Anti-magnetic Interference Adaptive Kalman Filter Algorithm based on Quaternion

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Abstract

For the problem that the accuracy of Orientation Estimation is affected by the interference from surrounding local magnetic disturbances, a For the problem that the accuracy of Orientation Estimation is affected by the interference from surrounding local magnetic disturbances, a quaternion based adaptive Kalman filter algorithm is proposed. The algorithm utilizes the gyroscope outputs to establish the state equation of attitude error angle and construct the adaptive measurement noise covariance matrix with the outputs of the magnetometer. The simulation results show compared to the UKF algorithm and the EKF algorithm, the attitude error angle obtained by the q-AKF is less than 1°. Using the q-AKF algorithm to compensate the magnetometer can effectively suppress the error of magnetometer interference, improve the precision of attitude algorithm in magnetic interference environment,which has high engineering application value

Keywords

Quaternion, Adaptive Kalman Filtering, Magnetometer, Orientation Estimation.

1. Introduction

The application of attitude measurement is very extensive, such as: detection of random walking action [1], pedestrian positioning [2], indoor navigation [3], human tracking [4].Gyroscope, accelerometer, magnetometer can be used alone to measure the attitude.But the use of accelerometer output value of the attitude angle will emerge larger error due to the linear acceleration [5];The magnetic susceptibility meter is easily disturbed by the magnetic field generated by the surrounding environment such as ferromagnetic material, mobile phone and so on, which seriously affects its output. This random error can not be eliminated in advance [6].Therefore, the use of three-axis magnetometer alone can not complete the carrier relative to the reference coordinate system attitude measurement [7,8].

Domestic and foreign scholars have put forward different solutions to the above problems.Lizarraga and so on using the quaternion complementary filter,applying gyroscope, accelerometer and magnetometer to the attitude measurement, to achieve three degrees of freedom attitude measurement [9].Rehbinder and so on based on the gyroscope and accelerometer proposed an attitude measurement algorithm, but owing to the lack of magnetometer information, heading angle cumulative error can not be eliminated [10].Harms and Bachmann use a quaternion-based Kalman filter to further improve the accuracy of MEMS sensor attitude measurement [11].

In this paper, an adaptive Kalman filter based on quaternion is proposed.According to the output of the micromachined gyroscope, the error state equation is established. The output of the magnetometer is used as the observation of the attitude error angle, and the output of the magnetometer is compensated by the adaptive Kalman filter method.The method is flexible and can effectively reduce the influence of magnetic interference, and has high precision. At the same time, the algorithm proposed in this paper is evaluated experimentally.

2. Establishment of quaternion differential equation and sensor model

When the angular velocity and the initial attitude of a three-axis gyroscope are known, the differential equation of the quaternion is:

$$\begin{cases} q(t_0) = q_0 \\ \dfrac{d}{dt} q = \dfrac{1}{2} q \otimes \varpi \end{cases} \tag{1}$$

Where ϖ is the quaternion of the angular velocity of the carrier coordinate system. $\otimes$ is the quaternion multiplied.

Generally three-axis accelerometer, three-axis gyroscope, three-axis magnetometer are used for attitude measurement .Considering the factors that affect the measurement accuracy of MEMS sensors, the sensor model is established:

$$\begin{cases} \chi_a = \Delta(q)G + a_p + \mu_a \\ \chi_g = \omega + \mu_g \\ \chi_m = \Delta(q)m + \mu_m \end{cases} \tag{2}$$

Where $a_p \in R^{3\times3}$ is the external acceleration vector of the carrier; $G = \begin{bmatrix} 0 & 0 & g \end{bmatrix}^T$ is the gravity vector ($g = 9.81 m/s^2$); $m = \begin{bmatrix} m_x & m_y & m_z \end{bmatrix}^T = \begin{bmatrix} \|m\|\cos\theta & 0 & \|m\|\sin\theta \end{bmatrix}^T$ is the magnetic field vector of the earth.It is assumed that the sensor output error μ_a , μ_g , μ_m ,for the zero mean Gaussian white noise, which is not related to the covariance matrix.

3. Design of Adaptive Kalman Filter Based on Quaternion

3.1 State equation

The equation of attitude change in the discrete interval:

$$q_k = \mathrm{X}_k q_{k-1} + \omega_k \tag{3}$$

Where q_k is the quaternion of the posture and X_k is the matrix associated with the angular velocity vector $\chi_{g,k}$:

$$X_k = \exp\left(\frac{1}{2} \begin{bmatrix} 0 & -\chi_{g,k}^T \\ \chi_{g,k} & -[\chi_{g,k}^*] \end{bmatrix} \Delta t \right) \tag{4}$$

Where Δt is the sampling interval, $\omega_k \sim N(0, Q_k)$ is the process noise vector.

In order to facilitate the calculation, modify the equation (3) as follows:

$$q_{k+1} = \gamma_k \mathrm{X}_k q_k + (1-\gamma_k)\mathrm{X}_{k-1} q_k + \gamma_k \omega_k + (1-\gamma_k)\varpi_k \tag{5}$$

Where γ_k are two values can be taken: when the gyro measurement is available, $\gamma_k = 1$; otherwise, $\gamma_k = 0$. $\varpi_k \sim N(0, \hat{Q}_k)$ Is the process noise when the angular velocity is zero? $\hat{Q}_k$ Is defined as follows:

$$\hat{Q}_k = Q_{k-1} \exp(\partial k \Delta t) \tag{6}$$

∂ Is a constant that is adjusted according to the actual situation?

3.2 Observation equation

In the discrete interval, the relationship between the output of the accelerometer and the magnetometer (χ_a^T and χ_m^T) and the rotation quaternion:

$$\begin{cases} \phi_{a,k} = q_k^{-1} \otimes \bar{G} \otimes q_k \\ \phi_{m,k} = q_k^{-1} \otimes \bar{m} \otimes q_k \end{cases} \tag{7}$$

Where $q_k^{-1} = \begin{bmatrix} q_{0,k} & -q_{1,k} & -q_{2,k} & -q_{3,k} \end{bmatrix}$ is a complementary quaternion? According to the above two formulas to derive the quaternion observation equation:

$$\Omega_k q_k + \upsilon_k = 0 \tag{8}$$

Where Ω_k include the output of the accelerometer and magnetometer .In the quiescent state, the accelerometer can accurately calculate the inclination of the carrier relative to the horizontal plane by measuring the acceleration due to gravity. However, when the carrier moves up, the use of accelerometer output value to calculate the carrier attitude angle will be a large error owing to the linear acceleration of the carrier. Therefore, in the case of carrier motion, the main consideration is to use the magnetometer to calculate the attitude angle, that is, using the magnetometer to construct the covariance matrix R_k .E.q.(7) can be expressed as:

$$\begin{cases} \Omega_k = \begin{pmatrix} 0 & -(\nabla_{m,k} - m)^T \\ (\nabla_{m,k} - m) & -(\nabla_{m,k} + m)^* \end{pmatrix} \\ \upsilon_k = \left(\omega_{mg,k}^q\right) = -\frac{1}{2}\Gamma\left(q_k\right)\left(m_k + \mu_{m,k}\right) \end{cases} \tag{9}$$

Where $\omega_{g,k}^q \sim N\left(r_k, R_{mg,k}\right)$ is an unknown noise associated with a magnetometer? The value of r_k and $R_{mg,k}$ are derived from the filter adaptive estimation.

4. The design of q-AKF anti-magnetic interference algorithm

Combining the state equations and observation equations presented in sections 3.1 and 3.2, the design of the q-AKF is as follows:

a. Initialize the systems state estimation $\hat{q}_0$ and error covariance matrix P_0.

b. Calculate a priori state estimate

$$\hat{q}_{k/k-1} = [\gamma_k \mathrm{X}_k q_k + (1-\gamma_k)\mathrm{X}_{k-1} q_k]\hat{q}_{k-1/k-1} \tag{10}$$

c. Calculate a priori error covariance estimate

$$P_{k/k-1} = BP_{k/k-1}B^T + \mathrm{K} \tag{11}$$

Where $B = \gamma_k \mathrm{X}_k + (1-\gamma_k)\mathrm{X}_{k-1}$, $K = 1/4[\Delta t^2 \Gamma(q_k) R_g \Gamma(q_k)^T]$, $\Gamma(q_k)$ is associated with the matrix q_k .

d. Calculate the Kalman gain

$$\Delta_k = P_{k/k-1}\Omega_k(\Omega_k^T P_{k/k-1}\Omega_k + R_k)^{-1} \tag{12}$$

Where

$$R_k = \begin{pmatrix} R_{acc,k} \\ \hat{R}_{mg,k} \end{pmatrix} \tag{13}$$

$$R_{acc,k} = \frac{1}{4}\Gamma(\hat{q}_{k/k-1}) R_{acc} \Gamma(\hat{q}_{k/k-1})^T \tag{14}$$

e. Calculate posterior state estimation

$$\hat{q}_{k/k} = (I - \Delta_k \Omega_k)\ \hat{q}_{k/k-1} \tag{15}$$

f. Calculate the posteriori error covariance estimate

$$P_{k/k} = (I - \Delta_k \Omega_k)\ P_{k/k-1} \tag{16}$$

In the above formula, a predictor with a "^" sign, with a"∗" is symmetric matrix.

The covariance $\hat{R}_{mg,k}$ of E.q. (13) is obtained by using the adaptive method [12] to compensate for the magnetometer. The observation noise equation m_k given in equation (9) is unknown.

The magnitude of the heading angle is largely influenced by the measured value of the magnetometer, but the magnetometer is susceptible to magnetic field interference to produce measurement errors. According to the specific situation can be divided into two cases of magnetic interference:

1) Random interference of magnetic sources in real-time environments.

2) Magnetic interference caused by the carrier of the magnetometer.

The interference of the first case results in a larger output deviation of the magnetometer, and this type of interference is random and it is difficult to eliminate; the interference of the second case can be corrected in advance by means of compensation.

For the second kind of interference, this paper uses the adaptive method to update the covariance $r_k = -\Omega_{2,k}\hat{q}_{k/k-1}$ by using the output of the magnetometer, and then uses the covariance r_k to estimate the covariance matrix $\hat{R}_{mg,k}$.

$$\hat{r}_k = \sqrt{k_1(\|\|m_k\| - \|m_0\|\|) + k_2 \operatorname{var}(\|\|m_{k-N}\| : \|m_{k+N}\|\|)} \tag{17}$$

Which $\|m_k\|$ is the k moment of the three-axis magnetometer model; k_1 and k_2 are based on the experimental data calculated by the weight factor; $\operatorname{var}(\|\|m_{k-N}\| : \|m_{k+N}\|\|)$ is the variance of the modulus of the triaxle magnetometer, the length of the sliding window is N, the size of N is calculated from the experimental data.

The carrier compensation algorithm can effectively compensate the magnetometer data when the external magnetic field interference is stable. However, in the actual process, the external magnetic interference is not stable. Therefore, the paper uses the method of adjusting the threshold to correct the heading angle. In this paper, the model of the three-axis magnetometer is pre-processed, and then the variance of the modulus of the magnetometer is obtained. When the threshold is set and the interference is found at a certain point, the threshold is set as follows:

$$\begin{cases} \operatorname{var}(\|\|m_{k-2N}\| : \|m_{k+2N}\|\|) \\ |m_k - m_0| < 0.35 m_0 \end{cases} \tag{18}$$

Where $\operatorname{var}(\|\|m_{k-2N}\| : \|m_{k+2N}\|\|)$ is the variance of the modulus of the triaxial magnetometer for each point, the size of the sliding window is 2N, which m_0 is the standard local magnetic field strength.

When the condition of E.q. (18) is satisfied, it shows that the external field magnetic field interference is relatively stable or the magnetic field interference at this moment has little effect on the accuracy of attitude measurement. At this time the q-AKF algorithm to solve the attitude angle of has a larger weight. When the condition of the equation (18) is not satisfied, the accuracy of the pose angle of q-AKF is reduced, and the weight is shifted to the heading angle of the gyro output, so that the influence of the external magnetic field disturbance on the attitude angle accuracy is reduced.

5. Experimental verification and analysis

MEMS-IMU is a laboratory-based and MEMS sensor-based attitude meter that integrates a 3-axis accelerometer, a 3-axis gyroscope, a 3-axis magnetometer, and a barometer, as shown in Fig.1.The sensitivity of the gyroscope is 2000 dps,the range of accelerometer is8g,the sensitivity of magnetometer is 2.5Gauss.MEMS-IMU and PC is the use of RS232 interface for wired communications,using Matlab2014 design filter and carries on the data processing.

Fig.1 Homemade attitude meter

The MEMS-IMU is placed on a biaxial electric turntable so that the Z-axis of the MEMS gyroscope is perpendicular to the turntable plane. The MEMS-IMU was supplied, and then collect the experimental data separately under the following three sets of conditions:

(1)open the dual-axis electric turntable controller, set the turntable to $20^{\circ}/s$ speed rotation, so that MEMS-IMU around the z axis to regularly rotate, click on the host computer to save data.

(2)Open the two-axis electric turntable, to the spindle to unlock, MEMS-IMU will be placed on the dual-axis electric turntable, but placed a mobile phone in the turntable as a source of magnetic interference, while opening the host computer to collect data.

(3)In the dual-axis electric turntable on the cross frame placed a mobile phone as a magnetic interference source, open the controller of the dual-axis electric turntable, manipulate the turntable, make the IMU carry out fixed-point stop movement at 40°interval, so that IMU rotation 360 °, open the host computer to save data.

Now the KF, EKF, UKF, q-AKF four algorithms are used to process the first set of data collected, attitude step is $0.005ms$, filter step size is $0.01ms$,simulation time is $90s$.The simulation results are shown in Fig.2.

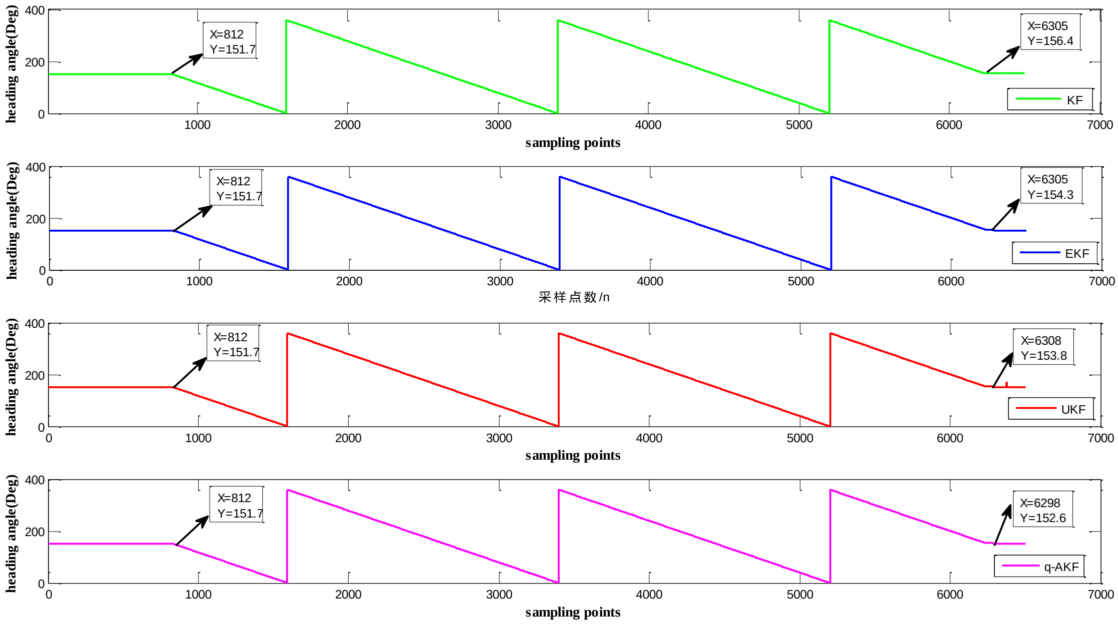

Fig.2 The first set of data using four filtering algorithms to solve the heading angle output comparison chart

It can be seen from Figure 2, in the MEMS-IMU do constant rotation, the use of gyro output information to resolve the attitude angle will produce cumulative error. The cumulative error of the four algorithms (the difference between the heading angle and the initial heading angle after the IMU is rotated uniformly) is shown in Table 1.

Table 1. Cumulative error comparison of four filter algorithms (unit: °)

Algorithm	Initial heading angle	Heading angle after turn	Cumulative error
KF	151.7	156.4	4.7
EKF	151.7	154.3	2.6
UKF	151.7	153.8	2.1
q-AKF	151.7	152.6	0.9

It can be seen from the table that the cumulative error of the heading angle obtained by the q-AKF algorithm is only 0.9°, which is better than the other three filtering algorithms. The jump in Fig. 2 is a 0°to 360°transition that occurs when the heading angle is pointing to the north or south. Figure 3 shows the estimate error of three algorithms that are EKF, q-AKF, UKF. It can be observed from the figure that the estimation error of EKF algorithm is obviously smaller than that of UKF and q-AKF in a short time, and the error is relatively stable. But with the change of time, EKF and UKF algorithm error will show a large fluctuations, which is very unstable. Considering that the q-AKF algorithm produces the estimated error when the attitude is solved for a long time, is better than the estimation error generated by UKF and EKF algorithm .Therefore, q-AKF algorithm is superior to EKF and UKF algorithm in terms of performance comparison.

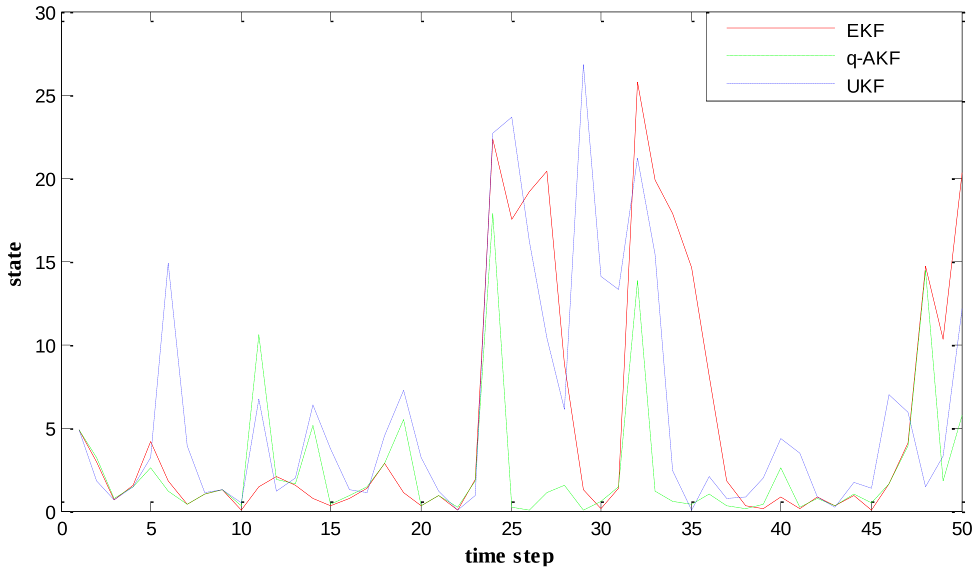

Fig.3 Three filter algorithm estimation error

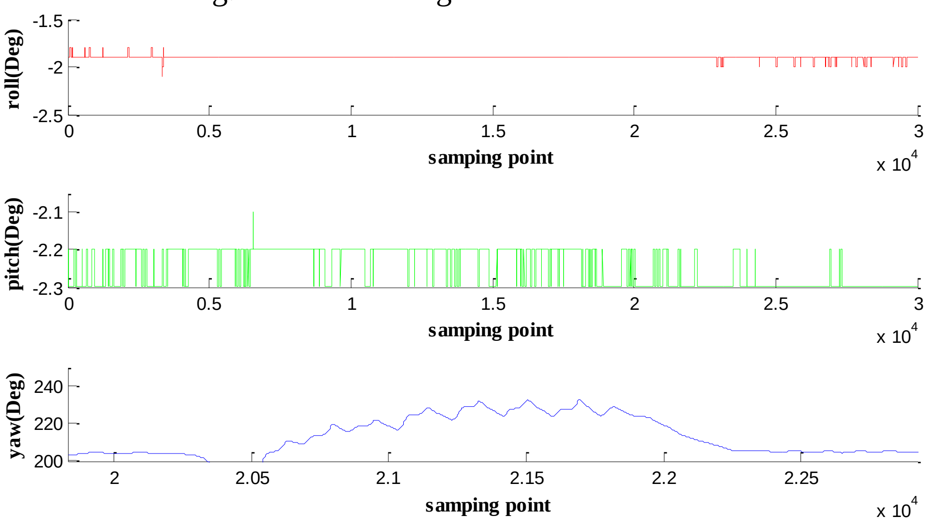

Fig. 4 Attitude angle output with magnetic interference in static environment

Fig.4 shows the attitude angle output of the MEMS-IMU in a static state with magnetic field interference. As can be seen from the figure, the heading angle emerge the larger fluctuations in the case of magnetic field interference. It can be seen that the interference of the magnetic field only affects the heading angle.Fig.5 shows the EKF and q-AKF algorithm to determine the heading angle of the comparison chart in the case of magnetic interference. In the still state, the ideal attitude angle output should be a straight line .However, it can be observed from Fig 5, EKF algorithm to determine the heading angle appear a lot of fluctuations, the maximum jump to 5.8°, and not a good elimination of the impact of magnetic interference. The q-AKF algorithm has little variation in the heading angle, and the maximum jump is 1.8°, which improves the influence of the magnetic interference on the heading angle.

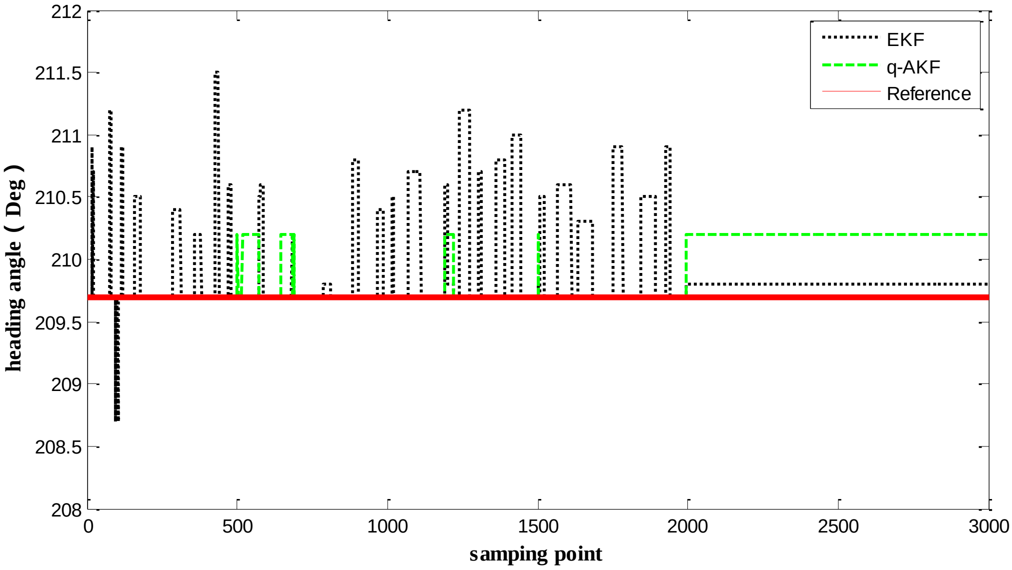

Fig.5 Comparison of heading angle for different algorithms under magnetic interference

Fig.6 shows the attitude angle output of the use of q-AKF algorithm to deal with fixed-point experimental data. It can be seen from the figure, the attitude angle calculated by q-AKF algorithm is basically coincident with the reference course, and the attitude angle solved by the q-AKF algorithm does not produce a large error in the case of magnetic interference in the surrounding environment. Which can effectively suppress the error caused by magnetic interference. And the simulation experiment verifies the effectiveness of the algorithm.

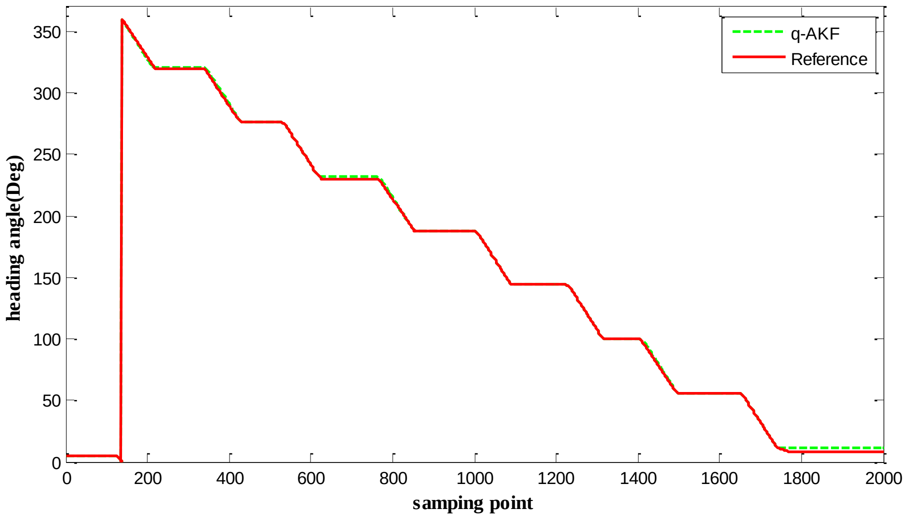

Fig. 6 the heading angle output of fixed-point rotation experiment

6. Conclusion

In this paper, the q-AKF anti-magnetic interference algorithm that using gyro and magnetometer measurements, which establishing the equation of state and the error observation equation of the magnetometer output based on the gyroscope attitude error angle, and using the adaptive Kalan filter method to suppress the filtering divergence and estimate the attitude error angle. The proposed algorithm improves the compensation of the magnetometer, and effectively suppress the gyro random drift of the error, the accuracy of the attitude measurement of the carrier is effectively improved in the magnetic interference environment. The main advantage of the q-AKF algorithm is that it is not necessary to set the threshold in advance or to establish an error model, and the optimal gain of the filter is adjusted adaptively by the magnetometer covariance matrix.

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