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A Novel Hybrid Attitude Fusion Method Based on LSTM Neural Network for Unmanned Aerial Vehicle

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***Abstract*—Unmanned aerial vehicle (UAV) is a highly coupled and multivariable nonlinear complex system, the attitude fusion of which is often disturbed by the noise of low-cost inertial measurement unit (IMU). In order to improve the UAV attitude fusion precision, a novel hybrid attitude fusion method is introduced in this paper. An error model between the IMU output and attitude is established by a long short term memory neural network (LSTM NN). The attitude fusion error can be estimated well by using the powerful nonlinear fitting and time series processing ability of the LSTM. The experimental results demonstrate that the root mean square error (RMSE) of pitch, roll and yaw can be reduced to 0.69 degrees, 0.73 degrees and 0.59 degrees respectively, which effectively improve the accuracy of attitude fusion.**

***Index Terms*—Attitude fusion, LSTM, neural network, UAV**

I. Introduction

In recent years, with the hot development of artificial intelligence, unmanned aerial vehicles (UAVs) are required to perform more intelligent and complex tasks, such as object detection [1], power inspection [2] and so on. One of the necessary conditions for these advanced missions is to accurately acquire the position and attitude of the UAV at each moment. Therefore, attitude measurement is the premise of UAV attitude control and an integral part of navigation system, which directly affects the overall performance of UAVs. UAVs mainly use micro-electro-mechanical gyroscope, accelerometer and magnetometer to construct a low-cost attitude and heading reference system (AHRS) to measure attitude. The triaxis gyroscope can measure the triaxial angular velocity under the UAV motion state. The attitude angles can be calculated by integrating the angular rate, which has good dynamic characteristics and high accuracy in the short term. However, this method will produce cumulative error when it is used for attitude calculation. If it is not modified regularly, the final attitude cannot be used in UAV navigation. The accelerometer can also be used for the inclination measurement of UAVs, but it is sensitive to the gravity and motion accelerations at the same time. When UAVs are maneuvering for a long time, the attitude measurement by a single sensor will produce a large measurement error. Therefore, it is an essential research subject to develop a multisensor data fusion algorithm for the low-cost IMU with high reliability and precision [3]-[5].

The algorithms commonly used for UAV attitude fusion include complementary filter algorithm [6]-[8], gradient descent algorithm [9]-[11] and Kalman filter algorithm [12]-[14]. The main idea of the complementary filter algorithm is to transform the gravity acceleration vector in navigation coordinate system into body coordinate system through rotation matrix, and then cross product the acceleration measurement value in body coordinate system to obtain attitude error. Finally, the attitude error caused by the gyroscope integral drift is modified by proportional-integral (PI) operation. Complementary filter algorithm has a small amount of calculation and good real-time performance, but its accuracy is not high. In particular, when UAVs are accelerating or decelerating, the measured value of the accelerometer will often include the motion acceleration. In this case, the cross product operation with gravity acceleration will generate large error. Gradient descent method is to calculate gravity acceleration and magnetic field error gradient to obtain attitude quaternion and compensate the gyroscope drift error. However, since the step size of gradient descent is always changing, it is often difficult to accurately determine the step size of gradient descent, resulting in low precision of attitude solution. Generally, Kalman filter algorithm takes the attitude angle obtained by gyroscope integration as the state variable, and the attitude angle calculated by accelerometer and magnetometer as the observation variable, to establish the corresponding state equation and measurement equation, and then uses Kalman equation for iterative filtering. Kalman filter is a linear optimal estimation algorithm. Although some scholars put forward unscented Kalman filter [15] and particle filter [16], which are suitable for nonlinear systems, the improvement accuracy is not obvious and the calculation is large.

Artificial neural network, which does not need to establish a mathematical model for problems specially and can fit the nonlinear system characteristics well, is a mainstream machine learning algorithm at present [17]. The UAV attitude solution is generally generated by integrating the measured value of IMU sensor, so the attitude error has a great correlation with IMU error. This correlation is often difficult to establish an accurate mathematical model, but it can be treated as a kind of time sequence data to be accurately fitted by artificial neural network [18]-[19]. The traditional feedforward neural network has no dependence between the input of the previous moment and the output of the present moment, that is, it can not store the previous time nodes information, which can not deal

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with the time sequence data well. As an important branch of deep learning, recurrent neural network (RNN) realizes the function of memory with its own unique recurrent structure, and can make predictions about the value of next moment which are related to the historical information. Since RNN has gradient vanishing problem, long short term memory neural network (LSTM NN) is designed to solve the one by adding special gate units [20]-[21]. LSTM NN will generate the corresponding threshold value through training, and the input value will be transmitted to the gate control unit after calculating with the weights of each node, and then compared with the corresponding threshold value. After a series of such operations, LSTM NN can selectively store hidden layer state outputs of previous moments according to the relationship between input and output of the training set, thus effectively solving the gradient vanishing problem. The "memory unit" of LSTM neural network is equivalent to a delay operator, which enables the network to have dynamic memory ability and also well conforms to the inertial characteristics of IMU sensor.

The remainder of the paper is organized as follows. In Section II, a brief overview of the complementary filter for UAV attitude fusion is given. Section III describes a novel hybrid attitude fusion algorithm based on LSTM NN. Simulation experiment and result analysis are provided in Section IV. Conclusion is given in Section V.

II. The UAV attitude fusion method

The purpose of UAV attitude calculation is to obtain the attitude angle of the aircraft body coordinate system in the geographical coordinate system. In the UAV navigation, the geographic coordinate system is usually determined by the local north, east and down direction according to the right-hand rule. Similarly, the body coordinate system is determined by the front, right and down direction of aircraft according to the right-hand rule. Euler angle method, direction cosine method and quaternion method are commonly used in attitude calculation. Euler angle is the simplest way to express rotation. Formally, it is a three-dimensional vector, the values of which represent the rotation angles of an object around three axes (X, Y and Z axis) in the coordinate system. The UAV attitude can be represented by euler angle, such as pitch, yaw and roll. This transformation of coordinate system can also be achieved by multiplying the position vector of a coordinate system by a 3×3 rotation matrix, which is usually called the directional cosine method. Quaternion is a four-dimensional complex, which can be used to express the direction of a rigid body or coordinate system in three-dimensional space. In this paper, the quaternion method is adopted to calculate the UAV attitude, because euler angle method has a gimbal lock problem, and can not be used to solve the whole attitude. The direction cosine can be used to solve the whole attitude, but the calculation is too heavy to meet the UAV real-time requirement. The quaternion method has the advantages of small computation, no singularity and can satisfy the real-time attitude calculation in the process of aircraft movement. According to literature [22], the quaternion at the current moment, namely the current attitude, can be calculated by solving the quaternion differential equation below,

$$\begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{bmatrix}_{t+\Delta t} = \begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{bmatrix}_t + \frac{1}{2}\Delta t \begin{bmatrix} -\omega_x q_1 - \omega_y q_2 - \omega_z q_3 \\ \omega_x q_0 - \omega_y q_3 + \omega_z q_2 \\ \omega_x q_3 + \omega_y q_0 - \omega_z q_1 \\ -\omega_x q_2 + \omega_y q_1 + \omega_z q_0 \end{bmatrix} \tag{1}$$

where $\begin{bmatrix} q_0 & q_1 & q_2 & q_3 \end{bmatrix}_t^T$ represents the quaternion of the current moment and $\begin{bmatrix} q_0 & q_1 & q_2 & q_3 \end{bmatrix}_{t+\Delta t}^T$ is the quaternion of the next sampling interval. Δt is the sampling interval. $\begin{bmatrix} \omega_x & \omega_y & \omega_z \end{bmatrix}$ expresses the rotation angular velocity of body coordinate system.

According to the above analysis, as long as $\begin{bmatrix} \omega_x & \omega_y & \omega_z \end{bmatrix}$ can be accurately measured, the quaternion at the present moment can be constantly updated and iterated to obtain the quaternion at the next moment. The $\begin{bmatrix} \omega_x & \omega_y & \omega_z \end{bmatrix}$ is usually measured by the gyroscope in the airborne IMU. However, due to the influence of noise in low-cost IMU, attitude error will accumulate under the effect of integration, so it is necessary to fuse the measurements of other sensors to correct gyroscope error.

Complementary filter algorithm is widely used in the attitude fusion of small and medium-sized UAVs. As shown in Figure.1, it is a block diagram of the complementary filter attitude fusion. Before the attitude calculation, each sensor measurement should be normalized to reduce the estimation error. By using the rotation matrix between the geographic coordinate system and the body coordinate system, the gravity acceleration vector and the magnetic field intensity vector in the geographic coordinate system can be rotated to the body coordinate system respectively, i.e., $\begin{bmatrix} v_x & v_y & v_z \end{bmatrix}^T$ and $\begin{bmatrix} w_x & w_y & w_z \end{bmatrix}^T$. Because the magnetic declination angle exists between the geomagnetic north pole and the geographic north pole, the local magnetic declination angle can be corrected by looking up the magnetic declination table. At this time, the acceleration and magnetic field intensity measured by the accelerometer and magnetometer in the body coordinate system are respectively $\begin{bmatrix} a_x & a_y & a_z \end{bmatrix}^T$ and $\begin{bmatrix} m_x & m_y & m_z \end{bmatrix}^T$. When the attitude angle is small, the cross product of $\begin{bmatrix} v_x & v_y & v_z \end{bmatrix}^T$ and $\begin{bmatrix} a_x & a_y & a_z \end{bmatrix}^T$, $\begin{bmatrix} w_x & w_y & w_z \end{bmatrix}^T$ and $\begin{bmatrix} m_x & m_y & m_z \end{bmatrix}^T$ can be approximated to the angle value of two groups of vectors, which is the cumulative error generated by the gyroscope noise. The purpose of correcting gyroscope can be achieved by adding the two sets of error and performing proportional-integral(PI) operation according to Equation.2, to compensate the error to the gyroscope measurements [6]-[8].

$$\begin{aligned} &\delta = K_p e + K_I \int e \\ &\omega = \omega_g + \delta \end{aligned} \tag{2}$$

where ω_g is the angular velocity without correction. ω is the angular velocity after correction. K_p and K_I are PI cofficents. δ is the error compenstaion value.

In this paper, LSTM neural network will be used to compensate the error of complementary filter attitude fusion algorithm,

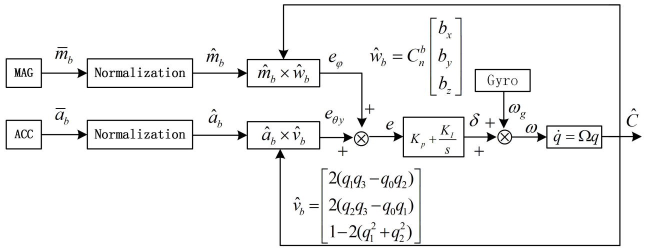

Fig. 1. Illustration of the attitude fusion using complementary filter

so as to improve its accuracy.

III. UAV ATTITUDE FUSION BASED ON LSTM NN

A. The LSTM Neural Network

LSTM NN, which are successfully in stock prediction [23], language translation and speech recognization [24], is a new breakthrough in machine learning. Three gates, i.e., input gate, forget gate and output gate, are designed in LSTM NN, which are known to be crucial to achieving good performance for dealing with sequence data. Figure 2 shows the basic unit structure of an LSTM neural network. The LSTM NN uses two gates to control the content of the cell state c. One is the forget gate, which determines how much data of the cell state at the last moment c_{t-1} is retained to the current moment c_t. The other is the input gate, which determines how much data is saved to the unit state at the current time of network input x_t. The LSTM NN uses the output gate to control how much data is output to the current output value h_t from the unit state c_t. These three gates correspond to the write, read and reset operation of the UAV IMU data sequence respectively in the attitude fusion. In Figure 2, the first one from left to right is the forget gate, and the specific mathematical expression is as follows [19]-[21],

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{3}$$

where W_f is the weight matrix of forget gate. b_f is the bias of forget gate. σ is the sigmoid function. The value of f_t denotes the degree of forgetting, where 1 denotes complete retention and 0 denotes complete removal.

After determining the value saved in the previous cell state c_{t-1}, it is up to the input gate to decide which new information is stored in the current cell state c_t. The input gate consists of two parts: one is the sigmoid layer, which determines which values will be updated, and the other is the tanh layer, which is used to describe the status of the current input unit c_t and calculated based on the previous output and the current input. The specific data expressions are as follows,

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{4}$$

$$c_t^{'} = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{5}$$

According to Equation.6, the current memory $c_t^{'}$ and long-term memory c_{t-1} of LSTM NN can be combined to form a new unit state c_t. Because of the forget gate control, it can keep the information from a long time ago, besides, because of the control of the input door, it can avoid the current irrelevant content entering the memory.

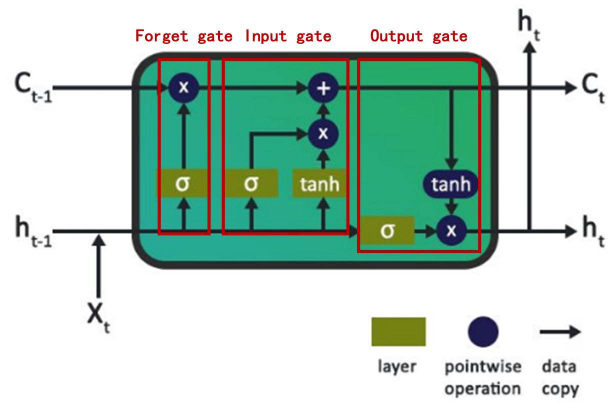

Fig. 2. Basic structure of a LSTM Unit

$$c_t = f_t \cdot c_{t-1} + i_t \cdot c_t^{'} \tag{6}$$

The final output of LSTM is determined by the output gate and the cell state as,

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{7}$$

$$h_t = o_t \cdot \tanh(c_t) \tag{8}$$

B. Design of attitude fusion structure based on LSTM NN

After data fusion, the traditional attitude calculation method usually has one-way output and lacks feedback. Therefore, based on the traditional complementary filter attitude fusion method, LSTM NN is used to fit the error of complementary filter attitude fusion and compensates it to the attitude angle, so as to improve the accuracy of complementary filter attitude fusion method effectively. As shown in Fig.3, the IMU on the UAV is calibrated firstly to reduce the zero drift error of the sensor, and then the attitude angles, namely pitch $\hat{\theta}$, roll $\hat{\phi}$ and yaw $\hat{\gamma}$, are solved by the complementary filter attitude fusion method. The deviation values $\delta\theta, \delta\phi, \delta\gamma$ between reference data and complementary filter output will be fitted and predicted by the LSTM NN. Considering the real-time requirement and many test experience results, a three-layer LSTM neural network is designed in this paper. The IMU

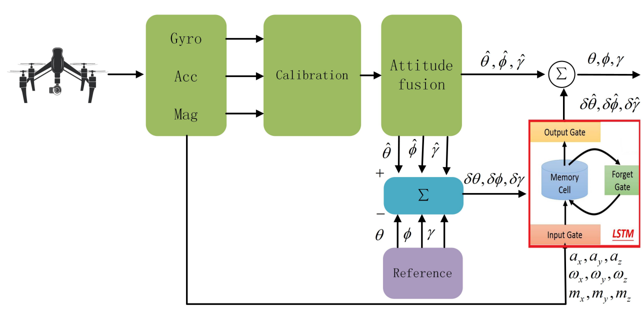

Fig. 3. The UAV attitude fusion scheme based on LSTM NN

output data are used as LSTM NN input, which are triaxial angular velocity, triaxial acceleration and triaxial magnetic field intensity. The first layer is the input layer, the neuron number of which depends on the dimension of the input vector, that is, nine neurons. The LSTM NN outputs are the error between the attitude angle fused by complementary filter and the actual attitude angle, namely pitch angle error, roll angle error and yaw angle error, namely three neurons. LSTM unit is used in the hidden layer, and the number of neurons can be determined according to the following empirical formula [25],

$$h = \sqrt{(x + y)} + a \tag{9}$$

where x, y and h are the number of neurons in the input layer, output layer and hidden layer, respectively. a is the adjustment parameter, the value of which is from 1 to 10. In general, the number of the hidden layer neurons is larger than that of the input neurons. Hence, the number of the neurons of the hidden layer is ranged from 4 to 13. The test results show that when the number of neurons in the hidden layer is 10, the fitting effect is the best.

After determining the basic network structure, the LSTM NN needs to be trained by gradient descent method to adjust the weights and bias values between neurons in the hidden layer, so as to fit the corresponding nonlinear relationship between input data and output data. When the actual output is inconsistent with the expected output, the stage of error backpropagation begins. Through the output layer, the error starts to modify the weight according to the gradient descent method and propagates back from the hidden layer to the input layer. The process of information propagation and error backpropagation cycles until the network reaches a predetermined performance level, or these steps have been repeated for a predetermined learning time. After the network training, IMU data are input into the trained LSTM NN to obtain the corresponding attitude angle error, which is then compensated to the attitude angle solved by the complementary filtering algorithm to further improve the accuracy of the attitude angle.

IV. Experimental Results and Analysis

In this paper, simulation experiments are carried out by using the software of MATLAB 2018b and Ubuntu 16.04+Python 3.6+Keras 2.0.9 deep learning framework. The computer configuration used in the experiment is: Intel Core i5-3210M 2.5GHz, 8GB RAM. In order to ensure that the experimental data are as close as possible to the real flight data, we independently developed a quadcopter to collect IMU data during flight. As shown in Fig.4, the quadcopter is equipped with a PIXHAWK autopilot which adopts dual processors and dual IMU redundancy design to ensure the data reliability. Invensense MPU 6000 and ST Micro LSM303D are as the main IMU sensors with a gyroscope bias of about 5 deg/s and an accelerometer bias of approximately 60mg [26]. Our experiment was carried out in a laboratory equipped with Vicon motion capture system, so the attitude data output by Vicon motion capture system was used as the standard reference data. As shown in Fig.5, it is the result of complementary filter attitude fusion using IMU data in Pixhawk, where the blue solid line represent the attitude angles fused by complementary filter and the reference data from Vicon motion capture system is depicted in orange. The data acquisition time is 45 seconds, and the sampling rate is 200 Hz, totally 9000 sets of data. In the first 10 seconds, when the UAV moves at a constant speed or at rest, the attitude fusion algorithm of complementary filter can track the attitude angle well. The root mean square error (RMSE) of pitch, roll and yaw are all less than 0.5 degrees, which shows that the attitude fusion algorithm of complementary filter has high accuracy when the UAV attitude angle changes little. However, starting from 11 seconds, when the UAV makes a large-scale maneuvering motion, such as turning and accelerating, there is large error in each attitude angle. As shown in Table.I, the maximum errors (ME) of pitch and roll are 12.53 degrees and 20.12 degrees respectively, and the RMSEs are approximately 2.41 degrees and 2.49 degrees, respectively. The yaw error is obviously larger, the ME of which is close to 16.31 degrees, and the RMSE is about 11.38 degrees. In this case, the UAV attitude is mainly carried out by gyroscope. Since accelerometer is affected by motion acceleration, the measurement accuracy is reduced. The magnetometer is disturbed by the surrounding magnetic field, and due to the inertial property of the inertial device, it is unable to track the motion change rapidly, so the

Fig. 4. The quadcopter equipped with PIXHAWK autopilot and vicon motion capture system

solution error will be relatively large.

TABLE I
THE ATTITUDE ERROR FROM COMPLEMENTARY FILTER FUSION METHOD

Pithch (deg)		Roll (deg)		Yaw (deg)	
ME	RMSE	ME	RMSE	ME	RMSE
12.53	2.41	20.12	2.49	16.31	11.38

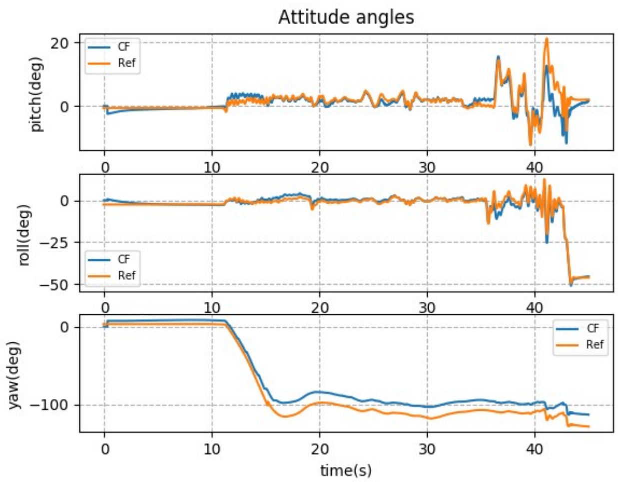

Fig. 5. The attitude angle fused by complementary filter (CF)

Aiming at the problem that the complementary filter algorithm does not work well when the maneuverability of UAV varies greatly, the hybrid algorithm based on LSTM NN proposed in this paper is tested. About 70% of the data collected in this study are used as training set for LSTM NN training, that is, the first 32 seconds, a total of 6300 sets of data. The specific configuration of LSTM NN is shown in Table.II, and the train time is about 5.35 seconds after testing. About 30% of the latter data are used as test sets, i.e., 32s to 45s, totaling 2700 sets of data, which is also the process of UAV large-scale maneuvering movement.

Figures 6, 7 and 8 describe pitch, roll and yaw error estimated by trained LSTM NN, where the error between the attitude fused by complementary filter and the reference attitude data is depicted in orange, that is, the data to be predicted by LSTM NN, and the actual attitude error predicted by LSTM NN in blue. From these figures, it can be easy to see that LSTM NN can predict the attitude the error well, where the RMSE of pitch, roll and yaw are 0.69, 0.73 and 0.59, respectively.

TABLE II
THE SPECIFICATIONS OF LSTM NN

Batch size	128
Training epoch	100
Learning rate	0.01
Input step size	3

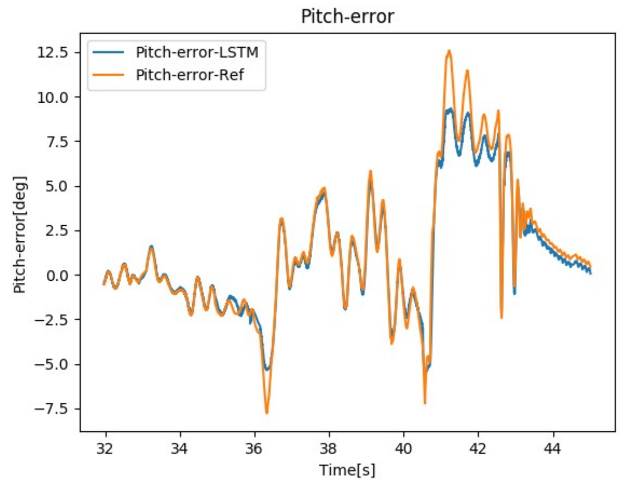

Fig. 6. The pitch error estimated from LSTM NN

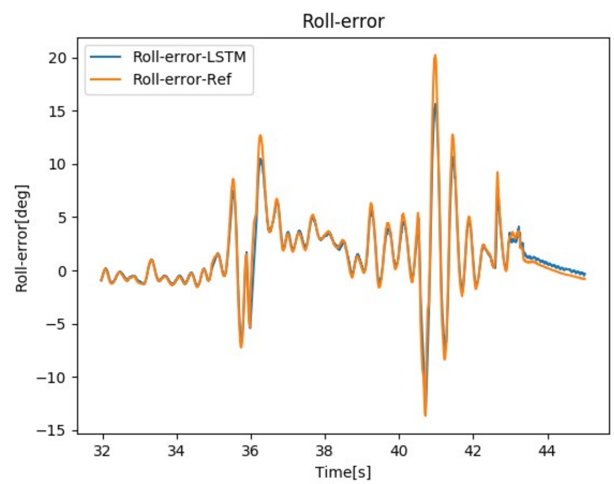

Fig. 7. The roll error estimated from LSTM NN

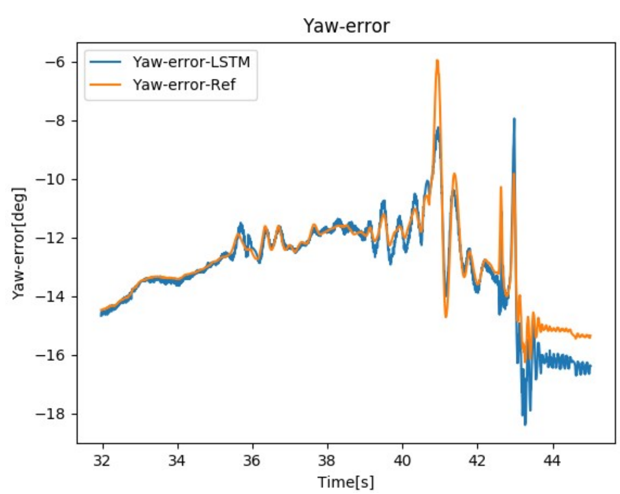

Fig. 8. The yaw error estimated from LSTM NN

Figure.9 is the final attitude fusion result after LSTM NN compensation. It can be seen that the attitude angle error of this hybrid attitude fusion method is smaller than that of the single complementary filter attitude fusion method. As shown in Table.III, the maximum error of pitch, roll and yaw are decreased from the original 12.53 degrees, 20.12 degrees and 16.31 degrees to 3.25 degrees, 4.16 degrees and 2.33 degrees, and the RMSEs improved by 71.4%, 70.7% and 94.8%, respectively. Therefore, the experimental results verify that the LSTM NN compensation method can greatly improve the accuracy of the complementary filter attitude fusion method. The method designed in this paper has a small coupling between modules, and can also be applied to improve the accuracy of other fusion algorithms, with good scalability.

TABLE III
THE ATTITUDE ERROR FROM CF/LSTM

Pithch (deg)		Roll (deg)		Yaw (deg)	
ME	RMSE	ME	RMSE	ME	RMSE
3.25	0.69	4.16	0.73	2.33	0.59

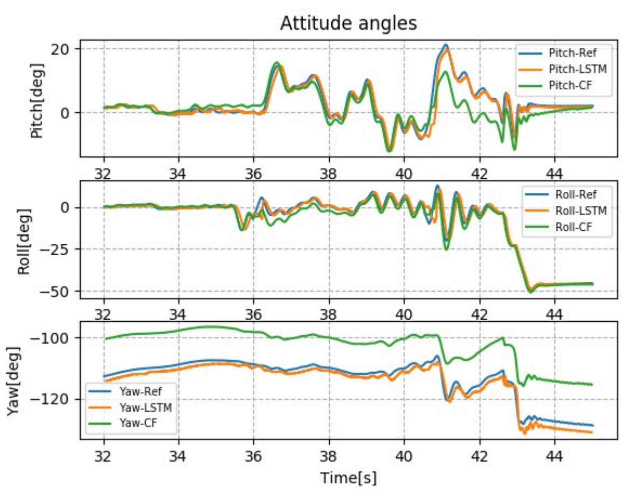

Fig. 9. The attitude fused by the LSTM/CF hybrid method

V. CONCLUSION

In order to solve the problem of poor accuracy of traditional attitude calculation algorithm in the process of UAV large-scale maneuver and considering the sequence characteristics of inertial devices, this paper proposes an attitude fusion algorithm based on LSTM neural network compensation, and establishes a hybrid model to compensate sensor drift and data fusion error. In this method, the IMU sensor output in the UAV actual flight process is used as the input of LSTM neural network , and the error compensation values of attitude angle are obtained through the trained LSTM neural network. The experimental results show that the proposed method can effectively reduce the attitude fusion error, and the hybrid structure has good compatibility with other algorithms. It can be easily applied to other algorithms to improve the accuracy of attitude fusion. In future research, we will consider the effect of changing LSTM step size and fusing more types of sensors.

REFERENCES

[1] A.F.M. Saifuddin Saif, et al. “Motion analysis for moving object detection from UAV aerial images: A review”, International Conference on Informatics, Electronics and Vision (ICIEV), 2014.

[2] M. Shi, K. Qin and L. Kai, et al. “Design and Testing on Autonomous Multi-UAV Cooperation for High-voltage Transmission Line Inspection”,Automation of Electric Power Systems, vol. 41, no. 10, pp. 117-122, 2017.

[3] X. Peng, T. Zhang and J. Yu, et al. “Attitude estimation algorithm of agricultural small-UAV based on sensors fusion and calibration”, Acta Automatica Sinica, vol. 41, no. 4, pp. 854-860, 2015.

[4] X. Guo, C. Sun and P. Wang. “Multi-rate cubature Kalman filter based data fusion method with residual compensation to adapt to sampling rate discrepancy in attitude measurement system”, Review of Scientific Instruments, vol. 88, no. 8, pp. 085002, 2017.

[5] L. Khot, L. Tang and B. Steward, et al. “Sensor fusion for improving the estimation of roll and pitch for an agricultural sprayer”, Biosystems Engineering, vol. 101, no. 1, pp. 13-20, 2008.

[6] R. Mahony, T. Hamel and J.M.Pflimlin. “Nonlinear Complementary Filters on the Special Orthogonal Group”, IEEE Transactions on Automatic Control, vol. 53, no. 5, pp. 1203-1218, 2008.

[7] R. Mahony, T. Hamel and P. Morin, et al. “Nonlinear complementary filters on the special linear group”, International Journal of Control, vol. 85, no. 10, pp. 1557-1573, 2012.

[8] Z. Wu, Z. Sun and W. Zhang, et al. “A novel approach for attitude estimation based on MEMS inertial sensors using nonlinear complementary Filters”, IEEE Sensors Journal, vol. 16, no. 10, pp. 3856-3864, 2016.

[9] S. O. H. Madgwick, A. J. L Harrison and R. Vaidyanathan, “Estimation of IMU and MARG orientation using a gradient descent algorithm”, IEEE International Conference on Rehabilitation Robotics, pp. 1-7, 2011.

[10] S. Yean, B. S. Lee and C. K. Yeo, et al. “Algorithm for 3D orientation estimation based on Kalman Filter and Gradient Descent”, IEEE 7th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), 2016.

[11] Z. Zheng, W. Long and Z. Cong. “Attitude Estimation Algorithm of Motion Acceleration Restrained with Dynamic Step Gradient Descent”, Information and Control, vol. 46, no. 2, pp. 136-143, 2017.

[12] S. Sabatelli, M. Galgani, L. Fanucci, and A. Rocchi, “A Double-Stage Kalman Filter for Orientation Tracking With an Integrated Processor in 9-D IMU”, IEEE Trans. Instrum. Meas., vol. 62, no. 3, pp. 590598, Mar. 2013.

[13] Y. Xu, J. Quo and Y. Guan. “EKF based multiple-mode attitude estimator for quadrotor using inertial measurement unit”, IEEE Control Conference, 2017.

[14] W. Li and J. Wang. “Effective Adaptive Kalman Filter for MEMS-IMU/Magnetometers Integrated Attitude and Heading Reference Systems”, The Journal of Navigation, vol. 66, no. 1, pp. 15, 2013.

[15] H.E. Soken and C. Hajiyev. “UKF-Based Reconfigurable Attitude Parameters Estimation and Magnetometer Calibration”, IEEE Transactions on Aerospace and Electronic Systems, vol. 48, no. 3, pp. 2614-2627, 2012.

[16] Y. Oshman and A. Carmi . “Attitude Estimation from Vector Observations Using a Genetic-Algorithm-Embedded Quaternion Particle Filter”, Journal of Guidance, Control, and Dynamics, vol. 29, no. 4, pp. 879-891, 2006.

[17] M. Gevrey, I. Dimopoulos and S. Lek. “Review and comparison of methods to study the contribution of variables in artificial neural network models”, Ecological Modelling, vol. 160, no. 3, pp. 249-264, 2003.

[18] K. Kolanowski, A. wietlicka, R. Kapela, J. Pochmara, and A. Rybarczyk, “Multisensor data fusion using Elman neural networks”, Applied Mathematics and Computation, vol. 319, pp. 236244, Feb. 2018.

[19] C. Jiang et al., “A MEMS IMU De-Noising Method Using Long Short Term Memory Recurrent Neural Networks (LSTM-RNN)”, Sensors, vol. 18, no. 10, p. 3470, Oct. 2018.

[20] S. Hochreiter and J. Schmidhuber.“Long short-term memory”, Neural Computation, vol. 9, pp. 1735-1780, 1997.

[21] F. Gers, J. Schmidhuber, F. Cummins."Learning to forget: continual prediction with LSTM", Neural Computation, vol. 12, no. 10, pp. 2451-2471, 2000.
[22] I. Baritzhack and Y. Oshman. "Attitude Determination from Vector Observations: Quaternion Estimation", IEEE Trans.aero.elec.sys, vol. 21, no. 1, pp. 128-136, 1985.
[23] K. Chen, Y. Zhou and F. Dai. "A LSTM-based method for stock returns prediction: A case study of China stock market", IEEE International Conference on Big Data, pp. 2823-2824, 2015.
[24] T. Nakashika, T. Takiguchi, Y. Ariki,"Voice Conversion Using RNN Pre-Trained by Recurrent Temporal Restricted Boltzmann Machines, IEEE Transactions on Audio Speech and Language Processing, vol. 23, no. 3, pp. 580-587, 2015.
[25] Y. Zhou, J. Wan, Z. Li, et al."GPS/INS integrated navigation with BP neural network and Kalman filter, IEEE International Conference on Robotics and Biomimetics (ROBIO), pp. 2515-2520, 2017.
[26] https://docs.px4.io/en/flightcontroller/mropixhawk.html