primary surveillance radars and secondary surveillance radars [6]–[8], have obvious technical limitations in meeting requirements of future dense air traffic management (ATM) such as high operating costs, limited coverage, and relatively low accuracy of tracking [9]–[11]. To address these challenges, an automatic dependent surveillance-broadcast (ADS-B) technique has been proposed to enhance the surveillance architecture [12]–[14]. In the future AGIVN and IoE, the ADS-B technique can play an important role to facilitate the management of aerial resources in an intelligent manner [15]. Traditional conflict detection and collision avoidance algorithms often rely on collaborative systems (e.g., traffic collision avoidance system (TCAS) [16]), or non-cooperative systems (e.g., stand-alone photoelectric sensors and airborne radars used for obstacle detection [17]). However, information provided by the TCAS and radars is generally two-dimensional and the maintenance cost is relatively high [18], [19]. Nevertheless, ADS-B messages obtained from the distributed ADS-B stations can provide a wealth of aerial vehicles-related information, and the maintenance cost of the ADS-B stations is much lower.

To determine whether there is a conflict alarm between arbitrary two aerial vehicles. G. Xiao *et al.* [20] divided the space around an aerial vehicle into four quadrants. Based on the four quadrants, the relative position, speed, and angle are compared with other aerial vehicles to determine whether there exists conflicts. B. Zhou *et al.* divided the three-dimensional area centered on the evaluated aerial vehicle into 26 areas, including 8 hexagram areas, 6 axial areas, and 12 quadrant areas [21]. The correlation between an invading aerial vehicle and the evaluated aerial vehicle is determined by the area where the invading aerial vehicle is located.

However, the position of the aerial vehicle is time-varying and dynamic, making the relative relationship between the invading aerial vehicle and the evaluated aerial vehicle also dynamic. Therefore, these algorithms using segmented areas to detect aerial vehicles conflicts are generally not real-time. In order to solve the above problems, an ADS-B based conflict detection scheme using a grouping strategy is proposed in this paper. The conflict detection algorithm is motivated by the time axis mapping algorithm [22]. First, the route conflict problem is converted into a three-dimensional coordinate (X, Y, Z) conflict problem, and the conflict area of the three-dimensional coordinate axis is uniformly mapped onto the time axis. The route conflict of the two aerial vehicles is determined by determining whether there is an intersection of the X, Y, and Z axes at the same time period. Here, the grouping strategy is utilized to divide multi-dimensional information [23] (including longitude, latitude, altitude, ground speed, vertical speed, heading angle, etc.) of all aerial vehicles at the same time into multiple small groups. By using the multiple small groups, the complexity and execution time of the conflict detection system can be notably reduced.

Although an aerial vehicle has a flight plan in advance, there could be a difference between the actual flight and the plan, and the error can be about 7km [24]. Hence, an aerial vehicle often fails to fly as scheduled, it often conflicts with other aerial vehicles. Hence, although there is a flight plan, it is still necessary to predict the trajectories of aerial vehicles. In order to further improve the safety and advancement of the conflict detection algorithm, this paper combines a long short-term memory (LSTM) [25], [26] based trajectory prediction method with the conflict prediction algorithm. In this way, the predicted trajectory information can be used to make conflict detection for future seconds, and can prepare for collision avoidance in advance. The contributions of this paper can be summarized as follows:

- A geometric model for detecting whether an aerial vehicle is in conflict is constructed, and a grouping-based aerial vehicle conflicts detection algorithm is proposed.
- To improve the safety of the conflict detection algorithm, it is combined with three machine learning-based methods, i.e., LSTM, convolutional neural networks (CNN) and least square (LS), which are used and compared in predicting the short-term and long-term trajectories of the aerial vehicles.
- To address the real conflict situations, we discuss the impact of the trajectory prediction accuracy on the conflict prediction method.

II. METHODOLOGY

A. ATM System based on ADS-B Technique

Based on the ADS-B technique, parameters such as an aerial vehicle's position, heading angle, speed, and identification signal can be automatically obtained from related equipment without manual operation. The ADS-B messages are broadcasted to other aerial vehicles and ground stations. Hence, the air traffic controller (ATC) can better understand the aerial space and monitor the aerial vehicles [14].

The ADS-B sub-system mainly consists of three parts, namely information processing and display, information transmission channel, and information staff [12]. There are three main types of transmission methods for ADS-B messages, which are as follows [27], [28]:

- VHF/UHF digital link mode, whose core technology is the SOTDMA protocol;
- Universal access transceiver, which uses binary continuous phase shift keying system;
- 1090 MHz S-mode extended Squitter, which uses selective interrogation and two-way data communication.

The air traffic management (ATM) can benefit from the ADS-B technique. The ATM generally adopts advanced monitoring, communication, and navigation technologies to dynamically monitor the aerial vehicles' behavior, thereby ensuring that the aerial vehicles can fly in an orderly and safe manner [29]. The ATM system mainly focuses on vertical and horizontal separations among aerial vehicles, and is responsible for guiding, identifying, and monitoring the aerial vehicles. The main components of the ATM system are ground control center, navigation facilities, communication facilities, and radar systems [10].

The ADS-B sub-system can be divided into ADS-B OUT and ADS-B IN modes [30]–[32]. An aerial vehicle equipped with ADS-B computer using onboard navigation receivers can automatically determine its precise position information. The ADS-B transmitter then broadcasts its location information (using the ADS-B OUT mode) every half a second to nearby aerial vehicles and terrestrial ADS-B receivers (i.e., surveillance stations). The ADS-B signal received by other devices is termed as the ADS-B input signal (using the ADS-B IN mode). On the other hand, the signal received by the ground receiver will be transmitted to the ATC, so that the ATC can understand the flight status of an aerial vehicle and to better monitor it. In addition, the ADS-B receivers can be connected to computers and cloud servers, which is promising for researches in the field of AGIVN [33], [34].

B. Aerial Vehicles Conflict Detection

According to ATC regulations, the space around an aerial vehicle is defined as collision avoidance area, and other aerial vehicles are prohibited from entering. Otherwise, there will be the possibility of collision, and collision avoidance measures must be taken [14]. Since it is often impossible to take timely collision avoidance measures in the collision avoidance area, it is necessary to construct an additional protection area to further improve flight safety and collision avoidance flexibility.

In this paper, an additional protection area is constructed outside the collision avoidance area, which is specified by ATC to enhance the collision avoidance performance. Hence, the space around the aerial vehicle is divided into a collision avoidance zone (CAZ) and a protection airspace zone (PAZ) [22], which is shown in Fig. 1. The CAZ is a cylindrical collision avoidance area stipulated by ATC, whose horizontal radius is 9.26 kilometers and the height is 366 meters. Since the ADS-B has a wide working range as large as 185

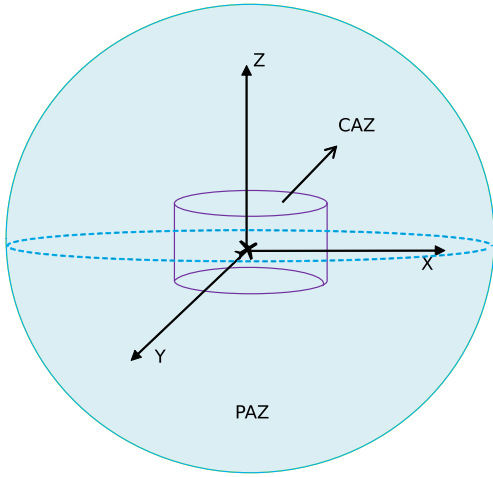


Fig. 1. The space around an aerial vehicle is divided into protection airspace zone and collision avoidance zone.

kilometers of radius, the PAZ is defined as a sphere with a radius of 185 kilometers.

The judgment of route conflict is conducted as follows: when an invading aerial vehicle enters the PAZ of the monitored aerial vehicle, the route conflict detection is triggered. If the invading aerial vehicle route enters the CAZ, it is judged that there is a conflict between the invading aerial vehicle and the target aerial vehicle.

C. Formulation of Aerial Vehicles Conflict Prediction

To execute the conflict detection algorithm, we need to extract the input parameters of the conflict detection algorithm. The work of predicting position and speed information of the aerial vehicles in the future can make the conflict detection and the collision avoidance preparation in advance, which can further improve the safety of the future denser air traffic. Before giving the definition of the input parameters, we first define the position vector \mathbf{w} , velocity \mathbf{v} , and velocity vector \mathbf{s} as follows:

$$\mathbf{w} = [w_1, w_2, w_3] \quad (1)$$

$$\mathbf{v} = [v_1, v_2, v_3] \quad (2)$$

$$\mathbf{s} = [v_g, v_s, \theta] \quad (3)$$

where w_1, w_2, w_3 are the longitude, latitude, and altitude of the aerial vehicles, respectively. v_1, v_2, v_3 are the component velocities of the aerial vehicles on the X-axis, Y-axis and Z-axis, respectively. v_g, v_s, θ are the ground speed, vertical speed, and heading angle of the aerial vehicles, respectively. Hence, the input parameters of the conflict detection algorithm can be defined as the vector \mathbf{x} , namely:

$$\mathbf{x} = [\mathbf{w}, \mathbf{s}] \quad (4)$$

where \mathbf{w} and \mathbf{s} are the position vector and velocity vector of the aircraft at a certain time.

As it is known, artificial intelligence (AI) plays an important role in signal processing, and deep learning is the fastest growing branch of AI [35]–[37]. The deep learning is playing

a significant part in many fields such as computer vision, natural language recognition, edge computing, and wireless communications [38]–[42]. Therefore, in this paper, we aim to apply deep learning to conflict prediction algorithm.

The prediction model in this paper can be regarded as a regression model. The data at time t is the input of the neural network, and the predicted data at the next time is the output, which can be formulated as follows:

$$\mathbf{I} = y(x_1, x_2, \dots, x_t) \quad (5)$$

where x_t is the input vector at time t , y is the function performed by the layers of the neural network, and \mathbf{I} is the output vector, respectively.

III. PROPOSED GROUPING-BASED CONFLICT DETECTION ALGORITHM

A. Acquisition of Wide-Area Surveillance Data

By connecting an ADS-B receiver to a personal computer, ADS-B messages within a specific area can be obtained. The distributed ADS-B surveillance station can work in a cooperative manner to facilitate a wide-area conflict detection. The ADS-B messages mainly contain 6 kinds of information, which can be expressed as:

$$\text{message} = [w_1, w_2, w_3, v_g, \theta, v_s] \quad (6)$$

where $w_1, w_2, w_3, v_g, \theta, v_s$ denote the longitude, latitude, altitude, ground speed, heading angle, and vertical speed of the aerial vehicles, respectively.

In order to obtain the required wide-area surveillance dataset, the ADS-B messages can be preprocessed as follows.

Data cleaning: Because the ADS-B messages is obtained by the distributed surveillance stations, and contain flight status information of multiple aerial vehicles at different time, we need to filter the ADS-B messages according to time, and divide the aerial vehicles at different regions and moments into different groups. In addition, we need to remove duplicate data which are introduced by multiple factors [43].

Data conversion: Because the latitude and longitude information contained in the ADS-B messages cannot be used directly in the proposed algorithm, we adopt the World Geodetic System-1984 Coordinate System (WGS-84 coordinate system), and convert the latitude and longitude from the geographic coordinate to the WGS-84, which is written as

$$[X, Y] = f[w_1, w_2] \quad (7)$$

$$Z = w_3 \quad (8)$$

where f is the conversion function from the geographic coordinate to the projected coordinate, and X, Y, Z are the coordinates of the aerial vehicles in the WGS-84 frame. In addition, the proposed algorithm maps the sub-velocities and position coordinates on the X, Y and Z axes to the time axis. Therefore, the ground speed needs to be decomposed:

$$v_x = v_g * \cos(\theta) \quad (9)$$

$$v_y = v_g * \sin(\theta) \quad (10)$$

$$v_z = v_s \quad (11)$$

where v_x, v_y, v_z are the partial speed of the aerial vehicles on the X, Y, and Z coordinate axes, respectively. After data pre-processing, the ADS-B messages can be standardized.

B. The Idea of Aerial Vehicles Grouping

If two aerial vehicles are far away, the probability of conflict between the two vehicles is very low. Therefore, conflict detection in this scenario is meaningless, and will reduce the efficiency of the algorithm. This problem motivates us to divide the entire space into different regions, and thus the aerial vehicles can be grouped.

First, considering the location of arbitrary two airports P and Q, we construct a rectangular route area as shown in Fig. 2. Then we filter out all the aerial vehicles in the rectangular route area, and build a small rectangle area P1 at the bottom of the large rectangular area, and areas P2, P3, P4 are sequentially built along the boundary of the large rectangle.

Notice that the grouping method will make the next small rectangle overlap with the previous small rectangle. The overlap areas are denoted as Q1, Q2, and Q3 in Fig. 2 (the shaded parts). In this way, the aerial vehicles at the edges of the small rectangles will be detected without omission.

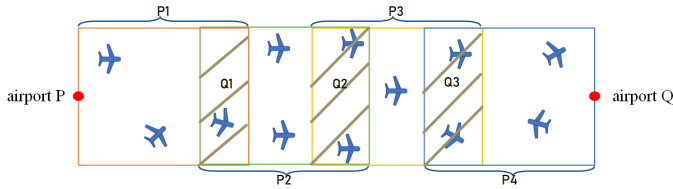


Fig. 2. The overall aerial vehicles are grouped to form several small aerial vehicle groups.

C. Conflict Detection Based on Aerial Vehicles Grouping

We assume that the target aerial vehicle is A and the intruding aerial vehicle is B, and the projected coordinate of A is (X_A, Y_A, Z_A) , and the velocity is (V_{xA}, V_{yA}, V_{zA}) . The projected coordinate of B is (X_B, Y_B, Z_B) , and the velocity is (V_{xB}, V_{yB}, V_{zB}) . Assuming a threshold u , the conflict between A and B can be understood as the distance between them is less than u , hence there is a conflict. Specifically, the judgement of the conflict between A and B are based on certain conditions, namely, there exists a certain area in the route that occurs conflicts on the X, Y, and Z axes at the same time [22], which is expressed as

$$|X_A - X_B| < Th_a \quad (12)$$

$$|Y_A - Y_B| < Th_b \quad (13)$$

$$|Z_A - Z_B| < Th_c \quad (14)$$

where $X_A, X_B, Y_A, Y_B, Z_A, Z_B$ represent the distance coordinates (in kilometers) on the X, Y, and Z axes, respectively. Th_a, Th_b, Th_c represent the threshold distance (in kilometers).

By mapping the conflict area on the coordinate axis to the time axis, the above three formulas are converted into

conflict time periods $[t_{X1}, t_{X2}], [t_{Y1}, t_{Y2}]$ and $[t_{Z1}, t_{Z2}]$. The existence of a conflict is determined by judging whether there is an intersection between the three conflicting time periods. Since the detection algorithms for the X, Y, and Z axis directions are similar, the X axis is used as an example to illustrate the aerial vehicle route conflict detection algorithm, and the direction of the speed is the positive direction of the X axis.

When $X_A > X_B, V_{xA} > V_{xB}$ or $X_A < X_B, V_{xA} < V_{xB}$, the distance between the two aerial vehicles on the X axis will increase.

When $X_A > X_B, V_{xA} < V_{xB}$ or $X_A < X_B, V_{xA} > V_{xB}$, the distance between the two aerial vehicles on the X axis will decrease.

In general, when $(X_A - X_B)(V_{xA} - V_{xB}) > 0$, the distance between the two aerial vehicles on the X axis will increase; when $(X_A - X_B)(V_{xA} - V_{xB}) < 0$, the distance will decrease. Otherwise, the distance will not change.

The following 5 cases can be obtained [22]:

Case 1: If $(X_A - X_B)(V_{xA} - V_{xB}) \geq 0, |X_A - X_B| \geq Th_a$, it indicates there is no conflict.

Case 2: If $(X_A - X_B)(V_{xA} - V_{xB}) = 0, |X_A - X_B| < Th_a$, it indicates a conflict, and the conflict period is $[t_{X1}, t_{X2}] = [0, +\infty]$.

Case 3: If $(X_A - X_B)(V_{xA} - V_{xB}) > 0, |X_A - X_B| < Th_a$, it indicates a conflict, and the conflict period is $[t_{X1}, t_{X2}] = [0, (Th_a - |X_A - X_B|)/|V_{xA} - V_{xB}|]$.

Case 4: If $(X_A - X_B)(V_{xA} - V_{xB}) < 0, |X_A - X_B| < Th_a$, it indicates a conflict, and the conflict period is $[t_{X1}, t_{X2}] = [0, (Th_a + |X_A - X_B|)/|V_{xA} - V_{xB}|]$.

Case 5: If $(X_A - X_B)(V_{xA} - V_{xB}) < 0, |X_A - X_B| \geq Th_a$, it indicates a conflict, and the conflict period is $[t_{X1}, t_{X2}] = [(Th_a - |X_A - X_B|)/|V_{xA} - V_{xB}|, (Th_a + |X_A - X_B|)/|V_{xA} - V_{xB}|]$.

The above cases show the conflict situations between the two aerial vehicles in the X-axis direction. Similarly, the conflict situations in the Y-axis and Z-axis directions and the conflict time periods can be obtained. The part outside the virtual box in Fig. 3 shows the flowchart of the conflict detection algorithm between two aerial vehicles in the protected area.

If there is a conflict in the protection airspace zone, it is necessary to detect the conflict in the collision avoidance zone [22] which is set as

$$Th_a^2 < \left(\frac{(V_{xA} - V_{xB})(t_1 + t_2)}{2} + X_A - X_B \right)^2 + \left(\frac{(V_{yA} - V_{yB})(t_1 + t_2)}{2} + Y_A - Y_B \right)^2 \quad (15)$$

If the above formula does not hold, it indicates that there is a conflict between the invading aerial vehicle and the target aerial vehicle. Hence, all the conflict cases have been discussed.

IV. PROPOSED LSTM-BASED CONFLICT PREDICTION METHOD

Recurrent neural network (RNN) is one of the most important branches of deep learning [44]–[46]. The RNNs can

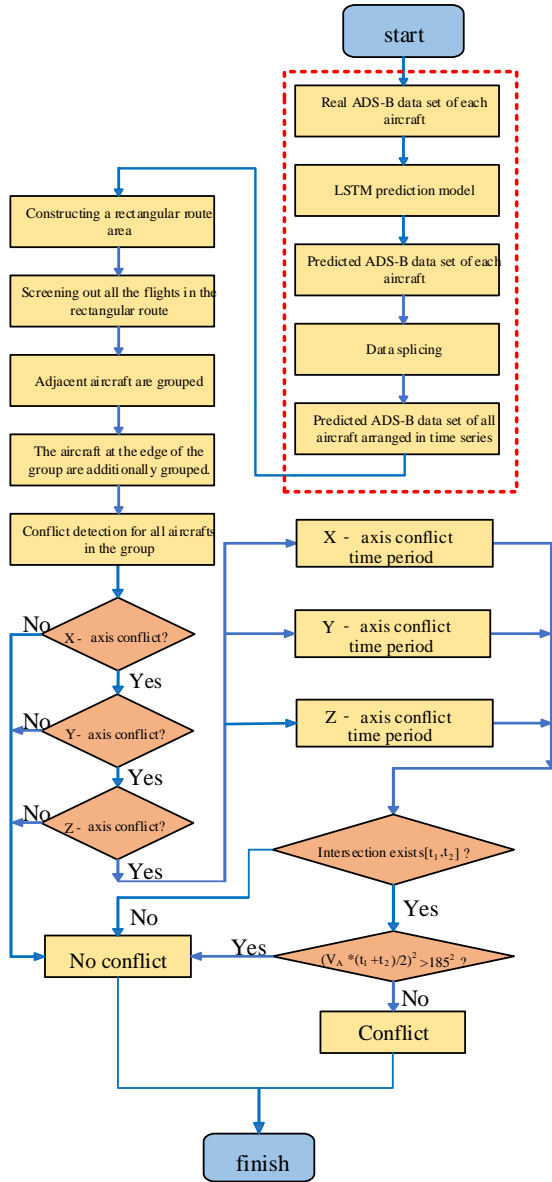


Fig. 3. Flowchart of the proposed conflict prediction algorithm based on trajectory prediction.

deal with sequence processing, and have been widely used in speech recognition, natural language processing, and other fields. The back-propagation through time (BPTT) algorithm is a commonly used method for training the RNNs [45]. The idea is to continuously find a better point along the direction of the negative gradient, and the parameters are updated periodically until convergence.

The problem of gradient disappearance can easily occur when using the BPTT, which is particularly serious when the sequence is relatively long. Therefore, a special case of the RNN, namely LSTM, can be adopted [47]. The LSTM introduces the concept of cell states, and uses three gates named input gate, forget gate, and output gate to maintain and control information passing and parameter update [48], [49]. In this paper, we utilize an architecture that combines the LSTM with fully-connected layers [50], as shown in Fig.

4. In Fig. 4, X and Y represent input and output, respectively, where the subscripts $t, t+1, \dots, t+N-1$ and $t+N, t+N-1, \dots, t+2N-1$ represent N times (the sampling interval is 1 second), respectively.

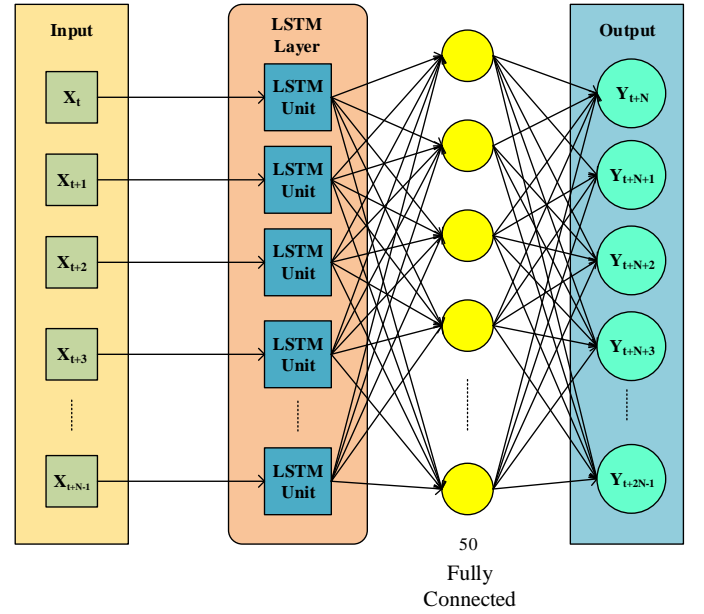


Fig. 4. Trajectory prediction model using LSTM and fully-connected layers.

Algorithm 1 The trajectory prediction algorithm of LSTM-based.

- Input:** Real ADS-B data sets of aerial vehicles $D = \{d_1, d_2, \dots, d_N\}$, time step t , lag time τ ;
Output: Predicted ADS-B data sets of aerial vehicles \hat{D} ;
- 1: Standardize the data sets;
 - 2: Transform the standardized time series data sets D into the supervised learning data sets D_{SL} ;
 - 3: **for** i in $1, 2, 3, \dots, N - t$ **do**
 - 4: $D'_{input} = \{d_i, d_{i+1}, \dots, d_{i+t-1}\}$;
 - 5: $D'_{output} = d_{i+t-1+\tau}$;
 - 6: $A_i = \text{data_splicing}(D'_{input}, D'_{output})$;
 - 7: **end for**
 - 8: $D_{SL} = \text{ensemble}(A_1, A_2, \dots, A_{N-t})$;
 - 9: Design the LSTM network, then train and test the supervised learning data sets D_{SL} ;
 - 10: Adjust the network parameters, select the LSTM network with the best performance, and get the corresponding predicted data sets \hat{D} with the best performance;
 - 11: **return** \hat{D} .

As explained in Section III, ADS-B messages have been preprocessed to form a dataset, and the input sequences can meet the requirement proposed by the LSTM-based neural network after data cleaning and conversion. The grouped longitude, latitude, altitude, ground speed, vertical speed, and heading angle information of multiple consecutive moments in the dataset are sequentially put into the network for training and testing. Through **Algorithm 1**, we obtain the trajectory information of aerial vehicles at the future time. As a result,

the future flight states predicted by the network can be fed into the conflict detection algorithm. Hence, we can predict the conflict situation for the future minutes, and we term the revised algorithm as LSTM-based conflict prediction method. After obtaining the predicted trajectory of each aerial vehicle, we arrange the predicted trajectories in time sequence through data splicing, and finally input the processed dataset into the grouping-based aerial vehicle conflict detection algorithm, as shown in Fig. 3.

V. PROPOSED CNN-BASED CONFLICT PREDICTION METHOD

Convolutional Neural Networks (CNN) is a type of feedforward neural networks that includes convolution calculations and has a deep structure [51]–[53]. In addition, CNN can also perform time series prediction tasks [54]. Hence, a CNN-based method can be also adopted for the trajectory prediction task as a comparison in this paper.

The CNN-based trajectory prediction method is generally similar to the LSTM-based method. The compared structure of the CNN-based method is shown in Fig. 5. The execution process of the compared CNN algorithm is shown in **Algorithm 2**. ADS-B messages of each aerial vehicle can be obtained through the local ADS-B receiver, and the preprocessed and standardized datasets are fed into the CNN network. As shown in Fig.5, the datasets successively go through the convolution operation of the convolutional layer, the maximum pooling of the pooling layer, and the dimensional transformation of the fully-connected layer [55]–[57]. Hence, the predicted trajectories of aerial vehicles can be obtained and finally fed into the grouping-based aerial vehicle conflict detection algorithm.

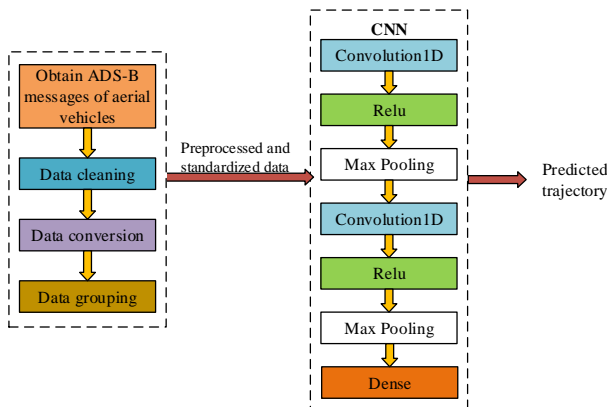


Fig. 5. Structure of the CNN-based network.

VI. PROPOSED LS-BASED CONFLICT PREDICTION METHOD

In a short period, it can be assumed that the trajectory of the aerial vehicles changes linearly, and least square (LS) method is a typical linear regression model. Therefore, this paper also adopts the LS-based method for the trajectory prediction task, which is convenient to make a comparison with the LSTM-based and CNN-based schemes. The principle of the LS-based

Algorithm 2 The trajectory prediction algorithm of CNN-based.

Input: Real ADS-B data sets of aerial vehicles D ;

Output: Predicted ADS-B data sets of aerial vehicles \hat{D} ;

- 1: Divide randomly the mixed samples D into training samples and validation samples by 7 : 3;
- 2: Construct CNN network according to Fig. 5 and choose adaptive moment estimation (Adam) and mean absolute error (MAE) as optimizer and loss function respectively;
- 3: Train CNN to minimize loss function;
- 4: Adjust the network parameters, select the CNN network with the best performance, and get the corresponding predicted data sets \hat{D} with the best performance;
- 5: **return** \hat{D} .

method is to construct a suitable estimator so that the residual sum of squares (RSS) is minimized [58], as shown below:

$$\left\{ \sum_{i=1}^N r_i^2 \right\}_{\min} = \left\{ \sum_{i=1}^N [f(x_i; \alpha_1, \alpha_2, \dots, \alpha_n) - y_i]^2 \right\}_{\min} \quad (16)$$

where $\sum_{i=1}^N r_i^2$ represents RSS, $\alpha_1, \alpha_2, \dots, \alpha_n$ represent n unknown estimators, $f(x_i; \alpha_1, \alpha_2, \dots, \alpha_n)$ is the predicted value of x_1, x_2, \dots, x_N at N different points, and y_1, y_2, \dots, y_N are the actual values of x_1, x_2, \dots, x_N at N different points.

Algorithm 3 The trajectory prediction algorithm of LS-based.

Input: Real ADS-B data sets of aerial vehicles $D = \{d_1, d_2, \dots, d_N\}$, time step t , lag time τ ;

Output: Predicted ADS-B data sets of aerial vehicles \hat{D} ;

- 1: **for** i in 1, 2, 3, ..., $N - t$ **do**
- 2: $data = \{d_i, d_{i+1}, \dots, d_{i+t-1}\}$;
- 3: $time = \{i, i + 1, \dots, i + t - 1\}$;
- 4: The curve equation $data = f(time)$ is obtained by data fitting;
- 5: $\hat{data}_{i+t-1+\tau} = f(i + t - 1 + \tau)$;
- 6: **end for**
- 7: $\hat{D} = \text{ensemble}(\hat{data}_{t+\tau}, \hat{data}_{t+\tau+1}, \dots, \hat{data}_{N-1+\tau})$;
- 8: **return** \hat{D} .

The LS-based method is effective in curve fitting problems. The fitted curve obtained by the LS method can reflect the overall distribution of the data without causing large local fluctuations, and can also reflect the characteristics of the approximated function. The execution process of the proposed LS algorithm is shown in **Algorithm 3**. Unlike the LSTM-based and the CNN-based methods, the LS-based method proposed in this paper executes segmented prediction, namely, it periodically refits a curve with the previous N seconds data to predict the next second data. For example, we use the actual data at time 0 to time t to fit the curve; and according to the fitted curve, we can predict the data at time $t + 1$; then we use the actual data at time 1 to time $t + 1$ to predict the data at time $t + 2$ based on the fitted curve, and so on. Finally, the predicted data are compared with the actual data to analyze the performance.

VII. EXPERIMENTAL RESULTS

In this section, performance of the group-based conflict detection algorithm is evaluated. The trajectory prediction algorithms of LSTM-based, CNN-based and LS-based methods are trained, respectively. Then the three aerial vehicles trajectory prediction models are compared in terms of prediction accuracy. We finally discuss the impact of the trajectory prediction accuracy on the conflict prediction.

A. Results of Route Conflict Detection Algorithm Based on Grouping

In this experiment, since the CAZ is a cylindrical collision avoidance area stipulated by ATC (see Fig. 1), we set its horizontal radius as 9.26 km and its height as 366 meters. Accordingly, we set $Th_a = 9.26$ km, $Th_b = 9.26$ km, $Th_c = 0.366$ km in (12)~(14). Fig. 6 shows a deployment of the ADS-B-based ground station. The ADS-B omnidirectional antenna is directly connected to the ground monitoring station, and continuously receives ADS-B messages from flight within a diameter of 300 kilometers, which are saved to our computer to facilitate our data processing.

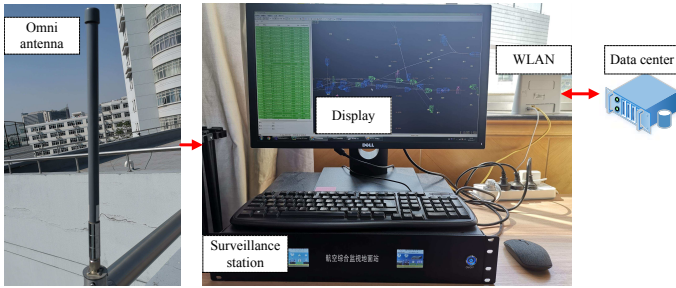


Fig. 6. Deployment of the ADS-B-based ground station.

In this experiment, we adopted our ADS-B platform to obtain all aerial vehicles surveillance information on July 10 of the year 2019. Using the surveillance information, we conducted the conflict detection experiment on 510,000 flight items from 12:00 pm to 1:00 am. Fig. 7 shows the route between Liaocheng and Tangshan at 00:00:10 on July 10. The blue aircrafts represent the conflict-free aerial vehicles. The red aircrafts represent aerial vehicles with conflict warning.

By using the grouping-based conflict detection algorithm, we conducted a conflict detection experiment on the 510,000 items of ADS-B messages from 12:00 pm to 1:00 am. As can be seen from Fig. 7, our experiment based on real-world ADS-B messages can realize the detection and visualization of aerial vehicles conflicts. Since the entire route area is divided into small areas, the burden of calculation can be significantly reduced, and thus the aerial vehicle conflicts can be detected and warned in a real-time manner. Fig. 8 shows the percentage of aerial vehicles conflicts in the total number of aerial vehicles. It is calculated that the average conflict probability in every second is approximately 0.383%.

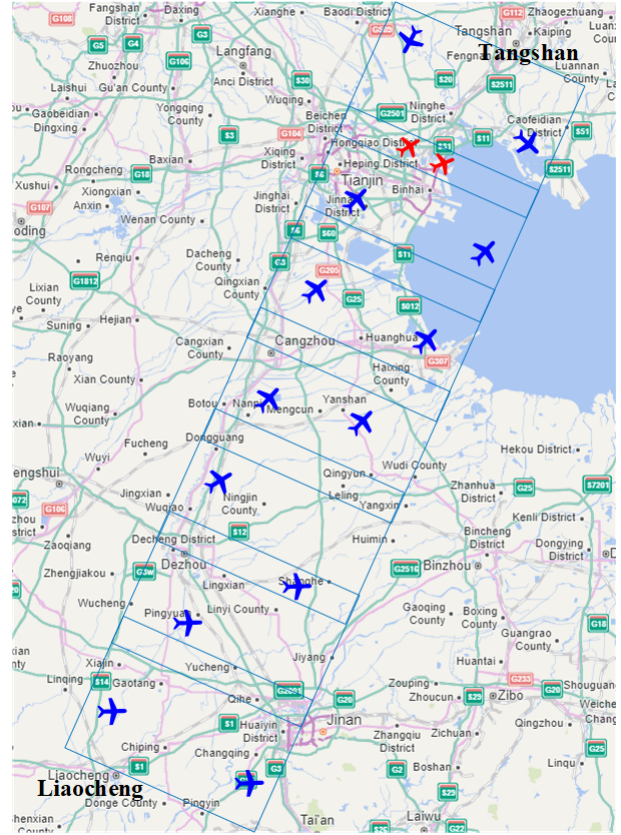


Fig. 7. Visualization of route conflict from Liaocheng city to Tangshan city.

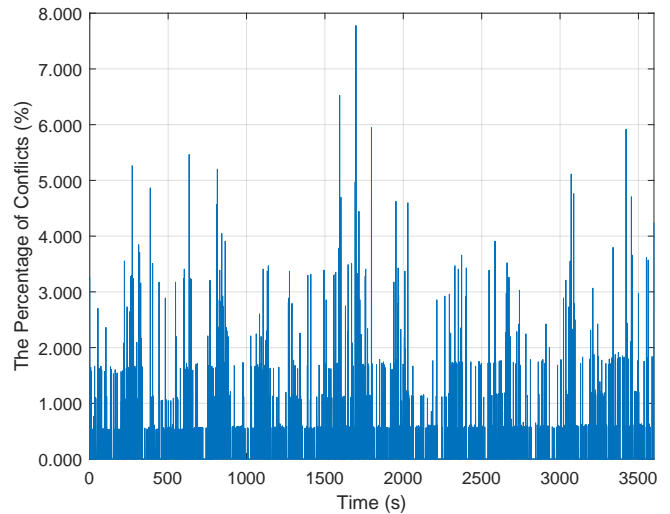


Fig. 8. Aerial vehicle conflicts per second as a percentage of the total number of aerial vehicles.

B. Results of the LSTM-based, CNN-based and LS-based Predictors

Before training the predictor based on the LSTM model, the dataset is divided into multiple datasets according to longitude, latitude, altitude, ground speed, vertical speed, and heading angle. Preprocess of the dataset before training is conducted as follows. Since we use the first n seconds of data to predict the data at t seconds ($t > n$), the data in a period of n seconds and the data after t seconds are bundled into a group. In order to ensure the fairness of the experiment, the input sequences of the CNN-based and the LS-based methods are the same as that of the LSTM-based scheme, including the same length and prediction conditions.

1) *Short-term Prediction*: In the short-term prediction experiment, we use the flight information of the first 16 seconds to predict the flight information of the next second. First, the items of the dataset are bundled into groups. Then the processed dataset is divided into training set and testing set. Finally, the longitude, latitude, altitude, ground speed, vertical speed, and heading angle data are fed into the LSTM-based model for training and testing, respectively. In this paper, we use root mean squared error (RMSE) to evaluate the prediction performance, which is formulated as follows:

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^N (y_t - \hat{y}_t)^2} \quad (17)$$

where N is the total number of samples; y_t is the true values; \hat{y}_t is the predicted values. Results of the LSTM-based, CNN-based and LS-based short-term prediction are depicted in Fig. 9. The light blue line, green line, and red line represent the predicted values of the LS-based, CNN-based, and LSTM-based methods, respectively. The dark blue line represents the true values.

2) *Long-term Prediction*: Because the LSTM units are good at dealing with long-term memory, we evaluate the performance of the LSTM-based scheme in terms of making long-term prediction [47]. In this experiment, the flight information of the aerial vehicles in a period of 16 seconds (e.g., from the 10th second to the 25th second) is used to predict the flight information after 40 seconds (e.g., the 65th second). We term this task as mid-term prediction. In addition, in order to enable the conflict alert can be triggered several minutes in advance, we evaluate minute-level trajectory predictions of aerial vehicles. In this section, the flight information of aerial vehicles in a period of 60 seconds (e.g., from the 1st second to the 60th second) is used to predict the flight information after 60 seconds (e.g., the 120th second). We term this task as long-term prediction. Experiments are also conducted by the CNN-based and LS-based methods. Results of the LSTM-based, CNN-based and LS-based mid-term predictions are shown in Fig. 10. And results of the long-term prediction are shown in Fig. 11.

3) *Analysis*: RMSE scores of the three different predictors are listed in Table I. It can be seen that the deep-learning-based prediction models (i.e., LSTM, CNN) show better prediction performance than the utilized traditional machine learning model (i.e., LS). Specifically, the scores of the LSTM-based

predictor are generally smaller than the CNN-based and LS-based predictors. However, in order to reach convergence point, the LSTM-based model requires more training time (6,000 iterations), while the CNN-based model requires 1,000 iterations and the LS-based model only takes a few seconds. It can be concluded that the LSTM-based predictor obtains better accuracy at the expense of adequate training.

In detail, the short-term prediction experiment shows that the LSTM-based, CNN-based and LS-based methods can predict the trajectories of the aerial vehicles with relatively low errors. The RMSE scores for the six metrics have differences, however, the prediction performance of LSTM-based is the best of the three methods. On the other hand, compared with the short-term prediction, the mid-term prediction experiment shows that the prediction errors increased. In addition, in terms of the long-term prediction tasks, when selected prediction time steps increase (from 40 seconds to 60 seconds), the three prediction models (especially the LSTM-based model) make their prediction errors generally lower than the mid-term prediction tasks by increasing the length of their input sequences (from 16 seconds to 60 seconds). Meanwhile, the prediction errors of the CNN-based and LS-based methods are much larger than that of the LSTM-based model, which demonstrates the effectiveness of LSTM units when dealing with the long-term prediction tasks.

C. Conflict detection of aerial vehicles based on trajectory prediction

In this section, we use LSTM to conduct conflict detection experiments on the predicted values of aerial vehicles trajectories. The datasets we use here are also the ADS-B data we collected from 12:00 pm to 1:00 am on July 10, 2019. We used the trajectory information of each aerial vehicle every 16 seconds to predict the trajectory information of the next second. Finally, the predicted aerial vehicle trajectory information from 12:00 pm to 1:00 am formed approximately 500,000 items. Using the proposed grouping-based conflict detection algorithm, we conducted conflict detection experiments on the 500,000 items. The experimental results are as depicted in Fig. 12~13.

Fig. 12 shows the percentage of conflicting aerial vehicles in the total number of aerial vehicles. The calculation results show that by using the trajectory prediction method, the average probability of detected conflicts per second is about 0.290%. Fig. 13 compares the difference between the number of detected conflicts and the number of predicted conflicts. Compared with the average conflict probability of 0.383% obtained by using the actual trajectories, the average conflict probability based on the predicted trajectories is slightly lower. It is inferred that the predicted trajectories could be more ideal, while the real trajectories have sudden variations. We also calculated the RMSE score for evaluating the defect when using the predicted trajectories, and the RMSE score was 0.8610. In fact, there could be an error in the trajectory information obtained from ADS-B receiver, but the error can be usually about 100 meters [24], which has little impact on the trajectory prediction tasks. If transmission process of

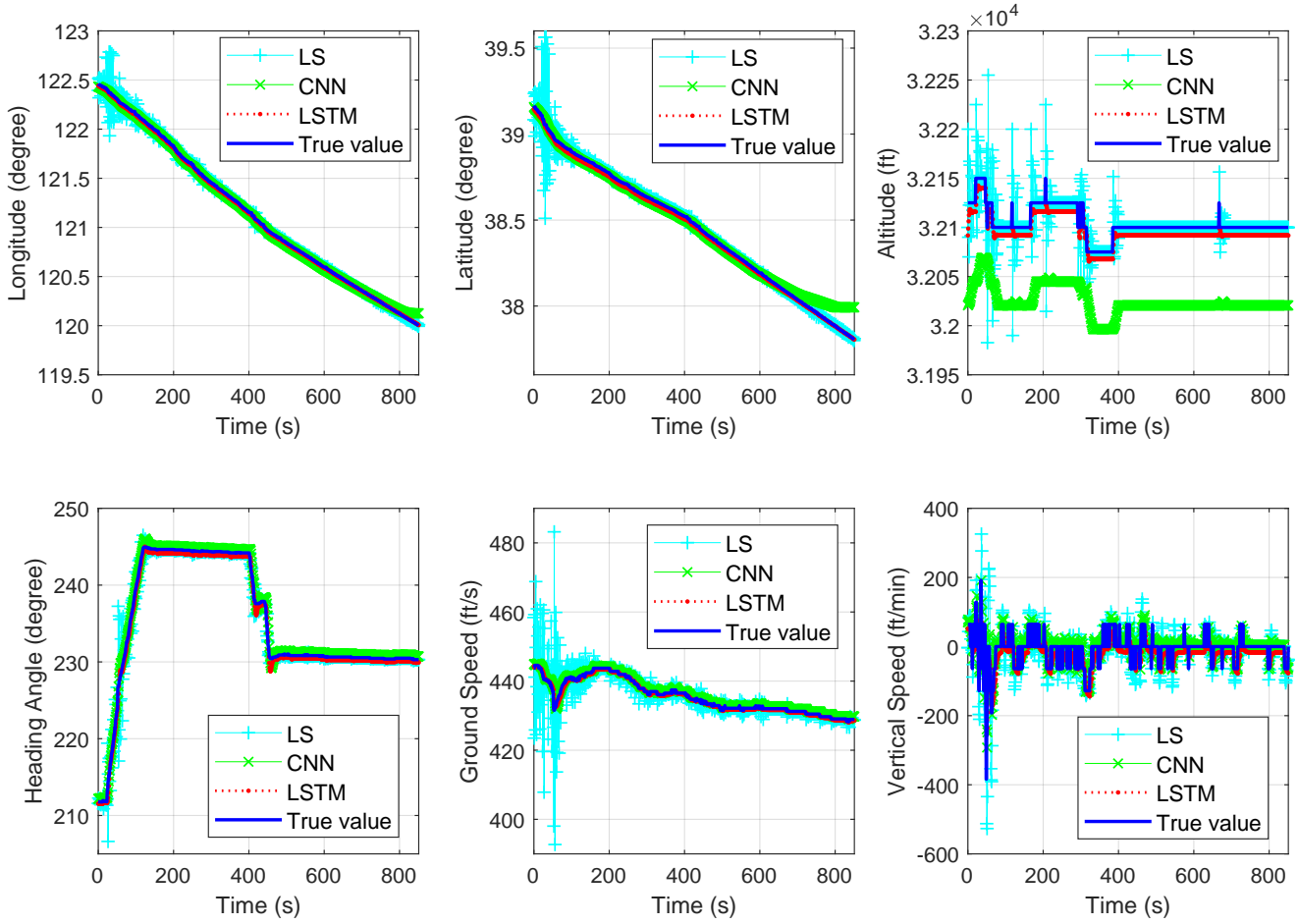


Fig. 9. Predicted short-term trajectories by using the LSTM-based, CNN-based and LS-based predictors.

TABLE I
PERFORMANCE COMPARISON OF THE LSTM-BASED, CNN-BASED AND LS-BASED SHORT-TERM, MID-TERM, LONG-TERM PREDICTION TASKS

	The LSTM-based short-term prediction error	The LSTM-based mid-term prediction error	The LSTM-based long-term prediction error	The CNN-based short-term prediction error	The CNN-based mid-term prediction error	The CNN-based long-term prediction error	The LS-based short-term prediction error	The LS-based mid-term prediction error	The LS-based long-term prediction error
Longitude (degree)	0.011	0.02	0.028	0.0247	0.045	0.076	0.054	0.339	0.286
Latitude (degree)	0.013	0.073	0.031	0.0468	0.078	0.126	0.058	0.468	0.408
Altitude (ft)	9.338	66.273	28.626	79.6723	32.526	138.706	17.357	718.344	665.836
Ground Speed (ft/s)	0.529	2.582	2.572	0.9058	2.979	2.797	4.511	4.732	4.747
Vertical Speed (ft/min)	39.515	45.329	44.850	37.1091	55.249	45.453	52.028	201.841	111.822
Heading Angle (degree)	0.491	4.704	6.295	0.6037	5.025	6.596	1.076	4.710	7.552

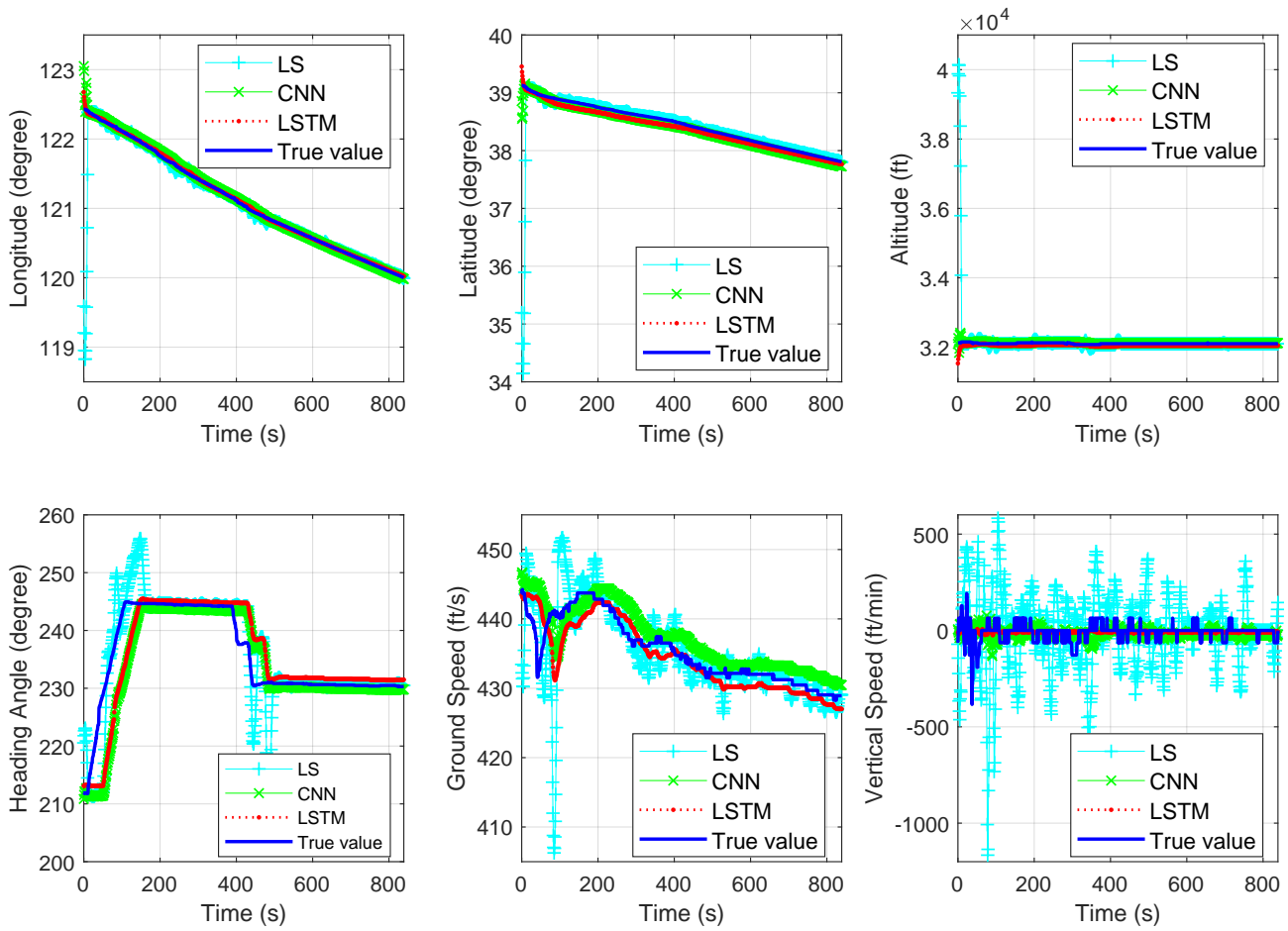


Fig. 10. Predicted mid-term trajectories by using the LSTM-based, CNN-based and LS-based predictors.

the error is further considered, the RMSE score calculated by the conflict detection method based on the trajectory prediction could be increased from 0.8610 to about 1 at most, which is still within the error range allowed by the conflict detection method. The result means that the predicted number of conflicts per second differs from the actual number by less than one aerial vehicle. Hence, the proposed method makes it is possible to detect whether there would be conflicts in the future seconds.

VIII. CONCLUSION

This paper proposes a conflict detection algorithm based on an aerial vehicles grouping strategy. In order to further improve the timeliness of conflict detection, we use the LSTM-based, the CNN-based and the LS-based methods to predict the trajectory of aerial vehicles, respectively. The trajectory prediction experiments are divided into short-term, mid-term, and long-term predictions. The results show that the short-term predictions can be more accurate than the mid-term and long-term predictions. In addition, the LSTM-based model generally outperforms the CNN-based and the LS-based methods in three prediction tasks, especially when predicting the mid-term and long-term trajectory of aerial vehicles. However, the problem is that for the mid-term and long-term predictions, the performance degradation will

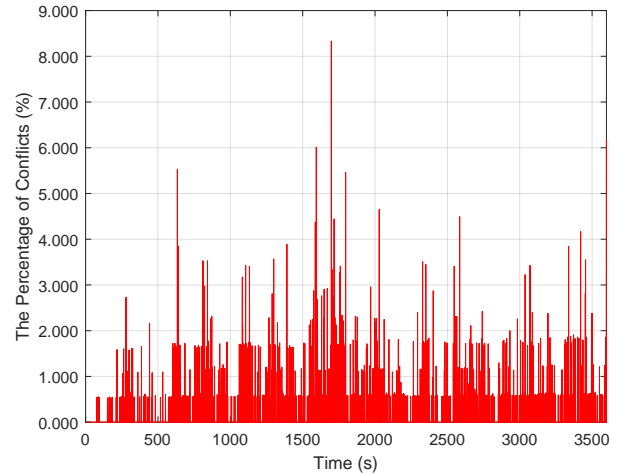


Fig. 12. Predicted aerial vehicle conflicts per second as a percentage of the total number of aerial vehicles based on trajectory prediction.

affect the performance of the conflict detection algorithm. Therefore, in order to overcome this problem, our future work will focus on designing more reliable neural networks and integrating more effective information into the training dataset. Finally, we evaluate influence of the trajectory prediction on the conflict detection algorithm. The experimental results

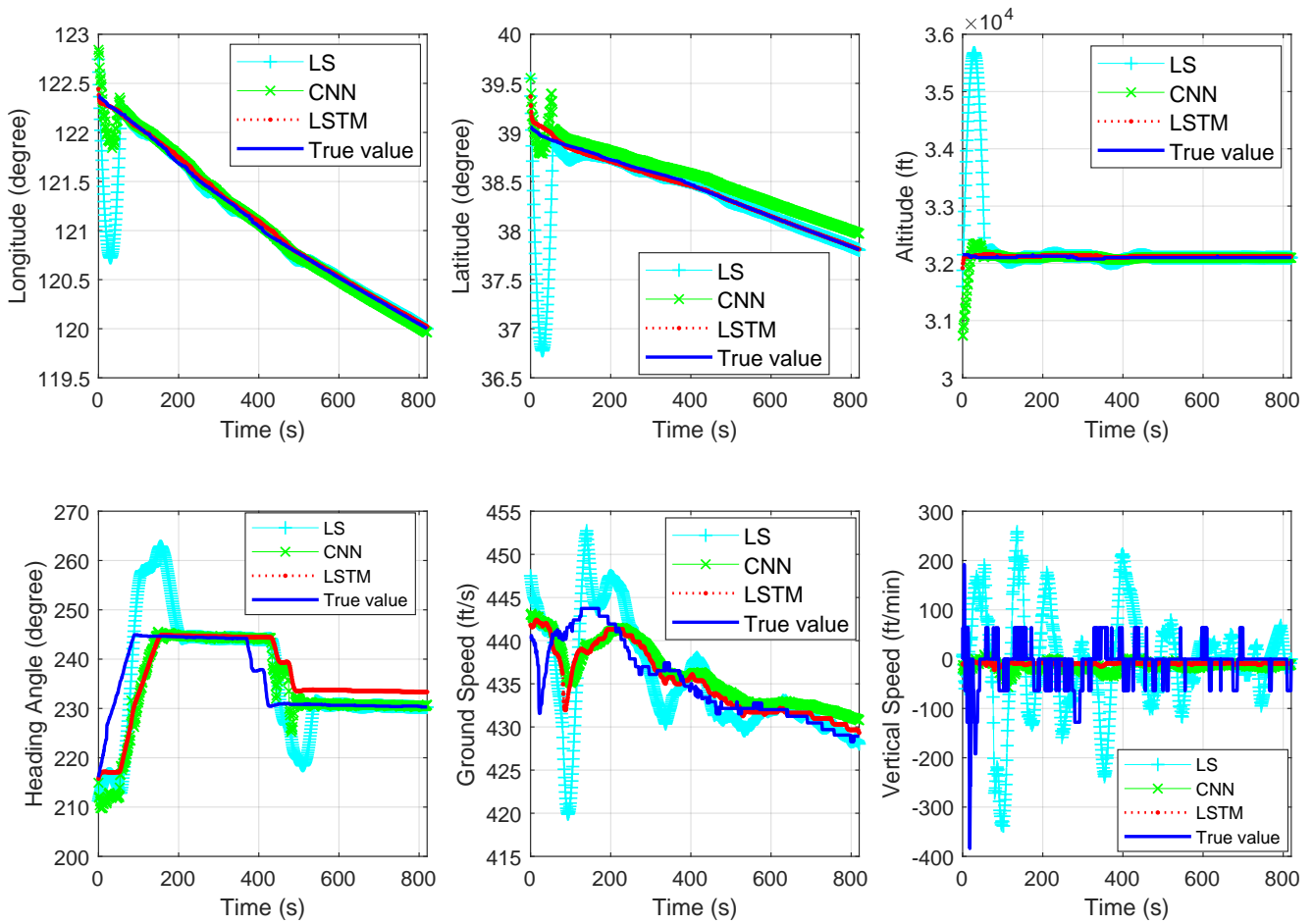


Fig. 11. Predicted long-term trajectories by using the LSTM-based, CNN-based and LS-based predictors.

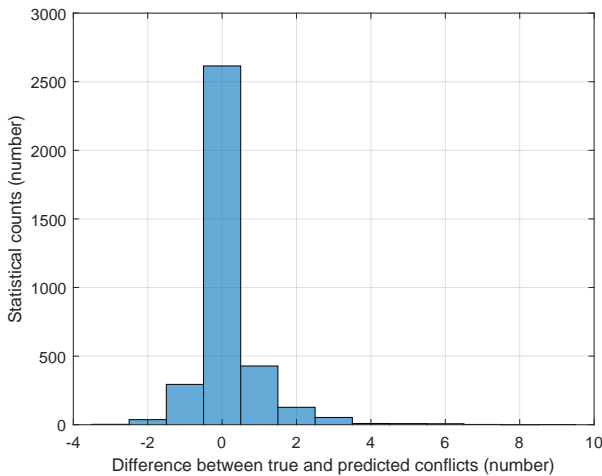


Fig. 13. Statistical difference between the actual number of conflicts and the predicted number of conflicts, and the RMSE score is 0.8610.

demonstrate the effectiveness of integrating the grouping strategy, the trajectory detection based on machine learning, and the conflict detection.

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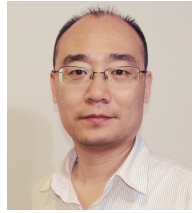
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