Vision / inertial integrated navigation method for quadcopter based on EKF state observer

Haibo Xu\textsuperscript{1,a}, Peixuan Li\textsuperscript{1,b}, Litao Wen\textsuperscript{1}, Zewei Wang\textsuperscript{1}

\textsuperscript{1}Xi’an Jiaotong University Xi’an, Shanxi, 710049, China
\textsuperscript{a}hbxu@mail.xjtu.edu.cn, \textsuperscript{b}1343916177@qq.com

Abstract. Quadrotor UAVs are widely used in the field of power line inspections because of their advantages such as high accuracy, strong adaptability, and strong obstacle surmounting capabilities. However, in practical applications, the autonomous navigation of the UAV still has problems such as poor anti-interference ability, insufficient accuracy and still dominated by manual control. Visual navigation is difficult to obtain sufficient information or to track feature points when there is insufficient lighting, sparse features, and large maneuver. These problems can reduce the accuracy of visual navigation. The position estimation error directly obtained by integrating the IMU data of the inertial navigation unit will gradually increase with time. A vision / inertial integrated navigation method for a quadcopter UAV based on loosely coupled extended Kalman filter algorithm is proposed in this paper. Design state observer for UAV based on extended Kalman filter. The visual/inertial integrated navigation algorithm is simulated in gazebo. Finally, an experimental platform is set up to verify the vision / inertial integrated navigation algorithm experimentally. The overall position calculation error meets the positioning accuracy requirements during power line inspections.

1. Introduction

State estimation is the basis of control and decision-making and plays a very important role. When the inspection robot automatically goes online and offline, the position controller needs accurate position and attitude feedback, and the position estimation error directly obtained by IMU data integration will gradually increase over time; the visual odometer position estimation obtained by the binocular camera The frequency is too low, and when the Euler angle changes drastically, a large error occurs due to less matching of the feature points or difficulty in tracking the feature points. Considering that the drift characteristics of the IMU device and the binocular camera are exactly complementary, the multi-sensor fusion method can be used to obtain more accurate position information. The frame structure diagram is shown in Figure 1. The sampling frequency of IMU is 100Hz, and the output frequency of binocular camera visual odometer pose is 20Hz. The information is fused by the multi-sensor fusion framework and then output accurate position and posture feedback to the position controller [1].

![Figure 1 Multi-sensor fusion framework structure diagram](image-url)
This paper adopts a loose coupling method to avoid adding the feature points of the image to the state vector, but treats the image information as a black box model, and then merges with the IMU raw data after outputting the pose through the visual odometer. The computational complexity is a constant.

2. Create a coordinate system

The establishment of the EKF frame coordinate system of the inspection robot is shown in Figure 2. The World coordinate system is the world coordinate calculated by the IMU. Its origin is the initial coordinate point of the robot taking off, and the coordinate axis direction is the same as the NED coordinate system. The Vision coordinate system is the world coordinate calculated by the binocular camera, and its origin is the starting point of the visual odometer. The IMU and the binocular camera are installed in different positions of the UAV. Therefore, \( q_w^c \) and \( p_w^c \) are constants and can be measured in advance. The origin of the Vision coordinate system is determined by the initial solution position of the binocular camera. Therefore, the relative position between the Vision system and the World system will not change after the IMU and binocular camera information are fused, so \( q_v^w \) and \( p_v^w \) are constants [2].

![Figure 2 schematic diagram of EFK frame coordinate system of power line inspection robot](image)

3. Observation equation based on extended Kalman filter

According to the observation equation of the system \( \dot{z} = Hx \), the observation noise of the system is divided into position observation noise \( n_p \) and attitude observation noise \( n_q \) [3]. Therefore, the observation matrix can be written as:

\[
H = \begin{bmatrix} H_p \\ H_q \end{bmatrix}
\]

First analyze the position observation noise, the corresponding position observation model is:

\[
z_p = p_b^c = R_{(q_w^v)}^T \left( p_w^i + R_{(q_b)}^T p_f^i \right) \lambda + n_p
\]

Define the position observation noise as:

\[
\tilde{z}_p = z_p - \hat{z}_p
\]

\[
\tilde{z}_p = R_{(q_w^v)}^T \left( p_w^i + R_{(q_b)}^T p_f^i \right) \lambda + n_p - R_{(q_v^w)}^T \left( p_w^i + R_{(q_b)}^T p_f^i \right) \lambda
\]

Therefore, the position observation equation can be written as:

\[
\tilde{z}_p = H_p \tilde{x}
\]

The position observation matrix \( H_p \) is:
Similarly, the attitude observation model is:

\[ z_q = q^c_{\omega} = q^c_{\omega} \otimes q^i_{\omega} \otimes q^w_{\omega} \]  

(7)

Define the attitude observation noise as:

\[ \tilde{z}_q = z_q - z_q \]  

(8)

Therefore, the attitude observation equation can be written as:

\[ \tilde{z}_q = H_q \tilde{x} \]  

(9)

The position observation matrix \( H_p \) is:

\[
H_p = \begin{bmatrix}
R^T_{(q^c_{\omega})} \tilde{\lambda} \\
0_3 \\
-R^T_{(q^c_{\omega})} R^T_{(q_{\omega})} p^c + R^T_{(q^c_{\omega})} \tilde{p}^c \\
R^T_{(q^c_{\omega})} R^T_{(q_{\omega})} \tilde{\lambda} \\
0_3 \\
-R^T_{(q^c_{\omega})} p^w + R^T_{(q^c_{\omega})} p^c \tilde{\lambda}
\end{bmatrix}\]  

(6)

Calculate the Kalman gain matrix \( K \) through the observation matrix \( H_q \):

\[
K = P H^T S^{-1} \]  

(11)

\[
S = H P H^T + R \]  

(12)

State estimation update:

\[ \hat{x} = K \tilde{z} \]  

(13)

Error covariance update:

\[
P_{k+1|k+1} = (I_d - K H) P_{k+1|k} (I_d - K H)^T + K R K^T \]  

(14)

4. Simulation analysis based on Gazebo

This paper builds a joint simulation experiment platform based on Simulink and Gazebo. The Simulink simulation platform is mainly used for the design of the airframe dynamics model, flight control model and position controller. The Gazebo simulation platform is used to simulate real visual data and IMU data, and to simulate the EKF state observer based on the airborne binocular [5].

The physical simulation environment established by Gazebo simulation is shown in Figure 3.

Figure 3 Gazebo physical simulation environment map
The body URDF model of the inspection robot is established with reference to the open source IRIS quadrotor [6]. The schematic diagram of the body URDF model is shown in Figure 4.

To analyze the observation error of the position, we directly compare the position value output by the EKF with the true value of the simulator, and the result is shown in Figure 5.

It can be seen from the figure that when the aircraft is at a standstill, the position error is close to 0, because the binocular visual odometer has spatial drift characteristics. At this time, the errors added in the observation model of the IMU are Gaussian white noise and random walk error. The observation value or the first derivative of the observation value is 0. Therefore, the weight of the visual odometer output in the EKF framework is larger. When the aircraft is moving, the visual odometer has spatial drift characteristics, and its measured value output proportion is decreasing in the estimated value of EKF, while the displacement output of the IMU relies on the second integration of the acceleration, so the position calculation part of the IMU in the EFK framework There will also be pulses with similar steps (caused by random walk error integrals).

In summary, the three-axis error of the spatial position calculation \( x, y, z \) are all less than 0.05m. And when the Euler angle of the aircraft changes, the position error will increase significantly, which is consistent with the theoretical results. Therefore, the design of the state observer meets the requirements of automatic online and offline.

5. State observation experiment

5.1. Experimental platform design
In order to ensure flight safety, a multi-sensor fusion experiment platform as shown in Figure 6 was built. The experimental platform is mainly composed of four parts: binocular camera, IMU module, wireless data transmission, battery.
During the experiment, the human hand-held the experimental platform quickly moved back and forth to simulate the extreme flight trajectory of the aircraft to evaluate the performance of the state observer. The IMU data is sent to the onboard processor through wireless data transmission, and the binocular camera data is sent to the onboard processor through the USB bus. The onboard processor runs the mavros node, zed_wrapper node and EKF output node, and records experimental data through rosbag.

5.2. Analysis of results
Because of the lack of external pose measurement equipment during the experiment, the truth value (ground_truth) in a similar simulation environment is also missing. Therefore, when comparing the position curve, the visual solution and the output value of EKF are used as a reference for comparison, and the performance of the observer is evaluated by the change of the curve. The spatial position trajectory during the experiment is shown in Figure 7. The red curve in the figure is the visual solution trajectory, and it can be seen that there are fewer sampling points at the same time. The blue curve is the output position of the EKF node.

Analyzing the results of the position calculation, due to the lack of true values, the position calculated by the visual odometer is compared with the position obtained by the EKF, as shown in Figure 8.
It can be seen from the figure that the overall solution error is small, basically less than 0.1m, which is consistent with the simulation results. Therefore, this state observer can be transplanted to the airborne platform to automatically go online and offline.

6. conclusion
The vision/inertial integrated navigation method of quad-rotor UAV based on the loosely coupled extended Kalman filter algorithm proposed in this paper. The vision/inertial integrated navigation algorithm is simulated through Gazebo, and the real experimental platform is built to perform the visual/inertial integrated navigation algorithm. Experiments verify that the overall position calculation error is less than 0.1m, which meets the positioning accuracy requirements during power line inspections. Therefore, this four-rotor UAV vision/inertial integrated navigation method based on the EKF state observer greatly improves the autonomous navigation of the UAV The accuracy of UAV improves the practicability of autonomous navigation of UAV.

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