Journal of Network Intelligence ©2021 ISSN 2414-8105 (Online)
Taiwan Ubiquitous Information Volume **6**, Number **1**, February **2021**

UAV decoy method based on LSTM neural network

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Received December 2020; revised January 2021

Abstract. *Aiming at the safety hazards caused by the rapid development of unmanned aerial vehicles(UAV) caused by the black flying and abuse of unmanned aerial vehicles, an improved UAV decoy method based on long and short-term memory neural network(LSTM) is proposed. The method is proposed improves the long and short-term memory network model, introduces the deception velocity vector, and uses the current flight trajectory of the UAV to predict the flight trajectory point of the UAV at the future time. Deceptive signals are accurately sent at the predicted trajectory point to make the drone deviate from the original track and slowly deviate from the no-fly zone. The experimental results show that the improved LSTM, combined with the speed deception vector, can predict the trajectory of the UAV more intelligently and accurately and successfully decoy its trajectory.*
Keywords: UAV, LSTM, Trajectory prediction, Velocity vector, Decoy.

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1. **Introduction.** With the continuous improvement and development of UAV technology, UAV not only plays an important role in the military field, but also has been widely used in the civilian field. However, while drones bring great convenience to people's production and life, black flying and abuse have also caused safety hazards to the country, society, and people Compared with the increasing maturity of UAV technology [1], the supervision technology of UAV is relatively backward, especially for some special occasions, such as the airport, prison and other no-fly zones around UAV supervision is shortage [2, 3].

A lots of methods of UAV decoys were proposed at domestic and abroad, Zhang et al. [4] put forward method that the detected trajectories, by applying different on each satellite transmission time delay and doppler control, to realize the position and speed at the same time spoofing, but the method for the short time of flight of low-altitude UAV that accurateness was not high. Guan et al. [5] proposed a decoy algorithm based on GPS navigation principle. The proposed algorithm used the principle of regional mapping to control the forwarding jamming system, the decoy of GPS deviated from its running track. Hu et al. [6] completed the interference of generative satellite navigation spoofing by using radio frequency radio hardware, and realized spoofing and trapping by using the no-fly zone function of UAV, but they could not achieve real-time decoying and had limitations. Wang et al. [7] proposed a method to prevent the intrusion of UAV into the electric patrol inspection work area by changing the speed of the induced point movement to improve the acceleration of driving away. However, the method has certain control risks for the control area with many obstacles. On the basis of analyzing the GPS spoofing principle, Li and Wang [8] used two methods of direct trajectory spoofing and trajectory fusion to realize UAV spoofing, which was not easy to be detected, the spoofing effect cannot be guaranteed under the circumstance that the UAV was disturbed in the real environment. Yan et al. [9] proposed a UAV no-fly zone warning algorithm for the disorderly flight of UAV, fit the flight curve through the least square method, and adjust the flight path of UAV by combining with the electronic fence , to judge whether the UAV breaks into the no-fly zone. Zhang et al. [10] the prediction method of convolution neural network proposed in this paper has small operation error and efficiency, but the limitation of convolution neural network structure leads to the increase of prediction error in large amount of trajectory. In reference [11], the method of long-term and short-term memory neural network is proposed to predict the trajectories of multiple targets, and pooling layer is used to share the information of adjacent targets. The results show that the method can reduce the prediction error of multi-target trajectories.

In view of the limitations of the existing schemes, this paper proposed improved the long short term memory (LSTM) into the UAV deception problem to improve the intelligence of UAV decoy.

(1) A decoy method for UAV based on LSTM neural network trajectory prediction is proposed. The model is combined with UAV deception vector. In this method, the flight trajectory of UAV is regarded as a group of time series models with linear relationship, and the predicted position of future time is obtained by LSTM, which provides location basis for deception.

(2) This paper improves the original deception method based on hardware, uses LSTM algorithm to predict the current flight status of UAV to make up for the deficiency of pure hardware deception, and improves the probability of UAV deception by using LSTM algorithm framework.

(3) A velocity vector synthetic decoy method based on UAV position prediction is proposed, which is used to change the current flight direction of UAV. Different from the

traditional forwarding deception, it uses the kinematic properties of UAV to improve the effect of deception.

2. **Related work.** LSTM is an extension of the traditional RNN model [12]. The expansion structures of the traditional RNN model and LSTM model [13, 14] are shown in Figure. 1 and Figure. 2 respectively. The difference between the two is mainly whether there is a structure to control the storage state. It can be seen that LSTM has better ability to learn long-term memory information than the traditional RNN model.

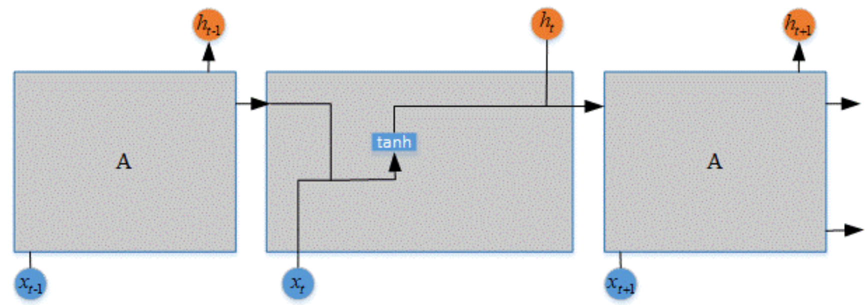


FIGURE 1. Unfolded structure diagram of traditional RNN model

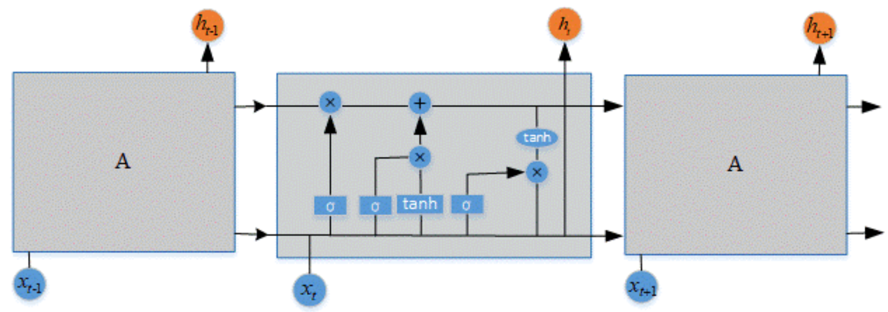


FIGURE 2. LSTM model expanded structure diagram

LSTM neural network [15] adds three controllers, input gate, output gate and forgetting gate. It draws on the long-term and forgetful characteristics of human neural memory, which can depend on information for a long time.The LSTM cycle neural network [16] is used to solve the time series problem for the trajectory prediction of the black flying UAV.The LSTM model was trained by taking the historical flight path characteristic data detected by the UAV countermeasures system as input, and the neural network training was obtained to establish the mapping relationship between the historical flight path of the UAV and the future trajectory of the UAV, so as to realize the flight trajectory prediction of the UAV.

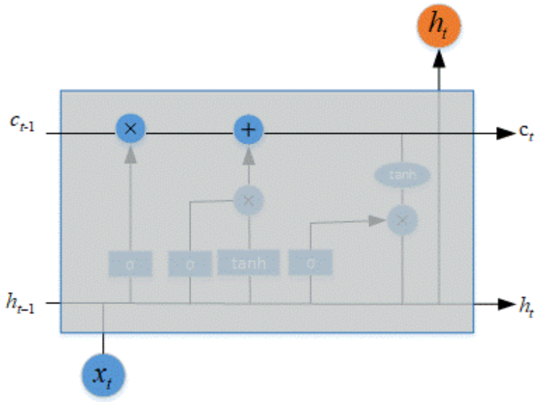


FIGURE 3. LSTM structure diagram

The structure of LSTM [17] is shown in Figure 3,x_t is the input sequence ; i_t is the input gate; f_t is forget gate ; O_t is the output gate; h_t is the output of hidden layer;σ is sigmoid activation function; Tanh is the tanh activation function; W is the weight matrix; · is the point-pair product.

According to the LSTM structure, we can get:

$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + b_f\right) \tag{1}$$

$$i_t = \sigma\left(W_{xi}x_t + W_{hi}h_{t-1} + b_i\right) \tag{2}$$

$$O_t = \sigma\left(W_{xo}x_t + W_{ho}h_{t-1} + b_o\right) \tag{3}$$

$$y_t = g\left(W_{\overrightarrow{h}y}\overrightarrow{h}_t + W_{\overleftarrow{h}y}\overleftarrow{h}_t + b_y\right) \tag{4}$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tanh\left(W_{xc}x_t + W_{hc}h_{t-1} + b_c\right) \tag{5}$$

$$h_t = O_t \cdot \tanh\left(c_t\right) \tag{6}$$

From equations (1) to (6), it can be seen that: the input gate controls when the activation state is transferred into the storage unit, that is, the writing of timing data; The output gate controls when the activation state is sent out, and the output of data is ordered in a timely manner;The forgetting gate controls part or all of the forgetting, and the three gates jointly complete the learning of the rules in the data.

At present, deep learning technology is developing rapidly, and most of the prediction learning methods based on LSTM are used for plane trajectory prediction, and there are few applications for UAV trajectory prediction in three-dimensional space [18].

In this paper, the combination of improved LSTM neural network and velocity vector deception, and trajectory deception based on the trajectory, is an innovative new UAV decoy strategy.

3. **Method.** In this paper, a UAV decoy method based on LSTM neural network model [19, 20] is proposed. The trajectory data of UAV detected by radar are preprocessed, and the processed data sample set is constructed. The sample set data is substituted into LSTM cyclic neural network for model training and trajectory point prediction ‘ [17]. The anti UAV system sends data to UAV Send velocity vector command to change the current flight trajectory of UAV.

The specific steps of UAV decoy method based on LSTM recurrent neural network are shown in FIGURE. 4.

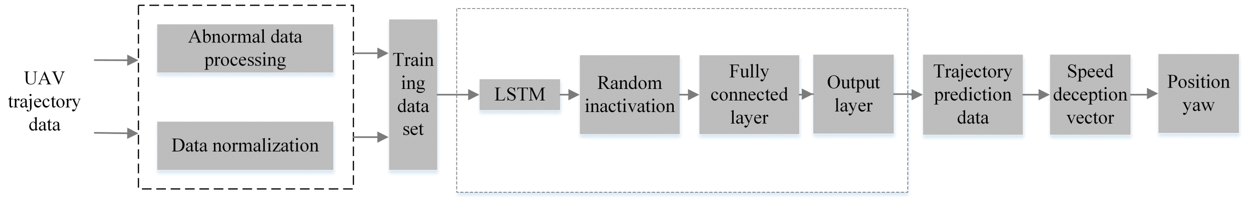


FIGURE 4. Step diagram of UAV decoy method

In FIGURE 4, the UAV trajectory data set detected by radar is processed and normalized to sort out the data set, and the processed data is divided into training set and test set, and the final UAV position prediction point is obtained through the training of three-layer LSTM neural network; the speed deception vector command is sent at the obtained position point, and the UAV is under the influence of the command To generate a yaw trajectory.

3.1. **Problem description.** In actual flight, the trajectory of the drone is affected by many factors such as itself and the environment. The trajectory of UAV obtained according to expert experience has the characteristics of continuity, timing and interaction [21].

(1) Continuity means that the trajectory of UAV changes continuously, rather than intermittently.

(2) Sequentiality means that the trajectory data is time-based, and the position of the next moment is related to the position of the previous moment, so the trajectory data is essentially a time series data.

(3) Interactivity is reflected in the drone's deception in the ability of the drone to receive the speed deception vector of the deception device and feed back the drone's trajectory data to the deception device. This process is a dynamic and complex interactive process.

Therefore, when conducting drone decoys, in addition to considering black flying, no one In addition to the position (x, y, z), attitude (heading angle ϕ, pitch angle θ , roll angle γ), and speed v of the aircraft, due to the interaction, the distance L between the predicted value of the black flying drone and the true value, and the angle α between the velocity vector are also considered [22, 23].

The UAV trajectory data is the time position, speed and relative information. It predicts the time of the black flying UAV, and receives the ground UAV speed deception vector at the time position at , so that the black flying UAV can change its trajectory.

Therefore, the trajectory prediction problem can be described as :

$$x_{t(n+1)} = f(x_{t1}, x_{t2}, \cdots, x_{tn}) \tag{7}$$

Where: $x_{t(i)}$ is the trajectory feature of the UAV at the moment $t(i)$, and f is the mapping relationship.

3.2. **Data preprocessing.** To improve the calculation stability, the data is normalized and the value range of the input data is included into the interval $[0, 1]$,normalization makes the feature values of different dimensions have a certain degree of comparison. UAV trajectory prediction adopts min-max standardization, that is, 0-1 standardization, and linear transformation is performed on the original feature values. The formula is shown:

$$\mathrm{Y} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{8}$$

Where: X is the actual value of a variable; X_{max} is the maximum value; X_{min} is the minimum value; Y is the flight trajectory value of the uav after normalization. After data normalization, the influence of value range between data can be eliminated. The LSTM model is used to reverse normalize the prediction results, and the formula is as follows:

$$X = (X_{\max} - X_{\min})\, Y + X_{\min} \tag{9}$$

The predicted trajectory value of the UAV is more in line with the actual flight state, which is more conducive to the execution of the uav receiving velocity spoofing vector instruction.

3.3. **Trajectory prediction model.** UAV trajectory prediction is trained by the LSTM model, and the trajectory point data set of the UAV is taken as the corresponding label. By training the LSTM cycle neural network, the mapping between the historical flight path of the UAV and the future flight path point is established to realize the model's prediction of UAV [24–26].

$x(t)$ set as the quaternion data of the UAV at each time, where the t represents the moment in the uav flight, and the quaternion information is expressed as $[\ln g_t, lat_t, alt_t, \overrightarrow{v}_t]$, where lng, lat, alt, v represents the longitude, latitude, altitude and velocity of the UAV at the t time, respectively. At the t time, the trajectory characteristics of the UAV are as follows: $x(t)$.

$$x\left(t\right) = \{\ln g, lat, alt, v\} \tag{10}$$

Through the trained LSTM model, the UAV flight trajectory can be predicted. The UAV flight trajectory data $[x\left(t-i+1\right), \cdots, x\left(t\right)]$ of i consecutive moments are taken as the input data of the LSTM model, and i steps are predicted backward. The UAV trajectory data $[x\left(t+1\right), \cdots, x\left(t+i\right)]$ for the future is output, in which the input layer step size.

Therefore, the UAV flight trajectory prediction model expression is:

$$\{x\left(t+1\right), \cdots, x\left(t+i\right)\} = f\left(\{x(t-i+1), \cdots, x(t)\}\right) \tag{11}$$

The distance between the predicted value and the real value is calculated by using the predicted trajectory point latitude and longitude. The formula of the distance is as follows:

$$\mathrm{L} = 2 \times \mathrm{R} \times \arcsin\sqrt{\sin^2\frac{lat_1 - lat_2}{2} + \cos(lat_1) \times \cos(lat_2) \times \sin^2\frac{\ln g_1 - \ln g_2}{2}} \tag{12}$$

The prediction line distance is obtained by the distance between the prediction point and the real point, and the accuracy of the prediction is judged.

3.4. **Speed vector deception.** From the trajectory prediction of the UAV, the latitude and longitude of the UAV at the t time can be obtained. At this time, the reverse UAV system sends the speed vector instruction at this point, and the UAV receives the speed vector instruction. p_1 is synthesized from the original speed direction. As shown in FIGURE 5, the UAV receives speed vector instructions.At point p_i , the deceptive speed vector direction is sent in the direction indicated by the arrow in the figure. The UAV synthetic speed vector is the actual flight direction of the UAV.

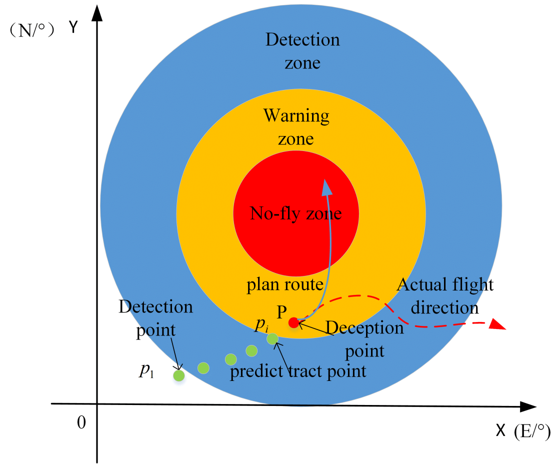


FIGURE 5. Synthesis diagram of velocity deception vector of UAV

As shown in FIGURE 6 the UAV vector spoofing synthesis diagram is presented. The UAV position is regarded as the p point without changing the UAV flight altitude, considering that the UAV is affected by the UAV spoofing vector in horizontal coordinates. The blue arrow is the actual flight trajectory direction of the UAV, the red arrow is the deception vector sent to the UAV, and the green arrow is the direction after the vector synthesis of the UAV.

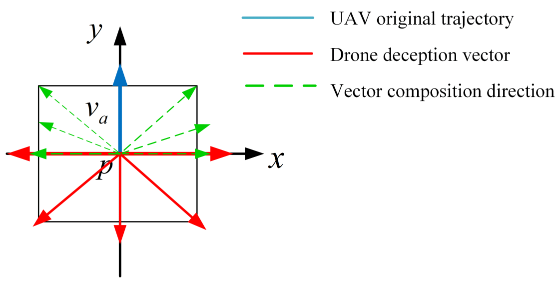


FIGURE 6. Vector Fraud Synthesis of UAV

4. Experiment.

4.1. Experimental data description and processing.

In this section, the experiments and results are described and analyzed to illustrate the feasibility and accuracy of this method. The experimental data are the measured longitude and latitude trajectory data of UAV after flying on the playground, including the longitude, latitude and speed of UAV. The flying altitude of UAV is 50 m, and the speed of UAV is about 4 m/s. when it flies stably over playground Using the measured data of UAV, the simulation experiment is carried out first, and then the trained data parameters are applied to the actual flight test. The parameters of the collected data set are shown in Table 1.

Table 1. Parameter Configuration Table

Parameter Name	Value
LSTM layers	3
Neuron abandonment rate	30%
Number of output layer nodes	3
batch	64
Number of rounds	100
Signal frequency	1575.42 MHz
Pseudocode type	C/A
Effective deception threshold	m 500
Activation function	Tanh

As shown in FIGURE 7, the UAV reverse system equipment diagram.The UAV counter-control device in the figure can detect the UAV trajectory by the UAV countermeasures system and send the UAV spoof signal by algorithm.

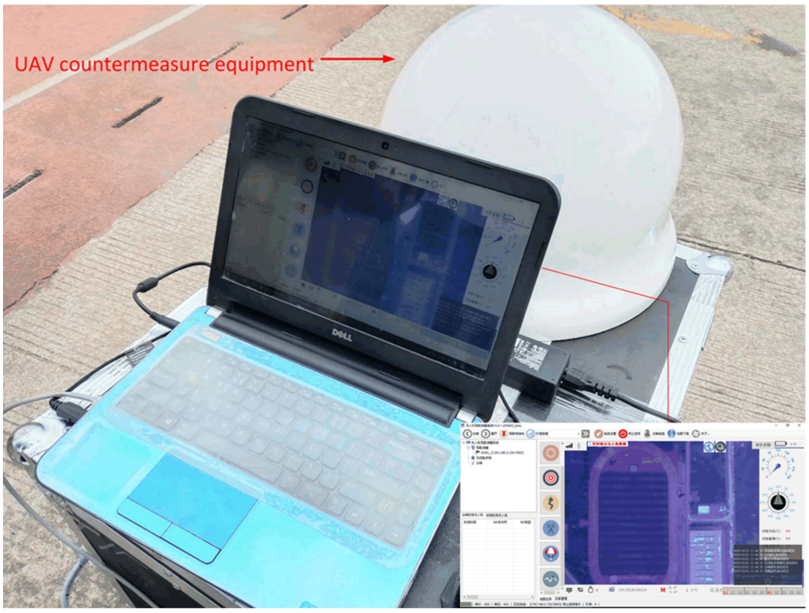


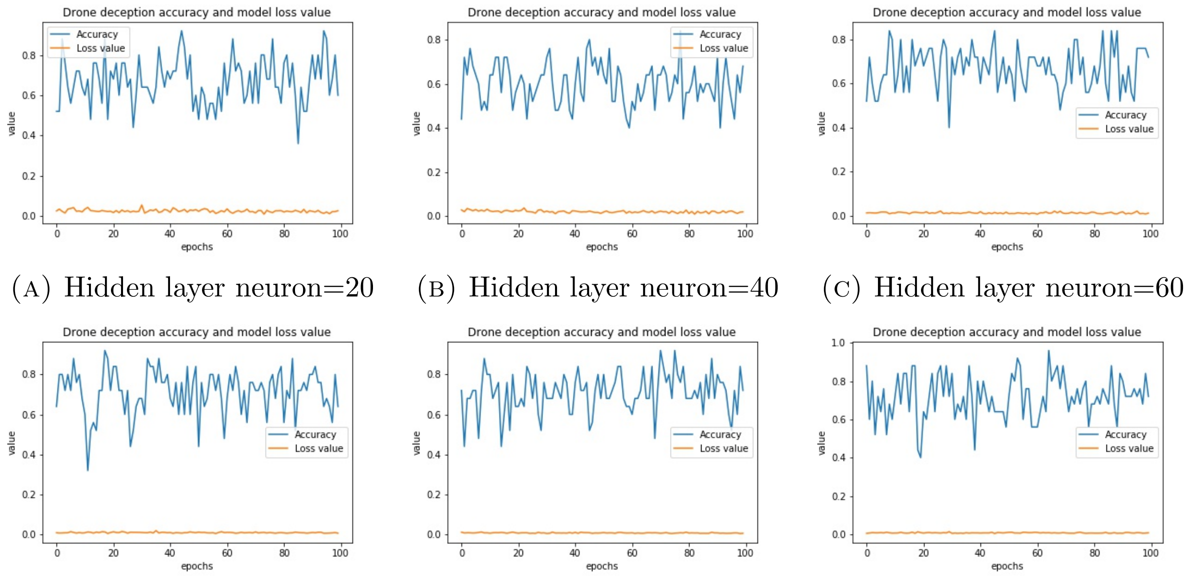
Figure 7. UAV counter system equipment diagram

4.2. **Results analysis.** Experiments in this section are mainly divided into two parts :

(1) Aiming at the LSTM model-based UAV decoy method proposed in this paper, the influence of different parameters on UAV decoy performance is studied, and the simulation results are obtained in the simulation experiment.

(2) The proposed method was applied to the actual flight deception and the experimental results are analyzed.

4.2.1. *Analysis of decoys parameters of UAV.* After the normalized processing of the obtained UAV data, the number of neuron nodes in the shadow reservoir layer was set, the UAV data at six consecutive moments was taken as the input of the model, and the trajectory data at the next moment was predicted as the output.The number of neuron nodes in different hidden layers also has great influence on the accuracy of UAV trapping.



(A) Hidden layer neuron=20 (B) Hidden layer neuron=40 (C) Hidden layer neuron=60

(D) Hidden layer neuron=80 (E) Hidden layer neuron=100 (F) Hidden layer neuron=120

FIGURE 8. Comparison of accuracy of different hidden layer neurons and neural network loss

As shown in Figure 8 above, when the number of hidden layer neurons with the highest inducing result was selected. when the number of neurons in the hidden layer was changed, the accuracy of the UAV receiving spoofing signals and changing the original flight direction increases. When the number of neurons in the hidden layer is determined to be 120, the UAV has the highest inducing accuracy and the loss value of the LSTM model is the lowest.

4.2.2. *The UAV decoys the simulated flight path.* By determining the flight simulation parameters of the UAV, the LSTM is used to establish a prediction model to obtain the spoofs track points, and the longitude and latitude coordinates [26.01759778 , 119.11545301] of the predicted values are obtained experimentally. By comparing the real latitude and longitude, the difference between the predicted spoofs track points and the real track points is [26.01759393 , 119.1154476], as shown in the figure, the linear distance difference between the predicted spoofs track points and the real track points is 0.0270km.

As shown in FIGURE 8 based on LSTM model using UAV deception equipment in predicting the trajectory of point velocity deception vector of UAV decoying in Matlab simulation rendering, solid line for UAV flight path, when no decoying with * line for UAV affected by cheating the velocity vector at track prediction after decoying route, when the UAV flight lose deceive signal interference, in the process of UAV to detect abnormal, the UAV will be shown in figure 8 triangle line.

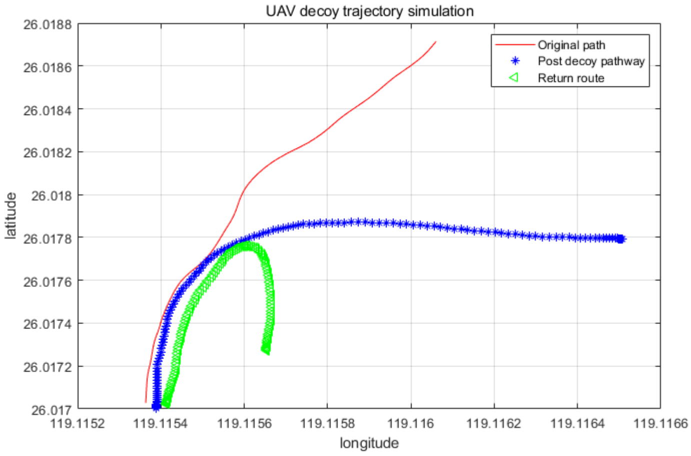


FIGURE 9. UAV decoy simulation

4.2.3. *Actual test.* To performance the simulation of the improved model based on LSTM, its feasibility was verified by actual measurement.

FIGURE 10. Drone deception actual test

The algorithm is proposed in the paper was used to establish the prediction model, and the spoofing velocity vector was used to obtain the spoofing trajectory point P.The red area in figure 10 is the no-fly zone. The original flight path of the UAV passes through the no-fly zone, and then the trajectory prediction point of the UAV is obtained in the detection area through trajectory prediction.As shown in figure 10, P is the trajectory prediction point of the UAV. The UAV starts to fly from the initial position, and gets the Point P through trajectory prediction, that is, the trajectory spoofing point of the UAV at Point P, where the UAV velocity spoofing vector is received.

In the remote control map of UAV, the actual trajectory direction of UAV flight is shown in FIGURE 11.

FIGURE 11. UAV offset route

The UAV received the deception signal at the predicted position point and generated a position offset. The offset direction is shown in FIGURE 11. The red position is the deception device position point. The UAV is affected by the signal and speed deception vector, and the flight direction is offset. The direction in the figure is the actual deviation direction of the UAV. The UAV route displayed in the remote control of the UAV deviates from the actual route, but there is a total deviation between the UAV route and the actual route The offset direction of is correct.

5. **Conclusions.** In this paper, the velocity vector of UAV is predicted by using the neural network to predict the trajectory of UAV. Specifically, firstly, the LSTM time series trajectory data model of UAV is established, and the UAV trajectory prediction is used to provide accurate deception location points for trajectory decoy, so as to improve the accuracy of UAV trajectory decoy. Secondly, this method sends velocity vector deception command to the obtained track deception point, and changes the flight direction of UAV by using the dynamic principle of UAV's own flight. Compared with the traditional electronic jamming and violent attack on illegal flying UAV, this method has higher security. Finally, the optimal neural network parameters are obtained by simulation training, and the feasibility and effectiveness of this method are verified by MATLAB simulation and actual test

Acknowledgment. This work is partially supported by the Key Project of the Fujian Science and Technology Department Grant 2018H0003, Quanhzou Science and Technology Bureau Grant 2017G012, Fujian University of Technology Grant GY-Z17011. Thank you very much for the valuable comments of reviewers and editors. We will continue to work hard to improve our work.

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