

A Novel Hybrid Attitude Fusion 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 the 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 with the aid of the powerful nonlinear fitting and time series processing ability of the LSTM NN. 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 can effectively improve the accuracy of the attitude fusion.

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

I. INTRODUCTION

In recent years, with the development of artificial intelligence, unmanned aerial vehicles (UAVs) are expected to perform more intelligent and complex tasks, such as mobile object detection [1], powerline 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 important part of the 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 the attitude. The tri-axis gyroscope can measure the triaxial angular velocity under the UAV motion state. The attitude angles can be calculated by integrating the angular rate, which process dynamic characteristics and high accuracy in short period of time. However, this method would 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 demand [3]- [5].

The algorithms commonly used for UAV attitude fusion include complementary filter (CF) [6]- [8], gradient descent algorithm [9]- [11] and Kalman filter [12]- [14]. The main idea of the CF is to transform the gravity acceleration vector in the navigation coordinate system into the body coordinate system through rotation matrix, and cross product the acceleration measurement value in body coordinate system to obtain attitude error. Finally, the attitude error caused by the gyroscope integral drift can be modified by proportional-integral (PI) operation. CF 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 used to calculate gravity acceleration and magnetic field error gradient to obtain attitude quaternion and compensate the gyroscope drift error. However, due to the varied step size of the gradient descent, it is often difficult to accurately determine the step size of gradient descent, resulting in low precision of the 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 state equation and measurement 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], for nonlinear systems, the improvement accuracy is not obvious with heavy calculation load.

Artificial neural network, which does not need to establish a mathematical model for the system and can fit the nonlinear system characteristics well, is a mainstream machine learning algorithm at present [17]. The UAV attitude solution is generally obtained 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

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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 current moment, that is, it cannot store the previous time nodes information, which cannot be used to deal with the time sequence data well. As an important branch of deep learning, recurrent neural network (RNN) can realize the function of memory with its own unique recurrent structure, and can be used to predict the value of the 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 can generate the corresponding threshold value through training, and the input values are 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 the input and the output of the training sets, thus effectively solving the gradient vanishing problem. The “memory unit” of LSTM NN is equivalent to a delay operator, which enables the network to have dynamic memory ability and also well conforms to the inertial characteristics of the IMU sensor. In [?], we use the attitude angle output of the PIXHAWK through Kalman filter as the training set Y of LSTM. The trained LSTM NN is used to directly estimate the UAV attitude angle. During the experiments, it is found that after a long time, the output attitude angle error of LSTM would drift. Therefore, we redesign the LSTM NN structure in this paper, while the difference between the attitude angle of pixhawk output and the attitude angle of the motion capture system output are used to train LSTM NN and assumed as the feedback compensation back of pixhawk output. It would reduce the UAV attitude angle error drift with higher accuracy.

The remainder of the paper is organized as follows. In Section II, a brief overview of the CF 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 UAV navigation, the geographic coordinate system is usually determined by the local north, east and down direction based on the right-hand rule. Similarly, the body coordinate system is determined by the front, right and down direction of the aircraft based on 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 the 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, as the Euler angle method has a gimbal lock problem, and it cannot be used for the whole attitude solution. 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 [23], the quaternion at the current moment, i.e., the current attitude, can be calculated by solving the quaternion differential equation,

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

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

According to the above analysis, as long as $[\omega_x \ \omega_y \ \omega_z]$ can be accurately measured, the quaternion at the current moment can be constantly updated and iterated to obtain the quaternion at the next moment. The $[\omega_x \ \omega_y \ \omega_z]$ is usually measured by the gyroscope in the airborne IMU. However, due to the 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.

CF algorithm is widely used in the attitude fusion of small and medium-sized UAVs. As shown in Fig. 1, it is a block diagram of the CF 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., $[v_x \ v_y \ v_z]^T$ and $[w_x \ w_y \ w_z]^T$. 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 $[a_x \ a_y \ a_z]^T$ and $[m_x \ m_y \ m_z]^T$. When the attitude angle is small, the cross product of $[v_x \ v_y \ v_z]^T$ and $[a_x \ a_y \ a_z]^T$,

$[w_x \ w_y \ w_z]^T$ and $[m_x \ m_y \ m_z]^T$ can be approximated to the angle value of the 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 Eq.(2), to compensate the error to the gyroscope measurements [6]- [8].

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

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

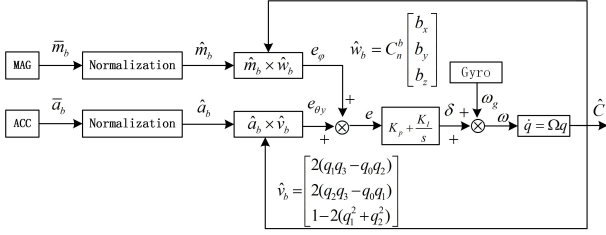


Fig. 1. Illustration of the attitude fusion using CF

In this paper, LSTM NN is used to compensate the error of CF attitude fusion algorithm, 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 [24], language translation and speech recognition [25], 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. Fig. 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 Fig. 2, the first one from left to right is the forget gate, and the specific mathematical expression is as follows [19]- [21],

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

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

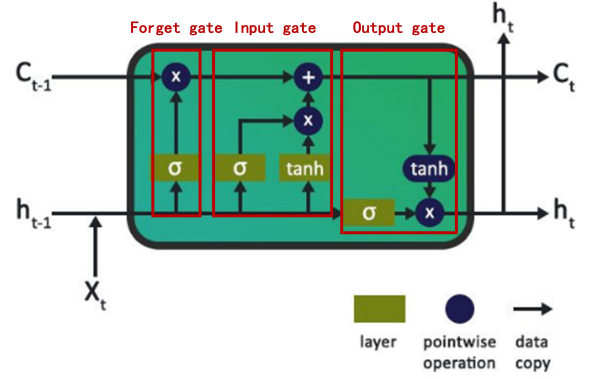


Fig. 2. Basic structure of a LSTM Unit

is stored in the current cell state c_t . The input gate consists of two parts: one is the sigmoid layer, to determine which values will be updated, and the other is the tanh layer, 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,

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

$$c'_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (5)$$

According to Eq.(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 previous moments and it can avoid the current irrelevant content entering the memory due to the input door.

$$c_t = f_t \cdot c_{t-1} + i_t \cdot c'_t \quad (6)$$

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

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

$$h_t = o_t \cdot \tanh(c_t) \quad (8)$$

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 CF attitude fusion method, LSTM NN is used to fit the error of CF attitude fusion and compensates it to the attitude angle, so as to improve the accuracy of the CF 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 the attitude angles, i.e., pitch $\hat{\theta}$, roll $\hat{\phi}$ and yaw $\hat{\gamma}$, are solved by the CF attitude fusion method. The deviation values $\delta\theta, \delta\phi, \delta\gamma$ between the reference data and the CF output are fitted and predicted by the LSTM NN. Considering the real-time requirement and human experience, a three-layer LSTM neural network is designed in this paper. The IMU 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

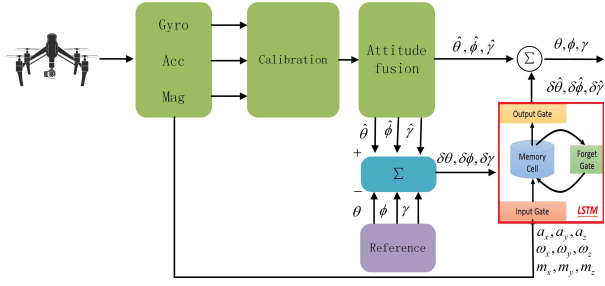


Fig. 3. The UAV attitude fusion scheme based on LSTM NN

neuron number of which depends on the dimension of the input vector, that is, 9 neurons. The LSTM NN outputs are the error between the attitude angle fused by CF 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 [26],

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

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 the 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 [27]. Our experiments are carried out in a laboratory equipped with Vicon motion capture system, so the attitude data output by Vicon motion capture system is used as the standard reference data. As shown in Fig.5, it is the result of CF attitude fusion



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

using IMU data in Pixhawk, where the blue solid line represent the attitude angles fused by CF 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 data. In the first 10 seconds, when the UAV moves at a constant speed or at rest, the attitude fusion algorithm of CF 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 CF 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 solution error will be relatively large.

Aiming at the problem that the CF algorithm does not function well when the maneuverability of UAV varies substantially, the hybrid algorithm based on LSTM NN proposed

TABLE I
THE ATTITUDE ERROR FROM CF FUSION METHOD

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

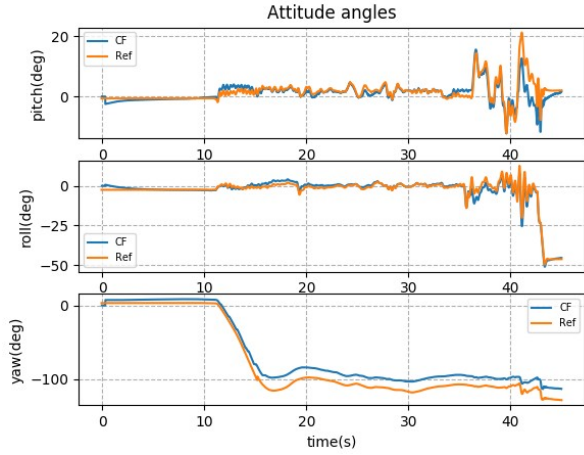


Fig. 5. The attitude angle fused by CF

in this paper is tested. About 70% of the data collected in this study are used as training set for the LSTM NN training, that is, the first 32 seconds, a total of 6300 sets of data. The configuration of the 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.

Figs. 6, 7 and 8 describe pitch, roll and yaw error estimated by trained LSTM NN, where the error between the attitude fused by CF 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 seen that LSTM NN can predict the attitude well, where the RMSE of pitch, roll and yaw are 0.69, 0.73 and 0.59, respectively.

Fig. 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 CF 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

TABLE II
THE SPECIFICATIONS OF LSTM NN

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

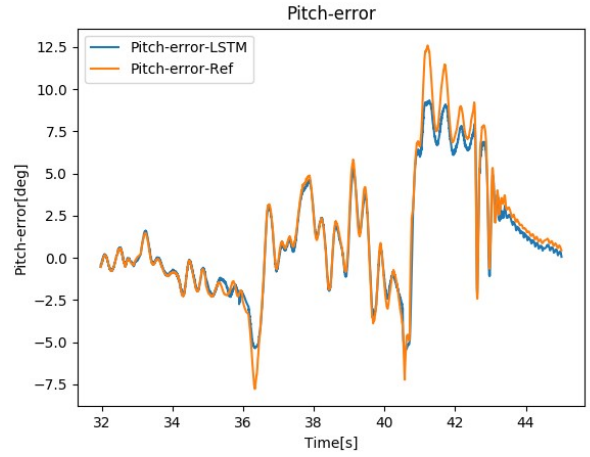


Fig. 6. The pitch error estimated from LSTM NN

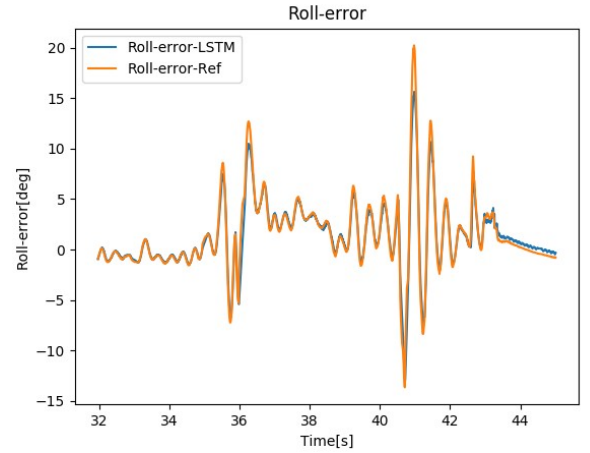


Fig. 7. The roll error estimated from LSTM NN

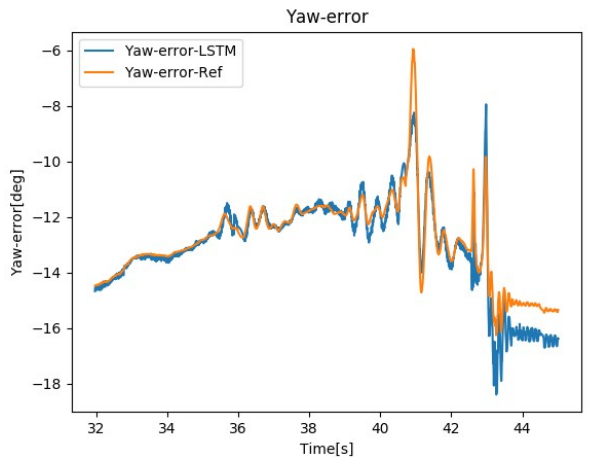


Fig. 8. The yaw error estimated from LSTM NN

RMSEs improved by 71.4%, 70.7% and 94.8%, respectively. Therefore, the experimental results can verify that the LSTM NN compensation method can greatly improve the accuracy of the CF 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

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

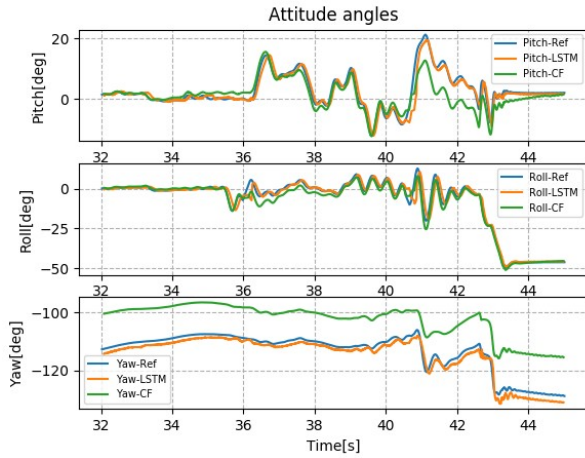


Fig. 9. The attitude fused by the LSTM/CF hybrid method

V. CONCLUSION

In order to solve the problem of poor accuracy of traditional attitude calculation for UAV large-scale maneuver and considering the sequence characteristics of inertial devices, this paper proposes an attitude fusion algorithm based on LSTM NN 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 NN, and the error compensation values of attitude angle are obtained through the trained LSTM NN. The proposed method can effectively reduce the attitude fusion error and the hybrid structure is compatible with other algorithms to improve the accuracy of attitude fusion. Future research will consider the effect of changing LSTM step size and fusing more types of sensors so as to design a general framework for the computation reduction.

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