A Framework for Low-cost Fusion Positioning with Single Frequency RTK/MEMS-IMU/VIO

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Abstract. In response to the demand for high-precision positioning in the consumer market for low-speed UAVs, this paper proposes an ultra-low-cost fusion positioning system architecture, selecting consumer-grade GNSS Ublox M8T, IMU MPU 9250 modules and binocular cameras as the main equipment. We fused raw data measured from multi-sensors by expansion Kalman filter(EKF), and tested the fusion positioning performance of MEMS-IMU and VIO through simulation interruption experiment. The experimental results show that the ultra-low-cost single-frequency RTK/VIO/MEMS-IMU multi-sensor fusion positioning system can provide high-precision, reliable, continuous and smooth positioning results.

1. Introduction

With the development of low-speed unmanned equipment, such as smart agricultural machinery, unmanned vehicles, drones, it will require low-cost, high-precision and real-time positioning systems. However, existing navigation and positioning systems, including GNSS, inertial navigation system (INS), etc., have some disadvantages. Consumer-grade inertial measurement unit (IMU) cannot recurse for a long time [1] and GNSS signals are easily interfered and blocked. So a lot of research has focused on the integration of other sensors such as magnetic sensors, cameras, ultrasonic sensors, laser scanners, barometers, etc. on the basis of GPS and INS [2]. Multi-sensor fusion using all the information of these sensors, can overcome their limitations and provide a foundation for the realization of a reliable navigation system. Chu TX et al. [3] developed an integrated camera/IMU/GNSS system based on EKF for ground vehicle navigation in challenging environments. The results shows that the proposed integrated system can provide accurate estimations, which is better than the tightly coupled GNSS/IMU integration in some challenging environments. But the IMU used in the experiment is relatively expensive. Yashar BS [4] combined multi-sensor information and map matching technology to solve the navigation problem of autonomous vehicles and Yashar BS et al. [5] integrated binocular visual-inertial odometry (VIO) and radar odometry to assist MEMS inertial navigation to solve the environment with weak GNSS signals. However, using map matching technology requires prior map information and the cost of radar odometry is high, which limit the scope of those fusion method. Gonzalez R and Dabove P [6] used consumer-grade IMU and GNSS modules for car navigation performance analysis, but only single-point positioning is used in the article, and the positioning accuracy is not ideal. In general, in the multi-sensor fusion research of predecessors, there are few studies on high-precision fusion positioning of consumer-grade GNSS/MEMS-IMU/VIO sensors.
Therefore, this paper proposes an ultra-low-cost fusion positioning system framework based on EKF, selecting consumer-grade GNSS Ublox M8T, IMU MPU9250 module and binocular camera as the main equipment and fuses multi-sensor data based on EKF. Simulation interruption experiment was conduct to analyse the performance of the fusion performance.

2. Equations and mathematics

The loose combination algorithm combines RTK data, IMU data (Gyroscope, accelerometer and magnetometer data) and VIO data based on EKF.

2.1. State equation

Due to the noise of consumer-grade MEMS-IMU, the differential equation of state is optimized in this paper. The differential equation of position velocity quaternion is as follows [1] [7] [8]:

\[
\begin{bmatrix}
    q \\
    \dot{V} \\
    \dot{P}
\end{bmatrix} = \begin{bmatrix}
    -\frac{1}{2} q \otimes (\omega_t - C_0^b \omega^g) \\
    C_0^a a_t + [0 \ 0 \ g]^T \\
    V
\end{bmatrix}
\]  

(1)

Where \( q, \dot{V}, \dot{P} \) are respectively the time derivatives of quaternion \( q \), velocity \( V \) and position vector \( P \) respectively; \( \otimes \) is multiplication of quaternions; \( \omega_t, a_t \) are the real output values of gyroscope and accelerometer respectively; \( C_0^b, C_0^a \) are rotation matrices to transform from the NED coordinate system to the carrier coordinate system and the carrier coordinate system to the NED coordinate system respectively; \( \omega^e_t \) is the rotation acceleration of the earth at the current position.

By the following equation (2), the values of \( \omega_t \) and \( a_t \) can be obtained [9]:

\[
\begin{bmatrix}
    \omega_m \\
    a_m
\end{bmatrix} = \begin{bmatrix}
    \omega_t + b_{\omega} + w_{\omega} \\
    a_t + b_a + w_a
\end{bmatrix}
\]

(2)

Where \( \omega_m, w_{\omega} \) are respectively the observed measurement and the driving white noise of the gyroscope output and \( a_m, w_a \) are accelerometer’s; \( b_{\omega}, b_a \) are the zero bias vectors of gyroscope and accelerometer respectively. They are modelled as random walk [8] [9], as is shown in formula (3), where \( w_{b_{\omega}} \) and \( w_{b_a} \) are the zero bias unstable noise values of gyroscope and accelerometer respectively:

\[
\begin{bmatrix}
    \dot{b}_{\omega} \\
    \dot{b}_a
\end{bmatrix} = \begin{bmatrix}
    w_{b_{\omega}} \\
    w_{b_a}
\end{bmatrix}
\]

(3)

The quaternion, velocity, position and IMU bias are selected as the state vectors, that is to say, \( x = [q \ V \ P \ b_{\omega} \ b_a]^T \). And the white measurement noise of gyroscope and accelerometer and the white noise of bias instability are selected as the driving vectors, in other words, \( w = [w_{\omega} \ w_a \ w_{b_{\omega}} \ w_{b_a}]^T \). The equation of state can be obtained by substituting \( [\omega_t \ a_t]^T \) transformed from equation (2) into equation (1). The state transition matrix \( \Phi \) and noise matrix \( \Gamma \) are calculated as:

\[
\begin{align*}
F &= \frac{f(x)}{dx} \\
\Phi &= I + F \Delta t
\end{align*}
\]

(4)
2.2. Measurement equation
In the single frequency GNSS RTK/IMU/VIO integrated positioning, the observations of RTK, VIO, barometer and magnetometer are taken as Kalman filter observations.

\[
\begin{align*}
\hat{h}(x) &= \begin{bmatrix} V_{\text{RTK}} \\ P_{\text{RTK,VIO}} \\ H_{\text{baro}} \\ \phi_{\text{yaw}} \end{bmatrix} = \begin{bmatrix} V_{\text{ned}} \\ P_{\text{ned}} \\ P_d \\ \arctan\left(\frac{2(q_1 \cdot q_2 - q_0 q_3)}{q_0^2 - q_1^2 + q_2^2 - q_3^2}\right) \end{bmatrix} \\
\end{align*}
\]

Where \( \hat{h}(x) \) is the observation vector; \( V_{\text{RTK}} \) and \( P_{\text{RTK}} \) are respectively the observations of the speed and position of GNSS RTK; \( P_{\text{VIO}} \) is the observation of VIO which is the value relative to the previous time; \( H_{\text{baro}} \) is the measured output value of the barometer and the heading value \( \phi_{\text{yaw}} \) is calculated by MEMS-IMU magnetometer.

The vector three-axis magnetic intensity output by magnetometer is converted into heading observation value by the following formula (7), Where \( \delta_{\text{decline}} \) are the projection of magnetic intensity in the carrier coordinate system in the navigation system, which can be obtained by rotating the tilt vector.

\[
\phi_{\text{mag}} = \arctan\left(\frac{M_x}{M_{\pi}}\right) + \delta_{\text{decline}}
\]

The VIO output is point data in the sensor coordinate system, which needs to be converted by the following formula (8). In formula (8), \( C_5^c \) is the rotation matrix of the sensor coordinate system converted into the carrier coordinate system, which can be obtained from the attitude data output by VIO.

\[
\Delta^p = C_5^c C_4^c \left( P_v - P_{t+1} \right)
\]

2.3. EKF fusion algorithm
The state equation and observation equation of Kalman filter can be expressed as:

\[
\begin{align*}
X_{k+1} &= \Phi_{k+1,k} X_k + \Gamma_{k+1,k} w_k \\
Z_{k+1} &= H_{k+1,k} X_{k+1} + v_k
\end{align*}
\]

Where \( X_k, X_{k+1} \) are respectively the filtering values of the state vector at \( t_k, t_{k+1} \), \( w_k \) is dynamic noise vector, \( v_{k+1} \) is observation noise vector, \( \Phi_{k+1,k} \) is state transition matrix, \( \Gamma_{k+1,k} \) is dynamic noise matrix and \( H_{k+1,k} \) is measurement matrix.

Since the fusion algorithm is nonlinear, EKF is needed, and Kalman filter is used after linearization of state equation and measurement equation. According to formulas (4) and (5), the state transition matrix and dynamic noise matrix are determined, and the measurement matrix can be determined according to formula (9). The dynamic noise is mainly due to the uncertainty of state prediction, which is mainly affected by the measurement white noise and bias instability of IMU gyroscopes and accelerometer which can be determined by Allan variance [10]. However, due to the poor performance of consumer grade IMU, the parameters need to be multiplied by several times [6]. The observation
noise is mainly determined by measuring the performance of the sensor. The time delay compensation of sensors can be referred to paper [11].

Finally, the state prediction of fusion positioning system is carried out, and the parameters of attitude, velocity, position and bias estimation can be output.

3. Experiment and results

3.1. Experiment

To test the low-cost single-frequency GNSS RTK/MEMS-IMU/VIO fusion positioning algorithm, this paper is based on a single frequency GNSS receiver with a self-developed GNSS RTK processor and Ublox M8T module, MEMS-IMU MPU9250, barometer MS5611 and VIO Intel T265. Both MPU9250 and MS5611 are consumer-grade sensors about $2. Ublox M8T is also a consumer-grade GNSS module, which is about $30. T265 with binocular cameras and consumer-grade IMU, built-in visual-inertial navigation system (VINS) and simultaneous localization and mapping (SLAM) algorithm processor, can output real-time attitude and position information [12]. Its main component is a low-cost binocular camera. Build an ultra-low-cost fusion positioning system platform, as shown in figure 1, to realize real-time positioning and post-processing of recorded data. Among them, figure 1 (a) is a rover station, and the GNSS module is connected to a single-frequency helical antenna for positioning. Figure 1 (b) is a base station. The GNSS module is connected to a geodetic antenna and transmits corrections to the rover station through the radio.

![Figure 1. Experimental setup](image)

Since GNSS signals are easily interrupted and interfered, the effects of MEMS-IMU recursive capability and VIO fusion are studied by collecting measured data for simulation interrupt processing. When the fusion positioning sensor is disturbed and there is no measurement update, the system adds a new non-holonomic constraint in a static or constant speed state [7] to make the navigation system run normally, but it cannot be restrained when turning. This paper collects real data in Chongqing Institute of Green and Intelligent Technology of Chinese Academy of Sciences, and then interrupts the RTK data in the trajectory by means of simulation interruption to test the system's fusion positioning performance.

3.2. Analysis

The measured raw data of RTK and VIO, and the fusion positioning track of single-frequency RTK/MEMS-IMU are shown in Figure 2. Figure 2(a) is a horizontal trajectory, and Figure 2 (b) is a vertical trajectory. In addition, difference the trajectory with the original uninterrupted multi-sensor fusion positioning result to obtain the error sequence, As is shown in Figure 3.

As is shown in figure 2: (1) There is a heading deviation between the horizontal trajectories of VIO and RTK in figure 2(a). This is because the heading of the RTK navigation coordinate system starts from true north, and the heading in VIO takes the north as the starting point before the start time. So
the heading difference needs to be included in the fusion process. (2) Around 130s, there was an abnormal jump in RTK in Figure 2(b). This may be due to artificial occlusion, which causes the fixed state to switch to single point mode. In the figure, the RTK point position has higher accuracy than the vertical data output by the visual SLAM, and the error distribution is more uniform. As time increases, the SLAM data will produce cumulative errors. Therefore, the relative position data measurement of the VIO data can avoid this situation.

From figure 3 we can know that while the RTK measurement data is restored, the error amount is quickly measured and updated to the normal value, and the error is about 0.1 m. In the vertical direction, due to the use of barometer as the data source, the error amount and trajectory diagram are relatively correct, but there is a fixed deviation of about 0.2 m, which may be caused by its own offset and the unification of the RTK elevation data benchmark.

From figure 3 and the horizontal trajectory of RTK/MEMS-IMU fusion positioning in figure 2 (a), it can be seen that in the first interruption part, in the case of the MEMS-IMU inertial navigation recursion, the data cannot be continuously generated large errors. The error in north is about 0.9 m, and the error in east is about 0.8 m. In the second interruption, under the MEMS-IMU inertial navigation recursion, the data is continuous but not smooth. The error in north is about 0.2 m, and the error in east is about 1 m.
Finally, on the basis of single-frequency RTK/MEMS-IMU fusion, VIO data is added to evaluate the fusion positioning performance. The positioning track is shown in figure 4, and the positioning error is shown in figure 5.

From figure 4 and 5, we can know that: (1) In the horizontal trajectory of RTK/MEMS-IMU fusion positioning, by fusing VIO data, the interrupted part of the data is relatively smooth; with the help of VIO data, the error becomes smaller. However, due to the noise of VIO measurement, the error in east of the first interruption reached 0.6 m, and the error of the second interruption was about 0.4 m. (2) It can be seen from the error graph that while the RTK measurement data is restored, due to the existence of the VIO data, the error amount slowly returns to the normal value; the elevation data due to the measurement assistance of the VIO data, the error is smaller than that in figure 4. The error is within 0.2 m under dynamic conditions. (3) Calculate the mean square error of the positioning error, the accuracy in north is 0.09 m, the accuracy in east is 0.15 m, and the accuracy in the vertical direction is 0.2 m.

Figure 4. RTK / IMU/VIO fusion positioning result

Figure 5. RTK / VIO / IMU positioning error

4. Conclusion
In response to the demand for high precision navigation and positioning in the market of low-speed consumer-level unmanned driving, this paper proposes an ultra-low-cost integrated positioning system. To set up an experimental platform to collect measured data, we select consumer-grade GNSS Ublox M8T, IMU MPU9250 module and binocular camera as the main equipment. Through physical
simulation interruption experiment, the recursive assistance capabilities of MEMS-IMU and VIO are analysed. The conclusions are summarized as follows: (1) Consumer-grade IMU can recurse autonomously without GNSS, and still have a relatively correct recursion when turning. When the RTK data is updated again, the data can quickly return to normal values, but the track is not enough smooth due to lack of measurement, which will cause the control system unable to control stably. (2) In the case of fusion of VIO data, the fusion positioning trajectory is smooth and consistent with the actual trajectory. However, due to the addition of VIO data, in the absence of RTK data, the accuracy is relatively lower then only fusing RTK data with 0.09 m in north, 0.15 m in east and 0.2 in the vertical direction. In general, the ultra-low-cost multi-sensor fusion positioning system with single frequency RTK/MEMS-IMU/VIO can provide high-precision, reliable, continuous and smooth positioning results.

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