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Research on High-precision Algorithm for Flight Attitude Evaluation of Quadrotor Aircraft

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Abstract. With the rapid development of UAV technology, quadrotor aircraft has shown wide application potential in many fields. In this paper, a high-precision algorithm based on multi-sensor data fusion and optimized extended Kalman filter (EKF) technology is designed and implemented for the flight attitude evaluation of quadrotor aircraft. By fusing the data of IMU (Inertial Measurement Unit), GPS (Global Positioning System) and magnetometer, the algorithm can effectively resist noise interference and reduce sensor errors, and realize real-time and high-precision estimation of aircraft attitude angle and position. The experimental results show that the algorithm performs well in a variety of flight trajectories, which is basically consistent with the real trajectory, especially in complex movements such as hovering and diving, and can still maintain high accuracy and robustness. Compared with the commonly used Mahony and Madgwick algorithms, the algorithm proposed in this study has obvious advantages in attitude estimation error fluctuation range, error stability and error average. This not only improves the maneuverability and safety of the aircraft, but also provides strong support for the autonomous flight and precise control of the UAV. This study provides an important reference for the field of flight attitude evaluation of quadrotor aircraft.

Keywords: Quadrotor aircraft; Flight attitude evaluation; Extended Kalman filter.

1. Introduction

With the rapid development of science and technology, UAV technology is becoming more and more mature and shows great application potential in many fields. As a kind of unmanned aerial vehicle, quadrotor aircraft has been widely used in military reconnaissance, civil aerial photography, search and rescue and other fields because of its unique flight stability and flexibility. However, with the complexity of application scenarios and the diversification of mission requirements, the performance requirements of quadrotor aircraft are getting higher and higher.

Among many performance indexes, the stability and control accuracy of flight attitude are particularly important. Accurate evaluation of flight attitude is the key to stable flight and mission execution of quadrotor aircraft [1-2]. A high-precision attitude evaluation system can not only improve the maneuverability of the aircraft, but also significantly enhance its adaptability and safety in complex environments [3]. Therefore, it is of great significance to develop a high-precision flight attitude evaluation algorithm for improving the overall performance of quadrotor aircraft.

In this study, the high-precision attitude evaluation of quadrotor aircraft is realized by exploring and optimizing the flight attitude evaluation algorithm. By fusing various sensor data and combining with advanced filtering and processing technology, an attitude evaluation algorithm which can effectively resist noise interference and reduce sensor error is developed.

2. Algorithm Design and Implementation

The flight attitude evaluation algorithm designed in this study is based on the extended Kalman filter (EKF) technology of multi-sensor data fusion and optimization (Figure 1). The basic principle is to accurately estimate the attitude of the aircraft by fusing data from various sensors such as IMU (Inertial Measurement Unit), GPS (Global Positioning System) and magnetometer [4-6]. The optimized EKF is used to process these data, provide real-time attitude angle and position estimation, and reduce the influence of noise and sensor error.

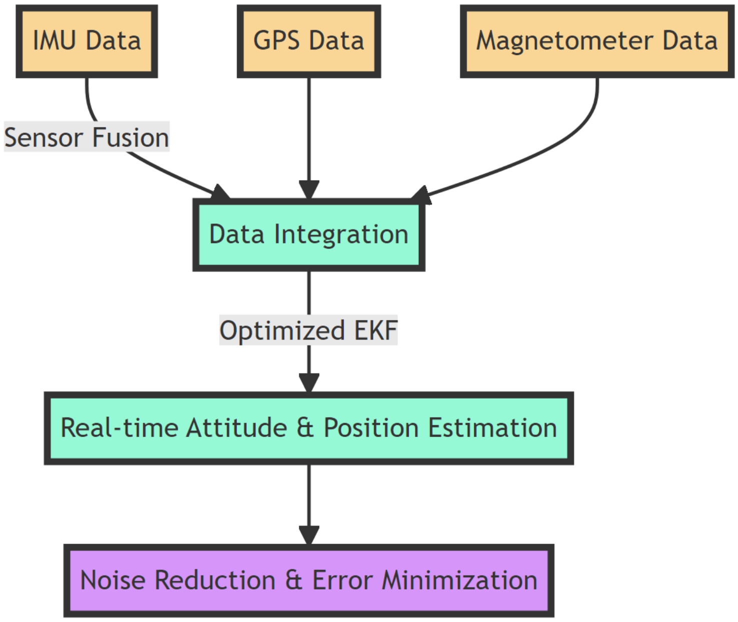

Figure 1. Principle of flight attitude evaluation algorithm

In the data acquisition stage, IMU is used to collect the data of accelerometers and gyroscopes, and GPS is used to obtain the position information of aircraft [7]. The geomagnetic field data is obtained by magnetometer to help determine the direction of the aircraft. In the data preprocessing stage, IMU data is denoised to reduce the influence of mechanical vibration and environmental noise on the data. Coordinate transformation of GPS data to make it match the IMU coordinate system. Finally, the magnetometer data is corrected to eliminate the interference of hard iron and soft iron [8].

In the data fusion stage, the optimized EKF is used to integrate the data of IMU, GPS and magnetometer [9-10]. Through the prediction and updating steps of EKF, the attitude angle and position of the aircraft are continuously refined. In the aspect of attitude estimation, quaternion is used to represent the attitude of the aircraft to avoid the problem of universal lock, and quaternion is calculated and updated in real time through the fused data, so as to obtain the attitude angle information of the aircraft, namely pitch angle, yaw angle and roll angle [11]. In the post-processing and output stage, the estimated attitude angle is smoothed to reduce the impact of sudden change, and the processed attitude angle data is sent to the flight control system to assist the stable control and navigation of the aircraft [12].

The state equation of EKF can be expressed as:

$$x_{k+1} = f(x_k, u_k) + w_k \tag{1}$$

Where, x_k is the state vector (including position, velocity, attitude, etc.) at k moment, u_k is the control input (accelerometer reading, etc.), f is the state transfer function, which describes how the state evolves with time, and w_k is the process noise.

The observation equation describes how to generate observations (GPS position, magnetometer readings, etc.) from the state vector:

$$z_k = h(x_k) + v_k \tag{2}$$

Where z_k is the observed value at k moment, h is the observation function, and v_k is the observation noise.

EKF update steps:

Forecast:

$$\begin{aligned}\hat{x}_{k|k-1} &= f\left(\hat{x}_{k-1|k-1}, u_{k-1}\right)\\ P_{k|k-1} &= F_{k-1}P_{k-1|k-1}F_{k-1}^{T} + Q_{k-1}\end{aligned} \tag{3}$$

Among them, $\hat{x}_{k|k-1}$ is the prior state estimation, $P_{k|k-1}$ is the prior estimation error covariance, F_{k-1} is the Jacobian matrix of the state transition function, and Q_{k-1} is the process noise covariance.

Update:

$$\begin{aligned}K_k &= P_{k|k-1}H_k^T\left(H_k P_{k|k-1}H_k^T + R_k\right)^{-1}\\ \hat{x}_{k|k} &= \hat{x}_{k|k-1} + K_k\left(z_k - h\left(\hat{x}_{k|k-1}\right)\right)\\ P_{k|k} &= \left(I - K_k H_k\right)P_{k|k-1}\end{aligned} \tag{4}$$

Where K_k is the Kalman gain, H_k is the Jacobian matrix of the observation function, R_k is the covariance of the observation noise, $\hat{x}_{k|k}$ is the posterior state estimation, and $P_{k|k}$ is the covariance of the posterior estimation error.

Quaternion $q = \left[q^0, q^1, q^2, q^3\right]^T$ can be converted into attitude angles (pitch angle θ, yaw angle ψ, roll angle ϕ):

$$\begin{aligned}\varphi &= \operatorname{atan2}\left(2\left(q^0q^1 + q^2q^3\right), 1 - 2\left(q_1^2 + q_2^2\right)\right)\\ \theta &= \arcsin\left(2\left(q^0q^2 - q^2q^3\right)\right)\\ \psi &= \operatorname{atan2}\left(2\left(q^0q^3 + q^1q^2\right), 1 - 2\left(q_2^2 + q_3^2\right)\right)\end{aligned} \tag{5}$$

This study not only relies on traditional IMU data, but also combines GPS and magnetometer data to improve the accuracy and robustness of attitude evaluation. By improving the parameter setting and noise model of EKF, it is more suitable for the dynamic characteristics of quadrotor aircraft, thus improving the accuracy of attitude estimation. Using quaternion instead of Euler angle to represent the attitude of aircraft avoids the problem of universal lock and can represent the attitude change more smoothly.

3. Experiment and Result Analysis

3.1. Experimental scheme

In order to verify the effectiveness of the flight attitude evaluation algorithm based on multi-sensor data fusion and optimized EKF technology designed in this study, an open and unobstructed outdoor venue was selected for flight test. Equip the quadrotor aircraft and ensure that it is equipped with sensors such as IMU (Inertial Measurement Unit, including accelerometer and gyroscope), GPS

(Global Positioning System) and magnetometer. Build a ground control station to monitor and record flight data in real time.

During the flight, real-time data is collected from IMU (acceleration range of ± 2g to ± 6g, gyroscope range of ± 100 °/s to ± 2000 °/s), GPS (accuracy of 2m CEP, update frequency of 5Hz), and magnetometer (range of ± 200 μ T to ± 700 μ T). Pre-processing the collected data, including denoising (Butterworth low-pass filter, cut-off frequency set to 10Hz), coordinate conversion (converting GPS data from WGS84 to ENU coordinate system matching IMU) and calibration (magnetometer data is calibrated by hard iron and soft iron calibration algorithm).

A variety of flight trajectories were designed in the experiment, including straight flight (speed from 5m/s to 15m/s), hovering (radius from 5m to 20m, angular velocity from 0.1rad/s to 0.5rad/s), climbing (vertical speed from 1m/s to 3m/s) and diving (vertical speed from -1m/s to -3m/s). Under each trajectory, the algorithm proposed in this study and other commonly used attitude evaluation algorithms, Mahony and Madgwick, are used to estimate the attitude respectively. The attitude estimation results of various algorithms under different trajectories are recorded and compared.

3.2. Analysis of experimental results

Fig. 2 shows the comparison between the real flight trajectory of an aircraft (solid blue line) and the flight trajectory estimated by the algorithm based on multi-sensor data fusion and EKF optimization (dashed red line) in three-dimensional space.

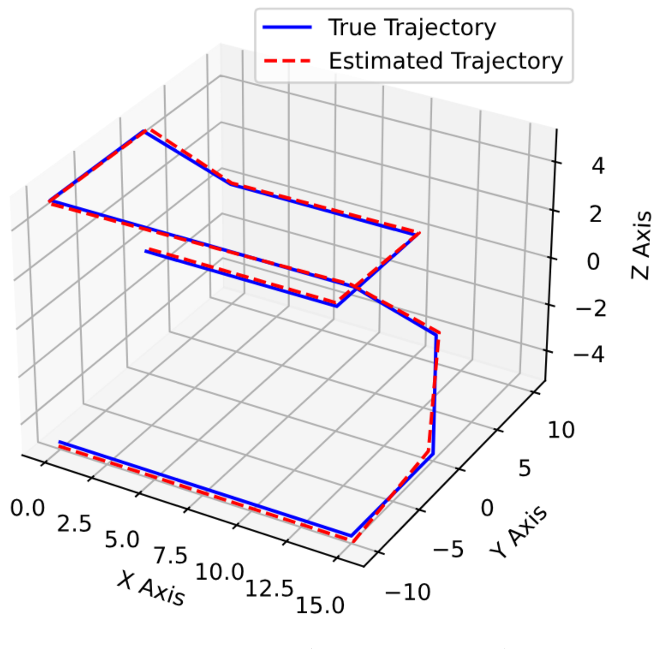

Figure 2. 3D trajectory comparison

On the whole, the shapes and trends of the real trajectory and the estimated trajectory in three-dimensional space are basically the same. This shows that the estimation algorithm used can capture the motion mode of the aircraft well, including straight flight, hovering, climbing and diving. Although the overall trend is similar, there is a certain degree of deviation between the estimated trajectory and the real trajectory in some local areas. These deviations may be caused by many factors, including sensor noise, algorithm error, environmental interference and so on. However, as can be seen from the figure, these deviations are relatively small and have not seriously affected the recognition of the overall trajectory.

The estimated trajectory can still closely follow the real trajectory when the aircraft performs complex actions (such as hovering and diving), which shows that the estimation algorithm has good robustness.

It can maintain stable performance under different flight conditions and effectively cope with various challenges. The results of 3D trajectory comparison show that the estimation algorithm can effectively capture the real motion state of the aircraft and maintain high accuracy and robustness in complex environment. This provides strong support for autonomous flight and precise control of UAV.

The effectiveness of the flight attitude evaluation algorithm designed in this study is verified by comparative experiments. The algorithm significantly improves the accuracy and robustness of attitude estimation by fusing the data of various sensors and combining with the optimized EKF. Compared with other algorithms (Mahony and Madgwick), the algorithm in this study shows better performance in various flight paths. Fig. 3 shows the trend of attitude estimation errors with time for three different attitude estimation algorithms (the algorithm proposed in this study, Mahony algorithm and Madgwick algorithm) under the straight flight trajectory.

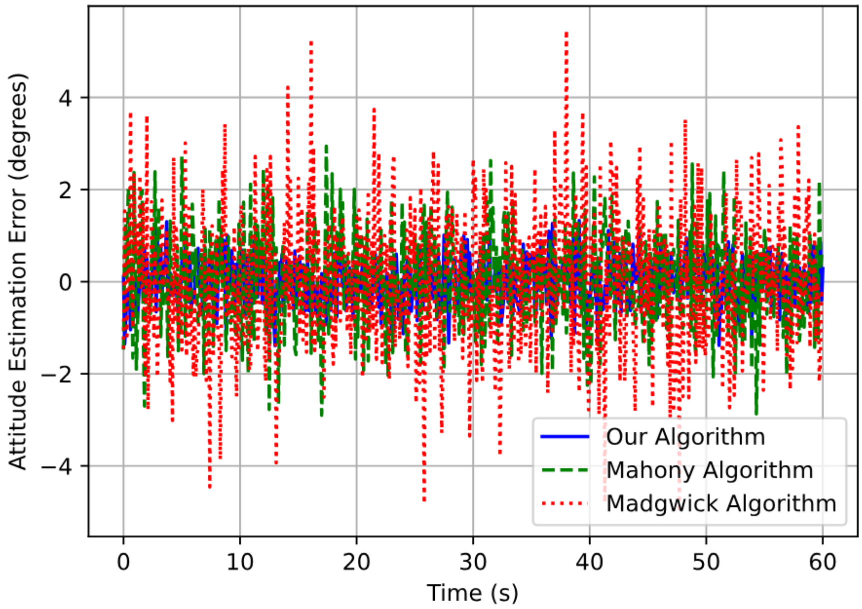

Figure 3. Comparison of attitude estimation errors with time

As can be seen from the figure, the attitude estimation error fluctuation range of the algorithm proposed in this study (represented by the blue solid line) is relatively small, mainly concentrated around 0 degrees, and the fluctuation range is small. In contrast, the error fluctuation range of Mahony algorithm (represented by green dotted line) and Madgwick algorithm (represented by red dotted line) is larger, especially Madgwick algorithm, whose error fluctuation is the most obvious. The algorithm proposed in this study shows high error stability in the whole test time. The error curve is relatively smooth, and there is no obvious abrupt change or periodic fluctuation. This shows that the algorithm has high robustness and reliability in processing sensor data and attitude estimation. The algorithm proposed in this study is superior to Mahony algorithm and Madgwick algorithm in error fluctuation range, error stability and average error. This shows that the algorithm has higher accuracy and reliability in attitude estimation, and is more suitable for attitude evaluation in complex flight environment.

The algorithm proposed in this study performs well in attitude estimation accuracy and robustness, which is superior to the traditional Mahony algorithm and Madgwick algorithm. This provides strong support for autonomous flight and precise control of UAV, and helps to improve the overall performance and safety of UAV.

Although the sensor data has been preprocessed, there may still be great noise interference in a highly dynamic environment. In the future, we can consider introducing more advanced filtering technology to further reduce the influence of noise on attitude estimation. Although the algorithm in this study is excellent in attitude estimation accuracy, the real-time performance of the algorithm may be challenged in some extreme cases. In the future, the computational efficiency of the algorithm can be optimized to ensure that it can still maintain real-time performance in more complex environments. This study is mainly verified by experiments in open fields, but its performance in complex environments such as urban canyons and forests needs further testing. In the future, the algorithm can be optimized for different scenarios to improve its adaptability in various environments.

4. Conclusion

In this study, a high-precision algorithm is proposed to evaluate the flight attitude of quadrotor aircraft. Based on multi-sensor data fusion and optimized EKF technology, the algorithm effectively integrates the data from IMU, GPS and magnetometer, and realizes the accurate estimation of aircraft attitude. The experimental results show that the algorithm is superior to the traditional Mahony and Madgwick algorithms in many flight trajectories, such as straight flight, hovering, climbing and diving, and has higher accuracy and robustness. In addition, the algorithm uses quaternion to represent the attitude of the aircraft, which avoids the problem of universal lock and can represent the attitude change more smoothly. Although there is still the challenge of noise interference in high dynamic environment, the results of this study provide strong technical support for autonomous flight and precise control of UAV, which is helpful to improve the overall performance and safety of UAV. The future work will focus on further reducing the influence of noise, improving the real-time performance of the algorithm and optimizing the algorithm for different environments.

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