Recurrent LSTM-based UAV Trajectory Prediction with ADS-B Information

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Abstract—Recently, unmanned aerial vehicles (UAVs) are gathering increasing attentions from both the academia and industry. The ever-growing number of UAVs brings challenges for air traffic control (ATC), and thus trajectory prediction plays an important role in ATC, especially for avoiding collisions among UAVs. However, the dynamic flight of UAVs aggravates the complexity of trajectory prediction. Different with civil aviation aircrafts, the most intractable difficulty for UAV trajectory prediction depends on acquiring effective location information. Fortunately, the automatic dependent surveillance-broadcast (ADS-B) is an effective technique to help obtain positioning information. It is widely used in the civil aviation aircraft, due to its high data update frequency and low cost of corresponding ground stations construction. Hence, in this work, we consider leveraging ADS-B to help UAV trajectory prediction. However, with the ADS-B information for a UAV, it still lacks efficient mechanism to predict the UAV trajectory. It is noted that the recurrent neural network (RNN) is available for the UAV trajectory prediction, in which the long short-term memory (LSTM) is specialized in dealing with the time-series data. As above, in this work, we design a system of UAV trajectory prediction with the ADS-B information, and propose the recurrent LSTM (RLSTM) based algorithm to achieve the accurate prediction. Finally, extensive simulations are conducted by Python to evaluate the proposed algorithms, and the results show that the average trajectory prediction error is satisfied, which is in line with expectations.

Index Terms—UA V, trajectory prediction, ADS-B, LSTM

I. INTRODUCTION

The unmanned aerial vehicles (UAVs) are gathering attentions from both the academia and industry, and are widely accepted in various applications [1] [2] [3]. However, with the increment of UAVs, the low-altitude airspace becomes extremely crowded. Therefore, it is imperative to deal with collisions among UAVs [4]. Besides, UAVs work in accordance with their pre-set flight routes, which means that they are unable to achieve real-time surveillance. Thus, it is intractable for UAVs to deal with emergencies such as collision avoidance with other UAVs or obstacles in time [5]. Consequently, an effective surveillance system for UAVs is essential to ensure flight safety. The primary issue for surveillance is acquiring the positioning information. For instance, radar is a candidate for detecting the UAV position [6]. However, there exist a couple of drawbacks by employing radar. In detail, UAVs are too small to be detected by the radar, especially in the bad weather [7]. Besides, it is prohibitive or even impossible to build sufficient radar stations due to the economic and geographical factors. Compared with the radar, automatic dependent surveillance-broadcast (ADS-B) is a competitive technique for the future air traffic control (ATC) [8], and it is widely applied in the field of civil aviation. ADS-B consists of two systems, ADS-B IN and ADS-B OUT, which are responsible for receiving and broadcasting, respectively. ADS-B helps avoid various flight occasions of UAVs. For instance, in [9], a case of collision avoidance is provided between UAVs and helicopters. In addition, the trajectory prediction for UAVs is an effective mechanism for surveillance. Based on the data of UAVs, the flight trend can be figured out via predicting the future trajectory, which provides useful information to avoid collisions and supervise the UAV intrusion in the controlled airspace.

The machine learning technique performs well when it meets the data prediction, and it is widely used in the applications related with the UAV [10]. The recurrent neural network (RNN) and long short-term memory (LSTM) specialize in capturing the characteristics of data in the time dimension. In this case, when predicting time series data, the two measures are outstanding [11]. The trajectory prediction for vehicles via machine learning becomes popular in the research area. The UAV trajectory prediction in the airspace is different with ground vehicles and vessels in the ocean. The vehicle trajectory prediction benefits from the orderliness of the road traffic network, which adds strong correlations to the neighbor trajectories. Thus, the trajectory of vehicles is relatively easy to be predicted, e.g., [12] employs the social generative adversarial network to predict the trajectory of automobiles. Due to the free path constraints, the movement of vessels is random, and the prediction is intractable, e.g., in [13], a novel sequence to sequence (seq2seq) model is leveraged to predict the trajectory of vessels, which utilizes the technique of gated recurrent unit (GRU) and LSTM. Different from the two-dimensional movement of vehicles and vessels, UAVs move freely in the airspace, i.e., flying in a three-dimensional space with both vertical and horizontal directions. Hence, it adds
greater uncertainty to the flight process of UAVs and greater difficulty for the prediction of the UAV trajectory. In addition, as for the civil aviation aircraft, it has a long flight distance and a high flight altitude (about 10 kilometers), so the changes of the trajectory directions are not arbitrary and frequent. Besides, due to the heavy body, wind can hardly affect the line of civil aviation aircraft. However, since UAVs are small and employed for special tasks, compared with the civil aviation aircraft, the trajectory of UAVs changes significantly due to the task properties or the influence of wind. The frequent and complex flight trajectories bring significant challenges on predicting the trajectory. Based on the neural relational inference, [14] proposes a framework for the two-dimensional trajectory prediction of UAVs swarm. [15] employs 4 continuous trajectory points to predict future trajectory data after the present time step via deep learning. The authors in [16] point out that, the prediction of the UAV trajectory should consider extra information such as speed information, which is an advantage of applying ADS-B on UAVs.

Therefore, in this paper, the surveillance system of UAVs is proposed to deal with the conflicts detection in the low-altitude airspace and emergency obstacle avoidance. ADS-B is adopted as the data source of positioning information during the flight of UAV, which can figure out the issue of insufficient trajectory data. Then, based on LSTM, we propose the recurrent LSTM (RLSTM) to train and predict the three-dimensional trajectory data for UAVs.

The rest of this paper is organized as follows. The system model and problem formulation are introduced in Section II. Then, the RLSTM based algorithm is presented in Section III. The simulation results are presented in Section IV and finally the conclusions are drawn in Section V.

II. SYSTEM MODEL AND PROBLEM FORMULATION

The ADS-B-based UAVs surveillance system is shown in Fig. 1. The airspace is divided into several sub-airspaces, and each sub-airspace has a corresponding ADS-B IN ground station (GS). The ground stations transmit the received information to the data processing center. The UAV can obtain its location from positioning information. The latitude and longitude information (Lat, Lon) can be acquired from the global positioning system (GPS) receiver via calculating the data transmitted by four GPS satellites. The altitude information Alt is obtained via the onboard pressure altimeter. When the airborne ADS-B OUT system acquires the three dimensional (3D) positioning information, it outputs the data according to a certain time interval. The broadcast trajectory data are transmitted to the data processing center for further monitoring and tracking.

It is assumed that in the sub-airspace g, a set of UAVs \(U_g\) \(\{U_g(1), U_g(2), \ldots, U_g(n)\}\), which contains n UAVs and each UAV in \(U_g\) broadcasts the positioning information according to the pre-set broadcast interval. When UAV \(U_g(i)\) employs ADS-B OUT in the \(t^{th}\) broadcast time step, it requires the positioning data \((\text{Lat}_g(i)_t, \text{Lon}_g(i)_t, \text{Alt}_g(i)_t)\) via the airborne

GPS module and pressure altimeter. It is noted that due to the lightweight and miniaturization of the current GNSS receiver and pressure sensor (such as MPL3115A2 [17]), the accurate positioning for UAVs becomes available. When the positioning data are obtained, the airborne ADS-B OUT system broadcasts the positioning information to the airspace, and the information is received at the corresponding ground station GS1. Since the information transmission has time order, the trajectory of UAV \(U_g(i)\) consists of a series of flight trajectory data. Finally, the positioning information is transmitted to the data processing center for storage, training and prediction.

Trajectory prediction is an effective way to achieve surveillance for UAVs, which can evaluate whether the future flight trend is safe, and help avoid collisions with other UAVs or obstacles. The data processing center employs the historical data of UAV \(U_g(i)\) to predict the future two trajectory points \((\text{Lat}_g(i)_{t+1}, \text{Lon}_g(i)_{t+1}, \text{Alt}_g(i)_{t+1})\) and \((\text{Lat}_g(i)_{t+2}, \text{Lon}_g(i)_{t+2}, \text{Alt}_g(i)_{t+2})\) at the broadcast time step \(t\). The predicted results provide a reference for the regulator to track and monitor UAVs, which guarantees the collision avoidance for all aircrafts in airspace \(g\).

During the process of UAV trajectory prediction, the prediction errors are key indicators for evaluating the performance of different methods. The flight of UAVs involves changes in longitude, latitude, and altitude. Therefore, the prediction errors are divided into \(J_{x_t}, J_{y_t}, J_{z_t}\) and \(J_{3d_t}\), which refer to
the prediction error of \( \text{Lat, Lon, Alt} \) and \( 3d \) at time step \( t \). Besides, it is considered that when the error of longitude and latitude is 1 degree, the error of distance is about 114.1 and 89.9 kilometers, respectively. Thus, the prediction errors are

\[
\begin{align*}
Jx_t &= \text{Lat}_t - \text{Lat}_t, \\
Jy_t &= \text{Lon}_t - \text{Lon}_t, \\
Jz_t &= \text{Alt}_t - \text{Alt}_t,
\end{align*}
\]

and

\[
J3d_t = \sqrt{\frac{Jx_t^2}{114,100} + \frac{Jy_t^2}{89,900} + Jz_t^2}.
\]

In formulas (1)-(4), \( \text{Lat}_t, \text{Lon}_t, \text{Alt}_t \) indicate the prediction of \( \text{Lat}_t, \text{Lon}_t, \text{Alt}_t \) at time step \( t \), respectively.

Since the predict process acquires two future trajectory points, according to formulas (1)-(4), the average prediction errors \( Jx_t, Jy_t, Jz_t \) at time step \( t \) are calculated as follows:

\[
\begin{align*}
\bar{J}_x &= \frac{Jx_{t+1} + Jx_{t+2}}{2}, \\
\bar{J}_y &= \frac{Jy_{t+1} + Jy_{t+2}}{2}, \\
\bar{J}_z &= \frac{Jz_{t+1} + Jz_{t+2}}{2},
\end{align*}
\]

and

\[
J3d_t = \frac{J3d_{t+1} + J3d_{t+2}}{2}.
\]

The trajectory prediction for only once cannot evaluate the performance of different algorithms. Consequently, continuous predictions for UAV \( U(i) \) for \( n \) time steps are more convincing. Therefore, in formulas (9)-(11) we leverage the mean squared error (MSE) \( Jx, Jy \) and \( Jz \) as the average prediction error:

\[
\begin{align*}
\bar{J}_x &= \frac{1}{n} \sum_{i=1}^{2n} Jx_i, \\
\bar{J}_y &= \frac{1}{n} \sum_{i=1}^{2n} Jy_i,
\end{align*}
\]

and

\[
\bar{J}_z = \frac{1}{n} \sum_{i=1}^{2n} Jz_i.
\]

Since the predicted trajectory points may perform different prediction accuracy in different dimensions, i.e., good accuracy prediction and poor altitude prediction. Hence, an accurate mechanism considering various dimensions is required. Based on formulas (9)-(11), we choose the multi-dimensional MSE \( \alpha \) as the loss function, i.e.,

\[
\alpha = \frac{1}{3n} \sum_{i=1}^{2n} (Jx_i^2 + Jy_i^2 + Jz_i^2).
\]

Algorithm 1 RLSTM for UAV trajectory prediction.

**Input:** Training epoch \( e \), training iteration \( k \), training set \( T \), predicted trajectory \( U \), learning rate \( lr \) and the trajectory data received time step \( t \).

**Output:** Predicted trajectory data: \( p_t+1 \) and \( p_t+2 \).

1. **Initialization:** \( e = 2, k = 300, lr = 0.01 \) and \( t = 0 \).
2. **for** \( i = 1 \) to \( e \) **do**
3. **for** \( j = 1 \) to \( k \) **do**
4. Leverage LSTM to train the model with training set \( T \).
5. Update the weights of model.
6. **end for**
7. **end for**
8. **repeat**
9. Receive new trajectory point: \( t = t + 1 \).
10. **while** \( t > 16 \) **do**
11. **for** \( f = 1 \) to \( k \) **do**
12. Leverage LSTM to train the model with data from 1st to \( t \)th.
13. **end for**
14. Leverage continuous data from \( (t - 15) \)th to \( t \)th to predict the next two trajectory points.
15. **return** \( p_t+1 \), \( p_t+2 \).
16. **end while**

17. **until** \( t \) is the last time step of the predicted UAV trajectory.

In order to achieve precise prediction accuracy, \( \alpha \) in formula (12) should be minimized. In Section III, we propose the RLSTM and leverage the gradient back propagation to deal with the minimization problem and predict future trajectory data.

III. ALGORITHM DESIGN

When the ground stations receive the ADS-B data from UAVs, the data are sequently transmitted to the data processing center. Therefore, algorithms specialized in predicting time series data are considered as effective candidates, such as the LSTM. LSTM is widely applied to the natural language processing, since the predicted output of LSTM is related to the input of current moment, and the state of the hidden layer at the previous moment. ADS-B data have similar characteristics with natural languages. For example, these data are generated in time order, and there exist strong correlations between adjacent data. LSTM has a unique structure to optimize the memory content. When new data come, the "memory gate" and "forgetting gate" determine which information should be recorded into the cell state, and which information should be forgotten. The cell state updates much slower than the hidden state. As above, LSTM is a competitive method for the UAV trajectory prediction.

Based on the advantages of LSTM, we further propose the RLSTM algorithm. The entire neural network consists of an LSTM network and a fully connected network. If there exist no data similar to the new data in the training set, it brings great
errors for the prediction results. In order to obtain the UAV’s trajectory prediction refer to the historical data and dynamically predict the new trajectory with high precision, we propose the RLSTM, which adopts a recurrent training-prediction structure. Based on learning the data features from the training set, the model is retrained with all the historical data, which belong to this predicted trajectory at the current moment during each prediction process. Then, the new model is leveraged to make prediction for future two time steps.

Due to the limitation of energy capacity, the flight distance of UAVs is limited, which leads to the latitude and longitude data varying in a small range. Thus, it results in slow gradient descent when training the model with LSTM, and causes negative effects. To deal with this issue, we can preprocess the ADS-B data before training the model. The RLSTM leverages Z-score normalization for processing the trajectory data. In the following formulas, \( \mu \) and \( \sigma \) are the mean and variance of the data, respectively. The processed data have a mean of 0 and a standard deviation of 1. The positioning data normalized by Z-score at time step \( t \) are

\[
Lat_g(i)_t^g = \frac{Lat_g(i)_t - \mu_{Lat_g(i)}}{\sigma_{Lat_g(i)}}, \tag{13}
\]

\[
Lon_g(i)_t^g = \frac{Lon_g(i)_t - \mu_{Lon_g(i)}}{\sigma_{Lon_g(i)}}, \tag{14}
\]

and

\[
Alt_g(i)_t^g = \frac{Alt_g(i)_t - \mu_{Alt_g(i)}}{\sigma_{Alt_g(i)}}, \tag{15}
\]

In formulas (13)-(15), \( Lat_g(i)_t^g, Lon_g(i)_t^g \) and \( Alt_g(i)_t^g \) refer to the normalized positioning data \( Lat_g(i)_t, Lon_g(i)_t \) and \( Alt_g(i)_t \), respectively.

Firstly, the previous trajectories of UAV which are preprocessed and leveraged serve as the training set. When the training process is finished, fifteen consecutive trajectory data are selected randomly as the training data for one round of recurrent training-prediction process, to calculate the loss function and update the entire model according to the learning rate. When new trajectory data are transmitted to the data processing center, recurrent training-prediction process is repeated. The RLSTM is described in detail as follows.

When the ADS-B data of UAVs are preprocessed, the RLSTM runs according to Algorithm 1. To begin with, the model training is performed on UAVs training set. The training set consists of different UAV trajectories in the current airspace, and each one has several trajectory points. We set the epoch of the entire training set \( e \) as 2 and count the number of trajectory data as \( t \). The algorithm begins when \( t > 16 \), since 17 consecutive trajectory data are the minimum requirements for starting recurrent training-prediction progress. In each epoch, every trajectory is trained for 300 times, and in each iteration, the first data \( x \) is randomly selected as the starting trajectory point. Then, employ the \( x \)th to \( (x+15) \)th as the training data for updating the model. We leverage the trained model to predict the trajectory points after 2 time steps. The \( (x+16) \)th and \( (x+17) \)th are used to calculate the loss function and update the weights of the model according to the learning rate. Then, we conduct recurrent training-prediction process. For example, when the 17th data comes, the model training is activated. The RLSTM uses the 1st to 15th trajectory points as training data and trains for 300 times. When the training process is finished, formula (12) is used to calculate the loss function. We leverage the Adam optimizer to optimize the gradient descent. The algorithm updates the cell state, hidden state and network weight, and sends the 2nd to 17th trajectory points into the model to predict the 18th and 19th trajectory points. When receiving the two trajectory points, formula (8) calculates the average prediction error. This process repeats until there is no new data received. When the training process is completed, the model is saved for further prediction.

IV. SIMULATION RESULTS

The simulation process is shown in Fig. 2. The multiple existing UAVs trajectory data set is the premise for subsequent simulations. The trajectories with inadequate data are removed from the data set, since they may lead to large prediction error. When the trajectory data are normalized, the data set is divided into training set and test set, and we employ different neural networks to train and predict the dataset and finally obtain the prediction error.

In order to evaluate the performance of the RLSTM in trajectory prediction for the proposed UAV surveillance system equipped with ADS-B, we select multilayer perceptron (MLP), RNN, LSTM and bi-directional LSTM (Bi-LSTM) as the comparison algorithms. MLP consists of 3 layers with fully connected network, and the quantity of weights in each fully connected layer is 100. RNN, LSTM and Bi-LSTM consist of a hidden layer and a fully connected layer. The hidden-size is set as 16. The parameters are set as: the training epoch and

![Fig. 2. Process of trajectory prediction.](image-url)
Fig. 3. Predicted trajectory and average prediction error in 3D via employing the RLSTM.

iteration we set are 2 and 300, respectively. The trajectories of UAVs in the training set are 67, and the trajectories in the test set are 7. Trajectory points in the test set are larger than 25, and larger than 20 in the training set. In order to make the simulation results more convincing, the prediction is repeated for 10 times. In each prediction process, the prediction error is the average of the two predicted trajectory points and the real data received.

In the simulation, the flight positioning data are chosen from Kaggle [18], which is broadcast by the ADS-B OUT system in the surveillance system. The broadcast interval of each trajectory point is about 2-3s. Frequent update of ADS-B information leads to the congestion and interference. Hence, it is unacceptable for the aviation aircrafts. Since the flying speed of UAVs is much slower than civil aviation aircraft, it is not necessary for the UAV to frequently update the ADS-B information. In short, the selection of data set is suitable for our proposed surveillance system.

Fig. 3 shows the complete prediction process of the trajectory T1 in the test set via leveraging the RLSTM, and the trajectory direction is counterclockwise. As validated in Fig. 3a, the first 16 points in the original trajectory point (OTP) are not employed for prediction. When the 17th point is received, the predicted trajectory points (PTP) of 18th and 19th time steps are predicted. The subsequent processes are made according to Algorithm 1. In order to observe the latitude and longitude variation, the ground projection of OTP (GPOTP) and ground projection of PTP (GPPTP) are validated in Fig. 3a. In Fig. 3b, the average error of T1 for each prediction time step is presented, according to formula (8). The reason for the rise of prediction error at 3rd to 8th time steps is due to that the direction of the UAV trajectory changes at this time period. The time steps 11 to 14 are the second surge of prediction error, and it is attributed to the change of trajectory. The 17th to 21st time steps vary since the predicted trajectory is continuously revised, and the prediction error drops to an acceptable range finally.

Fig. 4 is the average error according to 10 repeated predictions on the test set data via different algorithms. A low average
prediction error refers to satisfied performance. It is validated from Fig. 4 that the RLSTM performs better in predicting trajectory points with a prediction error of 0.25 meters. The prediction error on RNN, which is the suboptimal prediction accuracy is reduced to 14.96 meters, and it is also 8.71 meters smaller than the results of RLSTM.

Fig. 5 reveals the average prediction error of each trajectory in test set for repeating prediction 10 times. Obviously, the average prediction error of the RLSTM is lower than other compared algorithms. It is worth noting that for the trajectory at $T_1$, $T_3$, and $T_4$, large average prediction errors appear in all considered algorithms. RLSTM is the only algorithm, which is able to effectively control the error within 10 meters compared with the other algorithms.

It is confirmed from the simulation results that, compared with other algorithms, the RLSTM can achieve higher accuracy of trajectory prediction in the proposed UAVs surveillance system equipped with ADS-B.

V. CONCLUSIONS

In this paper, we propose a system for UAV surveillance based on employing ADS-B as the positioning data source. In order to reach high performance of the proposed system, we put forward the RLSTM to repeat the recurrent training-prediction process on the trajectory, and acquire the predicted two trajectory points for the next time steps. The simulation results reveal that, compared with other neutral networks, the RLSTM performs better. The prediction error of the RLSTM is about 6 meters in average, which is within the range of availability for UAVs in the airspace.

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