

AHRS Design based on STM32 and MEMS Sensors

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Abstract

Controlling UAV requires high-precision dynamic information input. However, mini UAV needs more demands because of its small volume. Using MEMS sensor can make the UAV become high-precision, low power consumption and inexpensive machine. In this research, the core part is focusing on STM32F405, designing and implement the attitude and heading reference system (AHRS) based on 3-axis MEMS gyroscope, 3-axis MEMS accelerometer and magnetometer. Quaternion Kalman filter has been adopted in this study in order to achieve the attitude measurement and error control of transporter.

Keywords: MEMS Sensor, AHRS, Kalman Filter, Data Fusion

1. Introduction

The attitude angle information of local geographic coordinate frame is provided by the AHRS[1-2], which is very essential for the UAV's navigation and control. The price of mechanical gyroscope and laser gyroscope is costly. For the reason of volume size and price limitation, it can't be popularized in the minitype UAV. With the development of micro-electronics, the MEMS devices with high-precision, low power consumption and small-size can satisfy aviation demands[3-5]. Due to the characters of the low cost, small size, and convenience of AHRS applied in MEMS, it can be applied in many fields in the future.

The hardware design of AHRS consists of inertial sensors and magnetic sensor. The angle of pitch angle, roll angle and yaw angle can be calculated by measuring angular velocity and linear velocity, respectively. The MEMS gyroscope could measure rotational angular rate of a rigid body. Through analyzing integration of angular rates, rotation Euler angle can be achieved. Nonetheless, there is severe zero bias error of the gyro and measurement errors in the angular rate gyroscope, which would lead to integral error in SINS (strapdown inertial navigation system) and difficulties of reaching the accuracy. Meanwhile, accelerometer and magnetometer can calculate the uncorrelated vector---acceleration of gravity and geomagnetic field, which can be used to correct the gyroscope as the attitude's observation vector.

The attitude angle can be achieved by calculating the integration of gyro angle rates during a short time. However, tiny measurement errors may turn into prodigious angle errors through adding integral time. Accurate static information can be obtained by gyroscope combined with accelerometer and magnetic sensor. while it is liable to be disturbed by other inertial forces, vibrations, or magnetic noises. Accelerometer and magnetic sensor could provide two uncorrelated estimation [7]. Gyro can follow the attitude angle change quickly and closely and cumulative errors can be corrected by using the observation datas of accelerometer and magnetometer.

Kalman filter is applied to data fusion of multiple sensors [8-9], which can combine the attribute of multiple sensors and obtain more precise attitude angle information by updating prediction by using angular rate obtained through gyro measurement and

observation by acceleration of gravity and magnetic field.

2. System Architecture

2.1. Hardware Architecture of AHRS

Attitude Heading Reference System can output the six-DOF of attitude and heading information. The hardware consists of STM32F405, MPU-6500 and HMC5883L. Hardware architecture of the AHRS, which is shown in Figure 1.

STM32F405RGT6 based on Cortex-M4 core is used as the CPU and dominant frequency is up to 168MHZ. IMU adopts MPU-6500 with 3-axis gyroscope and accelerometer and contains 16-bits A/D convertor and signal conditioning, which is convenient to the circuit design. The range of angular rate of gyroscope is $\pm 250^\circ/\pm 2000^\circ/s$ and that of accelerometer is $\pm 2g\text{-}\pm 16g$. Magnetoresistive sensor uses 3-axis digital compass, which is connected to CPU by I2C port. MPU-6500 can make sensor data into the STM32 processor with ARM framework through I2C port, which carries vast workload of attitude calculation. Finally, attitude and heading estimation output can be delivered through an USART port to a ground PC or other application devices, at the speed of 100 Hz.

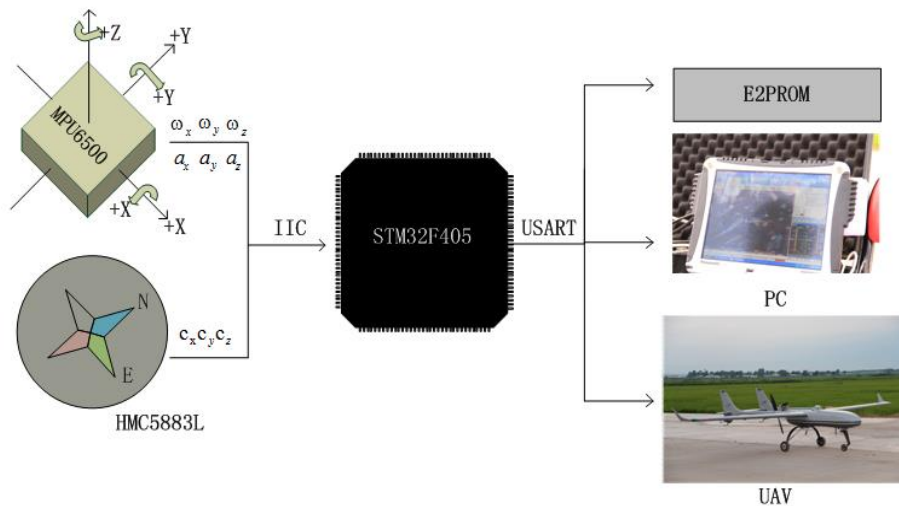


Figure 1. Hardware Architecture of AHRS

2.2. Coordinate Frame and Attitude Angle Estimation

AHRS is a system which make the gyroscope and accelerometer mounted directly on the carriers. It can provide pitch angle, roll angle ,yaw angle. The coordinate frame of this paper is ENU[10].The geographic coordinate frame is n. x_n to east, y_n to north, z_n to up.b frame is body coordinate frame , x_b points to right along horizontal axis, y_b to the forward along the longitudinal axis, z_b to the upward along the vertical axis.

Inertial device output the angular velocity and acceleration speed relative to the geographic coordinate frame. Using bias errors which after calibration to compensate the measured value. Gyroscopes and accelerometers are used to measure the rotation rate gyros and linear velocity to calculate the attitude angle respectively. There are three options to define attitude of rigid body in 3D space: Euler angles, quaternions, and the Direction Cosine Matrix[11]. Compared with euler angle, quaternion avoids a lot of trigonometric calculations and equation degeneration when the pitch angle reaches 90° , It means that euler angle equations cannot give effective attitude solution at some singular points of the

attitude space. Euler angle is only suitable for little change in attitude angle and cannot work in the whole attitude angle. But the quaternion has the advantage of smaller amount of computations, thus practical in engineering. Although quaternion have many advantages, euler angle seems to be more practical physical significance and easier to be understood. In fact, euler angle is more suitable for simple applications because it is easy to be observed and controlled in flight. Renewed q_0, q_1, q_2, q_3 are to be got to update attitude by solving the quaternion differential equation.

3. Attitude Calculation

3.1. Initial Value of the Quaternions

A quaternion is consist of a real number and three elements i, j, k , which are usually represented as $Q = q_0 + q_1i + q_2j + q_3k$, among which q_0, q_1, q_2, q_3 are four real numbers. Three times of rotation around different axes of rotation can be converted into one rotation around a fixed axis. A quaternion description of this rotation is appropriate, which is shown in the equation (1)

$$Q = \cos \frac{\theta}{2} + \sin \frac{\theta}{2} \mathbf{u} \cdot \mathbf{s} \quad (1)$$

In the equation, \mathbf{u} is a unit vector and θ is a the equivalent rotation angle. Q contains all the rotations information. It expressed the rotational motion of a rigid body. According to the measuring the three-axis projection of acceleration in the state of static balance, the initial attitude angle can be calculated. In the body coordinate frame, the gravitational acceleration vector is $\mathbf{g}^b = [g_x^b \quad g_y^b \quad g_z^b]^T$, we can concluded that the initial value of the θ, γ , which is shown in equation(2)[12].

$$\begin{aligned} \gamma &= \arctan \left(\frac{g_y^b}{g_z^b} \right) \\ \theta &= \arcsin \left(\frac{g_x^b}{g} \right) \end{aligned} \quad (2)$$

When magnetic field geographic coordinate frame coincides with the b frame, the output of the magnetic sensor is $M^n = [0 \quad M_N \quad M_U]^T$. In the b frame, the output of magnetic sensor $M^b = [M_x^b \quad M_y^b \quad M_z^b]^T$. The roll angle and pitch angle got after the calculation are taken into DCM to get the initial value of the magnetic yaw angle.

$$\Psi_m = \arctan \left(\frac{M_y^b \cos \theta - M_z^b \sin \theta}{M_x^b \cos \theta + M_y^b \sin \theta} \right) \quad (3)$$

Taking the initial value of the euler angle into the expression (4) to get the initial of q_0, q_1, q_2, q_3 .

$$\begin{aligned}
 q_0 &= \cos \frac{\psi}{2} \cos \frac{\theta}{2} \cos \frac{\gamma}{2} + \sin \frac{\psi}{2} \sin \frac{\theta}{2} \sin \frac{\gamma}{2} \\
 q_1 &= \cos \frac{\psi}{2} \cos \frac{\theta}{2} \sin \frac{\gamma}{2} - \sin \frac{\psi}{2} \sin \frac{\theta}{2} \cos \frac{\gamma}{2} \\
 q_2 &= \cos \frac{\psi}{2} \sin \frac{\theta}{2} \cos \frac{\gamma}{2} + \sin \frac{\psi}{2} \cos \frac{\theta}{2} \sin \frac{\gamma}{2} \\
 q_3 &= \sin \frac{\psi}{2} \cos \frac{\theta}{2} \cos \frac{\gamma}{2} - \cos \frac{\psi}{2} \sin \frac{\theta}{2} \sin \frac{\gamma}{2}
 \end{aligned} \tag{4}$$

3.2. Direction Transformation Matrix

According to the rotation order of the 3-axis, the direction cosine matrix is achieved. The quaternion is converted to the corresponding elements of the direction cosine matrix, The quaternion direction cosine matrix can be updated and the quaternion can make sure the coordinate transformation matrix from the b frame to the n frame.

$$C_b^n = \begin{bmatrix} q_0^2 + q_1^2 - q_2^2 - q_3^2 & 2(q_1q_2 - q_0q_3) & 2(q_1q_3 + q_0q_2) \\ 2(q_1q_2 + q_0q_3) & q_0^2 - q_1^2 - q_2^2 + q_3^2 & 2(q_2q_3 - q_0q_1) \\ 2(q_1q_3 - q_0q_2) & 2(q_2q_3 + q_0q_1) & -q_0^2 - q_1^2 + q_2^2 + q_3^2 \end{bmatrix} \tag{5}$$

C_b^n is coordinate transformation matrix shifting from the b to n frame. among which the b frame is body coordinate frame and fixed on the carrier. The origin is located in the mass center of the carrier. The body coordinate frame coincides with the coordinate frame of IMU[13].n frame is the geographic coordinate frame. The transformation relation of the quaternion and euler angle is shown in equation(6)

$$\begin{aligned}
 \theta &= \arcsin(2(q_0q_1 + q_2q_3)) \\
 \gamma &= \arctan \frac{-2(q_1q_3 - q_0q_2)}{1 - 2(q_1^2 + q_2^2)} \\
 \psi &= \arctan \frac{2(q_1q_2 - q_0q_3)}{1 - 2(q_1^2 + q_3^2)}
 \end{aligned} \tag{6}$$

3.3. Update Attitude Based on Quaternion Differential Equations

The quaternion differential equation is shown in equation (8), where ω_x , ω_y , ω_z are the measured value of the 3-axis gyroscope. Only four differential equations need to be calculated, which greatly reduce the amount of computation than the direction cosine attitude matrix differential equations. Thus it is easy to program for the microprocessors.

$$\dot{q}(n+1) = \Omega \dot{q}(n) \tag{7}$$

Where $q(n+1)$ and $q(n)$ are the quaternion in current time and previous time respectively.

$$\begin{bmatrix} \dot{q}_0 \\ \dot{q}_1 \\ \dot{q}_2 \\ \dot{q}_3 \end{bmatrix} = \begin{bmatrix} 0 & -\frac{\omega_x}{2} & -\frac{\omega_y}{2} & -\frac{\omega_z}{2} \\ \frac{\omega_x}{2} & 0 & \frac{\omega_z}{2} & -\frac{\omega_y}{2} \\ \frac{\omega_y}{2} & -\frac{\omega_z}{2} & 0 & \frac{\omega_x}{2} \\ \frac{\omega_z}{2} & \frac{\omega_y}{2} & -\frac{\omega_x}{2} & 0 \end{bmatrix} \begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{bmatrix} \quad (8)$$

3.4. Runge Kutta Algorithms

$$q(t+T) = q(t) + T \Omega_b(t) q(t)$$

$$\begin{aligned} q_0(n+1) &= q_0(n) + \frac{T}{2} \left[\dot{q}_0(t_0) + \dot{q}_0(t_3) \right] \\ q_1(n+1) &= q_1(n) + \frac{T}{2} \left[\dot{q}_1(t_0) + \dot{q}_1(t_3) \right] \\ q_2(n+1) &= q_2(n) + \frac{T}{2} \left[\dot{q}_2(t_0) + \dot{q}_2(t_3) \right] \\ q_3(n+1) &= q_3(n) + \frac{T}{2} \left[\dot{q}_3(t_0) + \dot{q}_3(t_3) \right] \end{aligned} \quad (9)$$

T is the data acquisition cycle, in which ω_x , ω_y , ω_z are the measured value of the 3-axis gyroscope. Quaternions are updated constantly by using the Runge kutta algorithm and new quaternions are taking into equation (5) to calculate the latest cosine matrix and update carrier's attitude. The quaternions will gradually lose its standardization properties due to the calculation errors and other factors. To ensure the quaternion attitude matrix is orthogonal, quaternions need to be processed normally after each quaternion update cycle

$$q_i = \frac{\hat{q}_i}{\sqrt{\hat{q}_0^2 + \hat{q}_1^2 + \hat{q}_2^2 + \hat{q}_3^2}} \quad i=0,1,2,3. \quad (10)$$

Where $\hat{q}_0, \hat{q}_1, \hat{q}_2, \hat{q}_3$ are the updated quaternion values.

4. Kalman Filter Algorithms

The 3-axis angular speed measured by MEMS gyroscopes is effective in high frequency. Without an additional observation to correct, it is inevitable to get the integral error. The integral attitude of gyroscopes based on angular rate would gradually diverge from the real attitude. The attitude error of pitch and roll angle can be observed by gravitational acceleration direction vector and the yaw angle error can be observed by geomagnetic direction vector. So using gravitational acceleration direction and geomagnetic direction vector are chosen to be the observation vectors to correct the attitude angle. [14]. Software configuration of AHRS solution is shown in Figure 2.

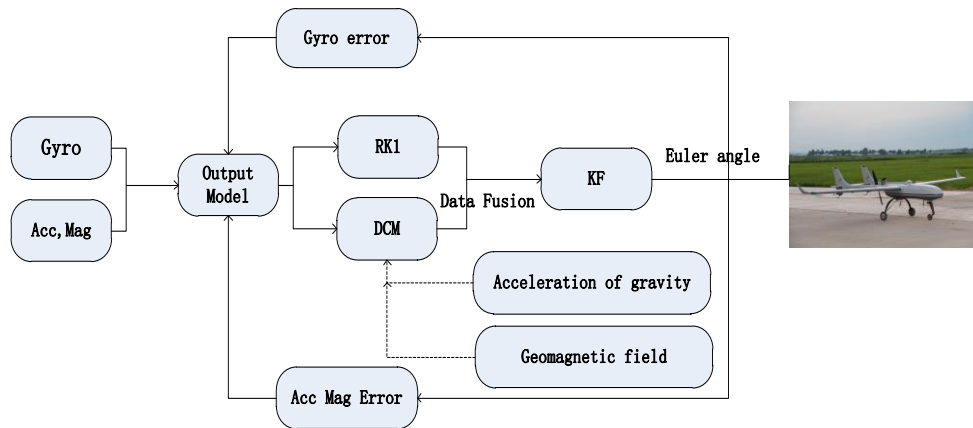


Figure 2. Software Coniguration of AHRS

4.1. State Equation

The basic idea of the Kalman filter is to process nonlinear problems by linear model. Then the linearized system is filtered. The data of engineering survey are generally dissociation. Firstly, to conduct data discretization. The state equation after discretization is shown as follows:

$$X(k|k-1) = Ax(k-1|k-1) \quad (11)$$

$$A = \begin{bmatrix} 1 & -\frac{\omega_x}{2} \Delta t & -\frac{\omega_y}{2} \Delta t & -\frac{\omega_z}{2} \Delta t \\ \frac{\omega_x}{2} \Delta t & 1 & \frac{\omega_z}{2} \Delta t & -\frac{\omega_y}{2} \Delta t \\ \frac{\omega_y}{2} \Delta t & -\frac{\omega_z}{2} \Delta t & 1 & \frac{\omega_x}{2} \Delta t \\ \frac{\omega_z}{2} \Delta t & \frac{\omega_y}{2} \Delta t & -\frac{\omega_x}{2} \Delta t & 1 \end{bmatrix}$$

A is the state transition matrix and $X(k|k-1)$ is the state estimates values of k time in k-1 time $x(k-1|k-1) = [q_0(k-1) \quad q_1(k-1) \quad q_2(k-1) \quad q_3(k-1)]^T$ are state vector. Δt is the cycle of measurement

4.2. Observations Update Equation:

$$x_k = x_{k|k-1} + kg_k(z_k - H_k x_{k|k-1}) \quad (12)$$

Observation vector is jointly provided by accelerometers and magnetometers. The measured value of accelerated velocity relative to body axis system and geomagnetic field are G^b and h^b . which are two independent reference vectors. Thus quantity of state needs to be revised twice. The direction vector of inertial frame is converted to carrier coordinate frame $h_b = C_n^b h_n$ H_k is a jacobian matrix which is the partial derivatives with h relative to X. H_k matrix is shown as following (13).

$$H_k = \begin{bmatrix} q_0 h_x + q_3 h_y - q_2 h_z & q_1 h_x + q_2 h_y + q_3 h_z & -q_2 h_x + q_1 h_y - q_0 h_z & -q_3 h_x + q_0 h_y + q_1 h_z \\ -q_3 h_x + q_0 h_y + q_1 h_z & q_2 h_x - q_1 h_y + q_0 h_z & q_1 h_x + q_2 h_y + q_3 h_z & -q_0 h_x - q_3 h_y + q_2 h_z \\ q_2 h_x - q_1 h_y + q_0 h_z & q_3 h_x - q_0 h_y - q_1 h_z & q_0 h_x + q_3 h_y - q_2 h_z & q_1 h_x + q_2 h_y + q_3 h_z \end{bmatrix} \quad (13)$$

The vectorial measured value of acceleration direction of gravity in the geographic coordinate frame is $g_n = [0 \ 0 \ -g]^T$. The output of the magnetometer is $h_n = [h_{nx} \ h_{ny} \ h_{nz}]^T$. $[G^b \ h^b]$ is used as a state vector $X(k)$. The output of the accelerometer and magnetic sensor are adopted as observation vectors $z(k)$, as shown in equation (14):

$$z(k) = H(k) x_k \quad (14)$$

In the equation, v_k is the measurement noise covariance matrix (Zero mean white noise as the measurement noise of the system).

4.3. Kalman Filter Iteration

Suppose the errors of the system and observation noise are stable. In the process of filtering, the attitude angle is updated by using quaternion attitude angle differential equation. Then the formula $x(k)$ and $z(k)$ are used to Kalman filter, and attitude angle is corrected by using the measured value of accelerometers and magnetometers. In the process of filter, according to gravity and magnetic measurements, the variance error needs to be updated to calculate kalman gain in the next step, which is shown in formula (18). The variance prediction formula and gain filter matrix kg_k are shown in equation (16) (17):

$$P_{k|k-1} = A P_{k-1} A^T + W Q W^T \quad (16)$$

$$kg_k = P_{k|k-1} H_k^T / H_k P_{k|k-1} H_k^T + R \quad (17)$$

$$P_k = (1 - kg_k H_k) P_{k|k-1} \quad (18)$$

In the equation, H_k is the observation equation and Q is the system process variance. The system noise matrix is introduced the shake of gyroscope and the noise of three-axis angular rates is separated to get system noise matrix as is shown in equation (19).

$$W = \begin{bmatrix} \frac{q_1}{2} \Delta t & \frac{q_2}{2} \Delta t & \frac{q_3}{2} \Delta t \\ \frac{q_0}{2} \Delta t & \frac{q_2}{2} \Delta t & \frac{q_3}{2} \Delta t \\ \frac{q_0}{2} \Delta t & \frac{q_1}{2} \Delta t & \frac{q_3}{2} \Delta t \\ \frac{q_0}{2} \Delta t & \frac{q_1}{2} \Delta t & \frac{q_2}{2} \Delta t \end{bmatrix} \quad (19)$$

Filtering process is shown in Figure 3.

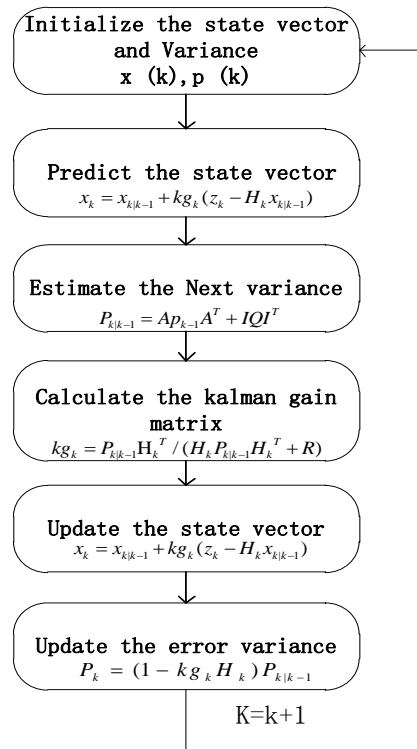


Figure 3. Kalman Filtering Process

5. Simulation and Analysis

A practical project is taken for a background to carry simulation for the system that composed by gyroscope and magnet compass. Simulation time is 300s, the sampling period of the sensor is 0.005s. Data transmission cycle is 1s.

The mean square error of gyroscope drift white noise is 0.1°/s and that of accelerometer measurement noise is 0.0005g. The mean square error of magnetometer measurement noise is 10^{-7} Gs. To adjust even by the gradienter, to test the filter performance of this kalman filtering algorithm in the static condition. The initial values of Kalman state vector is $X(k).X(k)=[1\ 0\ 0\ 0]^T$.

This paper uses the local gravitational acceleration and magnetic field strength in NanJing [15]. $g=[0\ 0\ -9.79494]^T$, Horizontal component of the magnetic field is 3.301×10^{-6} T. The vertical component is 3.684×10^{-6} T. The initial value of the variance is $p_{k-1}=\text{diag}(0.1,0.1,0.1,0.1)$

The pitch angle and roll angle is set to close to 0° and yaw angle equal to 58. In given conditions, the roll angle, pitch angle, and yaw angle are output by serial port, which is shown in Figure 4- Figure 6.

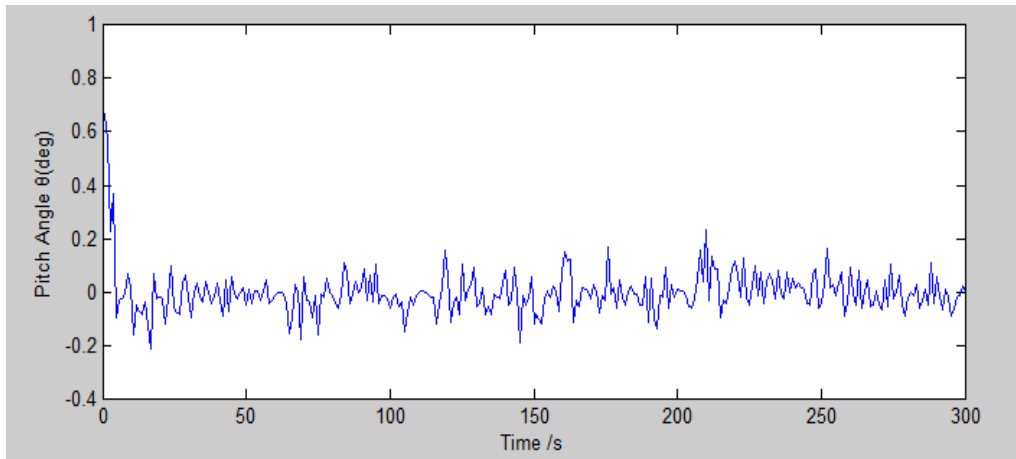


Figure 4. Pitch Angle Curve by Kalman Filtering

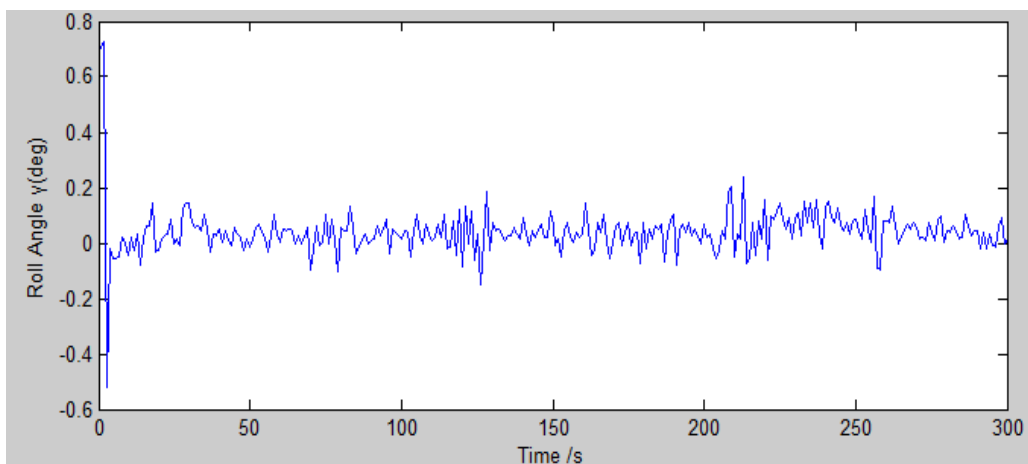


Figure 5. Roll Angle Curve by Kalman Filtering

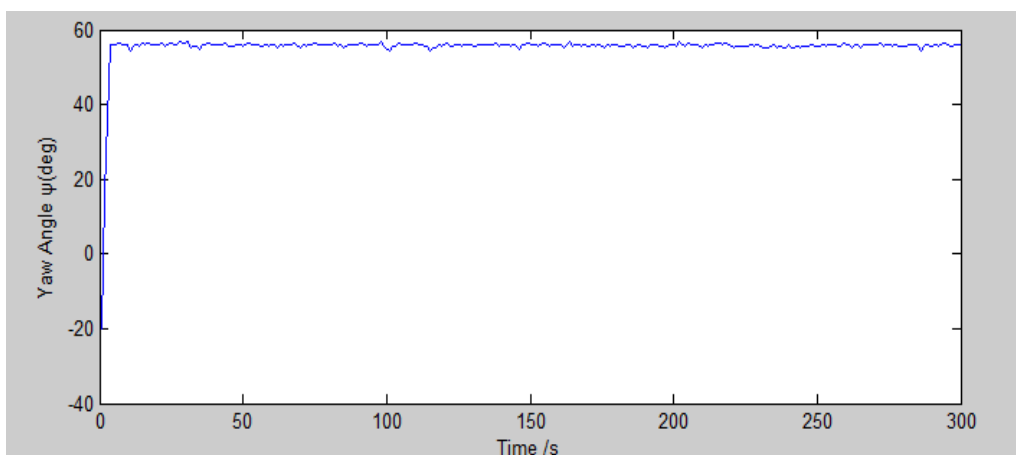


Figure 6. Yaw Angle Curve by Kalman Filtering

It can be seen from Figures 4-5 that the convergence speeds of pitch angle and roll angle are all rapid after the Kalman filter. It will become stable in 2s-3s when filter starts working. As you can be seen in Figure 6, convergence speeds of yaw angle also is rapid. After gathering the data that real attitude data and filtered data in the static condition to calculate the attitude angle error respectively. We can get average values of the attitude Angle error. It is shown in Figures 7-9.

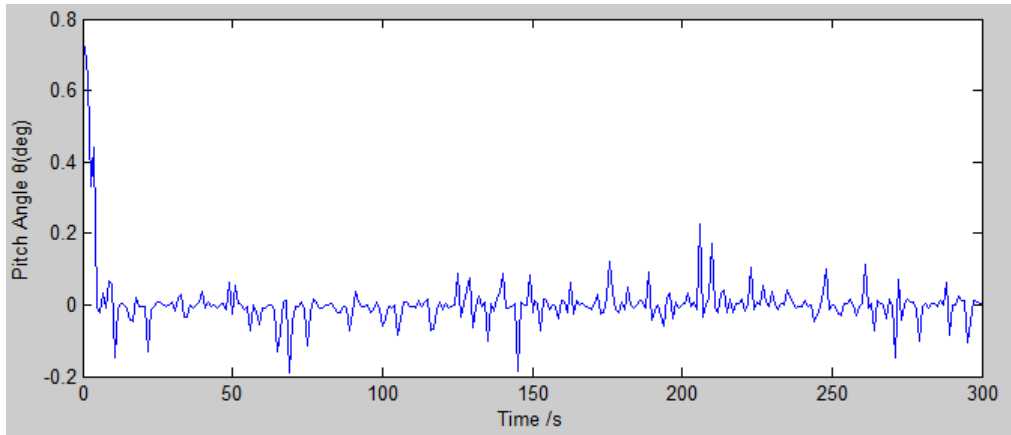


Figure 7. Pitch Angle Error of Curve by Kalman Filtering

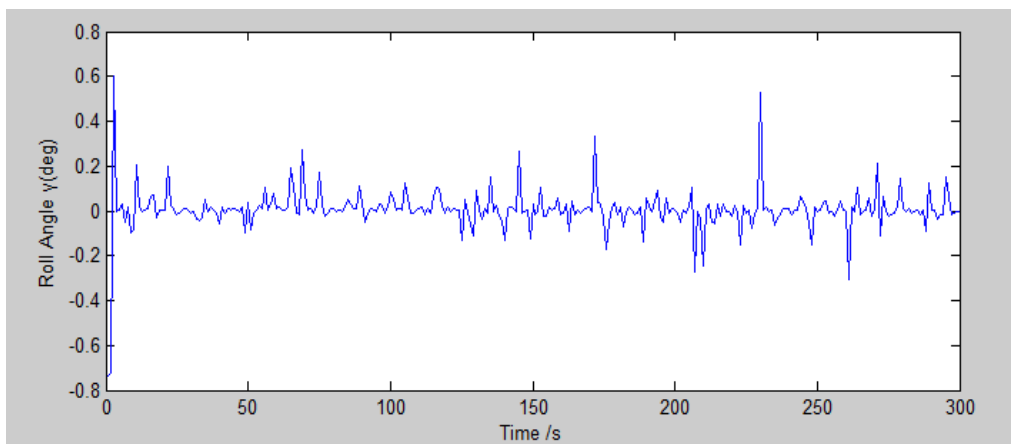


Figure 8. Roll Angle Error of Curve by Kalman Filtering

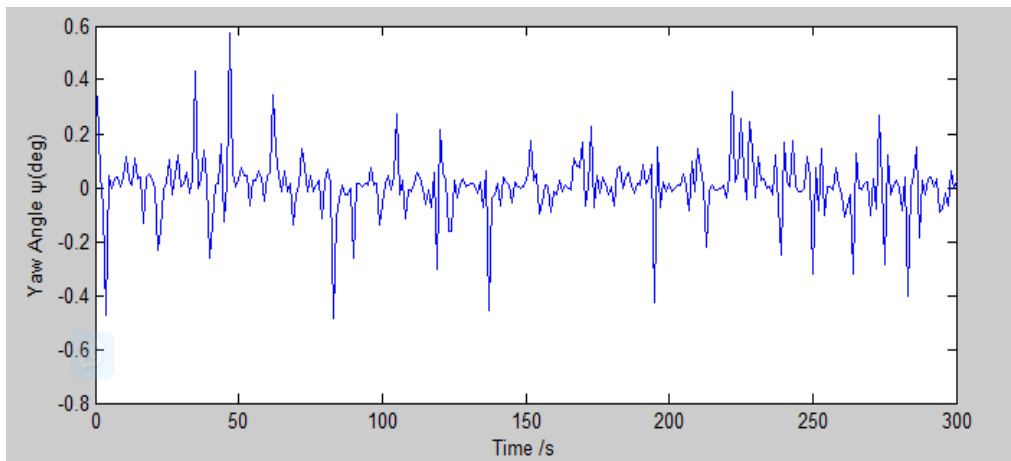


Figure 9. Yaw Angle Error of Curve by Kalman Filtering

Table 1. Error Estimation of Kalman Filtering

Error	Pitch angle	Roll angle	Yaw angle
Mean(°)	0.1135	0.1547	0.5261
RMSE (°)	0.2187	0.2833	0.9841

As can be seen in Figure 7-9, after performing Kalman filter, attitude angle doesn't drift with integration time. The drift error is limited in a certain range and the convergence speed is fast. It can be seen in Table 1, yaw angle error range of $\pm 0.5^\circ$, pitch angle error range of $\pm 0.2^\circ$, roll angle error range of $\pm 0.2^\circ$. Cumulative error is limited to some extent and improve the attitude determination accuracy.

6. Conclusion

In this research, the core part is focusing on STM32F405, designing and implementing the attitude and heading reference system (AHRS) based on 3-axis MEMS gyroscope, accelerometer and magnetometer. The adopt quaternions kalman filtering algorithm have the features of high accuracy and fast convergence speed. The simulations reveal that attitude angle error is small and attitude angle doesn't drift with integration time. Cumulative errors are limited effectively and improve the attitude determination accuracy. Meanwhile, this system has the advantage of small volume, high precision and low cost, which will offer prospects the future application.

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References

- [1] M. Euston, P. Coote, R. Mahony, J. Kim and T. Hamel, In 6th International Conference on Field and Service Robotics, (2007); Australia.
- [2] Y. Zhang, W. Li, X. Zhan and C. Zhai, Building of China, vol.49, no.183, (2008).
- [3] L. Jianhong, T. Weicheng and W. Tianmiao, Microcontrollers and Embedded Systems, vol.12, no.1, (2012).
- [4] L. Lou, X. Xu, J. Cao, Z. Chen and Y. Xu, Proceedings of the 6th IEEE Joint International Information Technology and Artificial intelligence Conference, (2011); Chongqing, China.
- [5] R. Li, J. Liu, Q. Zeng and B. Hua, Journal of Chinese Inertial Technology, vol.12, no.6, (2004).
- [6] C. Ouyang and Xiaokang Lin, Planetary Scientific Research Center Conference Proceedings vol.41, (2013); Pattaya, Thailand.
- [7] Y. Wang, N. Li, X. Chen and M. Liu, Advances in mechanical engineering, vol.11, (2014).
- [8] J. L. Marins, X. Yun, E. R. Bachmann, R. B. McGhee and M. J. Zyda, InProc. IEEE/RSJ International Conference on Intelligent Robots and Systems, vol. 4, (2001).
- [9] F. Wang, S. Zhu and H. Lei, Journal of Chinese Inertial Technology, vol.16, no.2, (2008).
- [10] Y. Qin, Inertial Navigation Technology, HarBin (2006)
- [11] C. Wu, Flight Control System(2nd Edition), (2013).
- [12] L. Xia, L. Zhao, F. Liu and H. Liu, Journal of Chinese Inertial Technology, vol.15, no.6, (2007).
- [13] J. Ding and Z. Zhao, Computer Simulation, vol.30, no.9, (2013).
- [14] H. Sheng, T. Zhang and D. Liu, System Engineering and Electronic, vol. 35, no.10, (2013).
- [15] H. Liu and J. Han, MatlabR2012a Entirely self-taught a pass, Electronic Industry Press, (2013); BeiJing.

