Design of Data Fusion Algorithm of 10-DOF AHRS for Underwater Vehicles

Yixuan Gao, Xueting Zhang, Qingpeng Kong, Yucheng Xu
Hangzhou Dianzi University
Hangzhou, Zhejiang Province, People's Republic of China

***Abstract*—This paper describes the design of a 10-Dimension of Freedom(10-DoF) Attitude and Heading Reference System (AHRS) by fusing gyroscope, accelerometer, magnetometer, and temperature data from MEMS sensors embedded in the system. This paper use Kalman filter to estimate orientation and use Gauss-Newton iteration method to get measurement state. In this filter, the system error and measurement error are estimated, also system error is sensitive to changes of temperature. The system is tested under quasi-static conditions and is compared with the orientation obtained with non-magnetic turntable. The results show ±1º error in row and pitch direction and ±5º in yaw direction.**

Keywords-AHRS;Kalman filter; data fusion

I. INTRODUCTION

Attitude and Heading Reference System(AHRS) play an important role when applying underwater vehicles to investigate the seafloor mineral resources, or applying buoys to measure the ocean environment. In many cases, the scientists or engineers cannot get valuable information from original output of sensors without the real-time accurate attitude of vehicles or buoys. Traditionally, the optical-fiber gyroscopes could give a satisfying solution, but the volume and cost limitation hindered the application of optical-fiber gyroscopes. As a low power consumption and small size measurement platform with high-level features in accuracy and sample rate, Inertial Measurement Unit fits well for detection the real-time attitude information of underwater sensors. The work in this paper was based on a 10-DOF MEMS AHRS, which is suitable to be integrated in underwater sensors. The 10-DOF AHRS is equipped with the following sensors: 3-axial gyro, 3-axial accelerometer, 3-axial magnetometer and one temperature sensor. A new design of data fusion algorithm with less computation is presented to get the attitude information. A testing platform was established including design PC software to display the 3D view of a randomly rotating underwater sensor in real-time. The result of the test shows effectiveness and real-time feature of this algorithm. The system block diagram is shown in figure 1.

II. APPROACH AND ALGORITHM

This paper use quaternion to express rotation from a frame to another reference frame since its parameters are fewer compared with rotation matrices. And quaternion is transformed to euler angle by upper computer so that it gives an obvious geometric meaning. A Kalman filter is designed to fuse signals from 3-axial gyro, 3-axial accelerometer and 3-axial magnetometer. The block diagram of data fusing algorithm is shown in figure 2.

Rotation vector represented by quaternion is shown as (1):

$$q = a \cdot i + b \cdot j + c \cdot k + d \tag{1}$$

where a, b, c and d are real numbers and i, j and k are unit vectors directed along the x, y and z axis respectively. In prediction step of Kalman filter, the prediction equation is

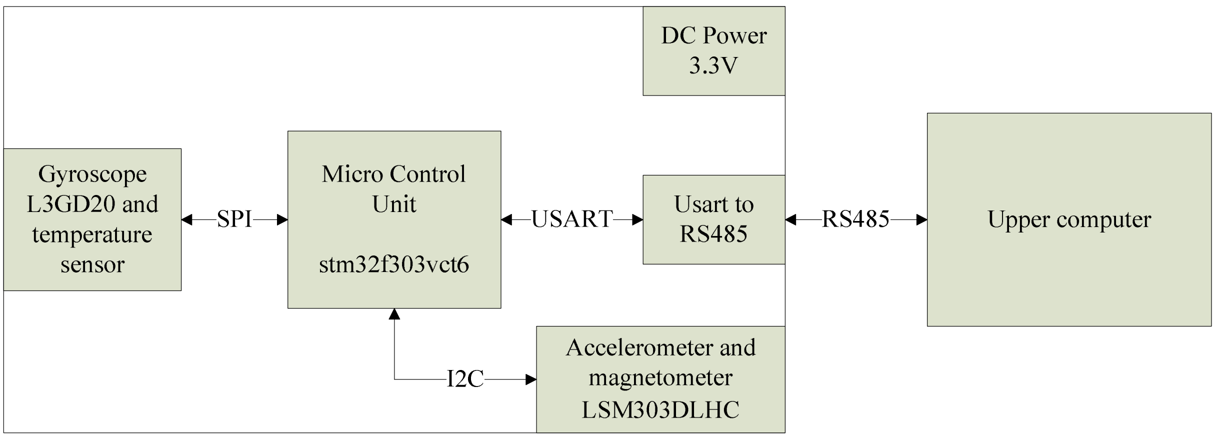

Figure 1. Block diagram of AHRS hardware platform

The work of this paper is part of the project 'research of three components observation technologies by near-seafloor magnetometers' (41006060), which supported by National Natural Science Foundation of China.

978-0-933957-40-4 ©2013 MTS

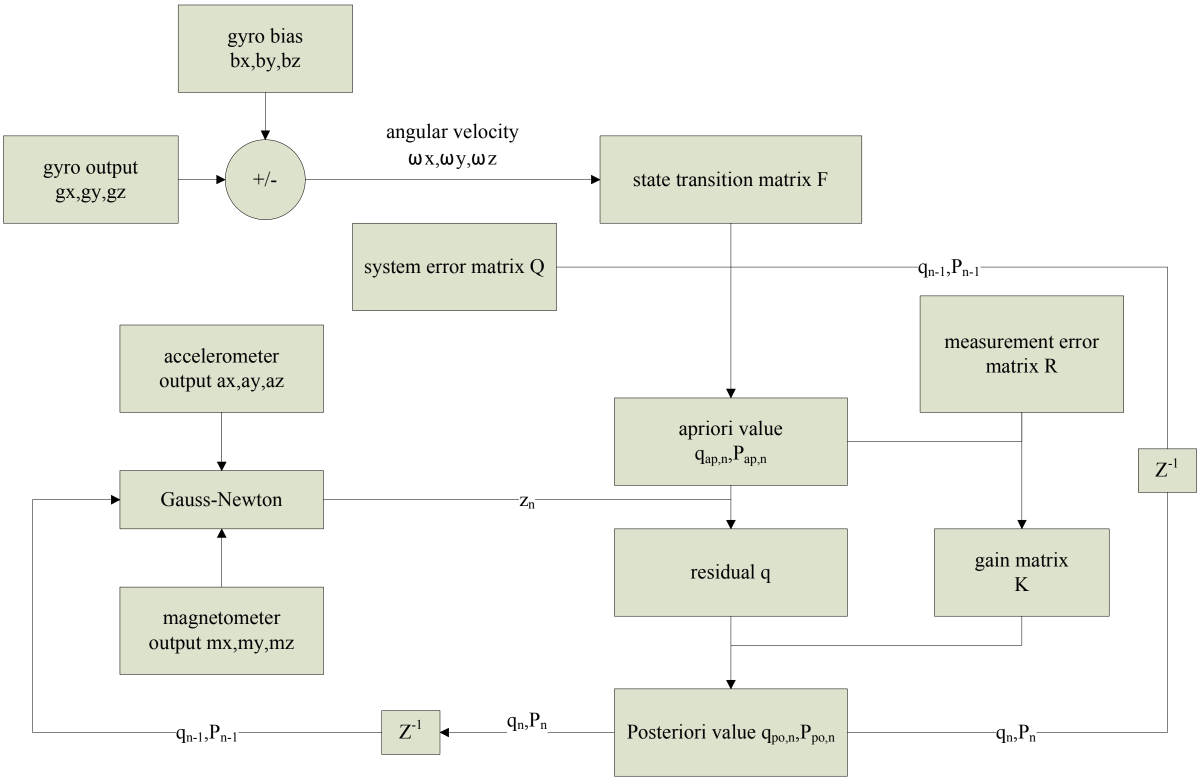

Figure 2. Block diagram of data fusing algorithm

shown as (2):

$$q_n = F \cdot q_{n-1} + B \cdot u_{n-1} + W_{n-1} \tag{2}$$

where q_n is the current rotation quaternion, q_{n-1} is the previous rotation quaternion and W_{n-1} is the system noise value. The Kalman filter input u_{n-1} in this system is equal to zero. So (2) could be expressed as (3), where $\dot{q}_n$ represent quaternion variation and δ represent sampling period.

$$q_n = q_{n-1} + \dot{q}_n \cdot \delta \tag{3}$$

A. apriori value by gyro data

Eq. (3) could be transferred into State Transition Matrix expression named F consists of gyro data, shown as (4):

$$q_n = q_{n-1} + \dot{q}_n \cdot \delta = F \cdot q_{n-1}$$

$$q_n = F \cdot q_{n-1} = \begin{bmatrix} 1 & -\frac{1}{2}\cdot\omega_x\cdot\delta & -\frac{1}{2}\cdot\omega_y\cdot\delta & -\frac{1}{2}\cdot\omega_z\cdot\delta \\ \frac{1}{2}\cdot\omega_x\cdot\delta & 1 & \frac{1}{2}\cdot\omega_z\cdot\delta & -\frac{1}{2}\cdot\omega_y\cdot\delta \\ \frac{1}{2}\cdot\omega_y\cdot\delta & -\frac{1}{2}\cdot\omega_z\cdot\delta & 1 & \frac{1}{2}\cdot\omega_x\cdot\delta \\ \frac{1}{2}\cdot\omega_z\cdot\delta & \frac{1}{2}\cdot\omega_y\cdot\delta & -\frac{1}{2}\cdot\omega_x\cdot\delta & 1 \end{bmatrix} \tag{4}$$

where ω_x, ω_y and ω_z represents the angle rate of x, y and z axis respectively, which could be derived from gyro data directly. The sampling period δ could be got from timer embedded in the chip. Now we have estimated the variance of the system noise as shown in (5):

$$Q = E\left|\begin{bmatrix} -\omega_x-\omega_y-\omega_z \\ \omega_x-\omega_y+\omega_z \\ \omega_x+\omega_y-\omega_z \\ -\omega_x+\omega_y+\omega_z \end{bmatrix} \cdot \begin{bmatrix} -\omega_x-\omega_y-\omega_z \\ \omega_x-\omega_y+\omega_z \\ \omega_x+\omega_y-\omega_z \\ -\omega_x+\omega_y+\omega_z \end{bmatrix}^T\right| \tag{5}$$

Assuming that $E|\omega_i| = 0$ and $E|\omega_i \cdot \omega_j| = 0, \forall i \neq j$ so the matrix Q can be simplified as (6):

$$Q = \begin{bmatrix} \sigma_x^2+\sigma_y^2+\sigma_z^2 & -\sigma_x^2+\sigma_y^2-\sigma_z^2 & -\sigma_x^2-\sigma_y^2+\sigma_z^2 & \sigma_x^2-\sigma_y^2-\sigma_z^2 \\ -\sigma_x^2+\sigma_y^2-\sigma_z^2 & \sigma_x^2+\sigma_y^2+\sigma_z^2 & \sigma_x^2-\sigma_y^2-\sigma_z^2 & -\sigma_x^2-\sigma_y^2+\sigma_z^2 \\ -\sigma_x^2-\sigma_y^2+\sigma_z^2 & \sigma_x^2-\sigma_y^2-\sigma_z^2 & \sigma_x^2+\sigma_y^2+\sigma_z^2 & -\sigma_x^2+\sigma_y^2-\sigma_z^2 \\ \sigma_x^2-\sigma_y^2-\sigma_z^2 & -\sigma_x^2-\sigma_y^2+\sigma_z^2 & -\sigma_x^2+\sigma_y^2-\sigma_z^2 & \sigma_x^2+\sigma_y^2+\sigma_z^2 \end{bmatrix} \tag{6}$$

where σ_x, σ_y and σ_z are the variance of angle rate noise of x, y and z axis respectively. Now we can get apriori value of rotation quaternion $q_{ap,n}$ and apriori value of covariance matrix $P_{ap,n}$ through (7) and (8):

$$q_{ap,n} = F \cdot q_{n-1} \tag{7}$$

$$P_{ap,n} = F \cdot P_{n-1} \cdot F^T + E\left|{W_n}^2\right| = F \cdot P_{n-1} \cdot F^T + Q \tag{8}$$

B. observed value by accelerometer and magnetometer data

Kalman filter need an observed value of state which is shown in (9):

$$z_n = C \cdot q_{n-1} + v_{n-1} \tag{9}$$

where C is the gain matrix and v_{n-1} is the measurement noise. C is equal to identity matrix H in this paper. We get z_n by Gauss-Newton method and first we get rotation matrix by rotation quaternion as (10):

$$R_n = \begin{bmatrix} d^2+a^2-b^2-c^2 & 2\cdot(a\cdot b-c\cdot d) & 2\cdot(a\cdot c+b\cdot d) \\ 2\cdot(a\cdot b+c\cdot d) & d^2+b^2-a^2-c^2 & 2\cdot(c\cdot b-a\cdot d) \\ 2\cdot(a\cdot c-b\cdot d) & 2\cdot(c\cdot b+a\cdot d) & d^2+c^2-b^2-a^2 \end{bmatrix} \tag{10}$$

Then we define error function $E(q_{n-1})$ as shown in (11):

$$E(q_{n-1}) = \varepsilon^T\varepsilon = (y^E - M\cdot y^S)^T \cdot (y^E - M\cdot y^S) \tag{11}$$

where y^E is a 6*1 vector consists of accelerometer and magnetometer data in the earth frame, y^S is a 6*1 vector consists of accelerometer and magnetometer data in the sensor frame and

$$M = \begin{bmatrix} R_n & 0 \\ 0 & R_n \end{bmatrix} \tag{12}$$

Then we define Jacobian matrix

$$J(q_{n-1}^z) = -\begin{bmatrix} \frac{\partial M}{\partial a}\cdot y^S & \frac{\partial M}{\partial b}\cdot y^S & \frac{\partial M}{\partial c}\cdot y^S & \frac{\partial M}{\partial d}\cdot y^S \end{bmatrix} \tag{13}$$

The value of rotation quaternion is updated in (14):

$$q_n^z = q_{n-1}^z - [J^T(q_{n-1}^z)\cdot J(q_{n-1}^z)]\cdot \varepsilon(q_{n-1}^z) \tag{14}$$

Now we have got the observed value of rotation matrix

$$z_n = H \cdot q_n^z \tag{15}$$

C. posteriori value by data fusion

At update step, we first calculate the difference between priori value and observed value which is called the residual or innovation as shown in (16):

$$q_{re,n} = z_n - q_{ap,n} \tag{16}$$

On the other hand we define gain of Kalman filter as shown in (17):

$$K = P_{ap,n} \cdot (P_{ap,n} + R)^{-1} \tag{17}$$

where R is the measurement noise variance. In this paper we define R as a $I_{4*4} \cdot 0.01$ matrix to get a stable rotation quaternion. At last, we get the posteriori rotation quaternion and covariance

$$q_{po,n} = q_{ap,n} + K \cdot q_{re,n} \tag{18}$$

$$P_{po,n} = (I - K)\cdot P_{ap,n} \tag{19}$$

Since gyro bias is sensitive to temperature, we define compensation equation as shown in (20):

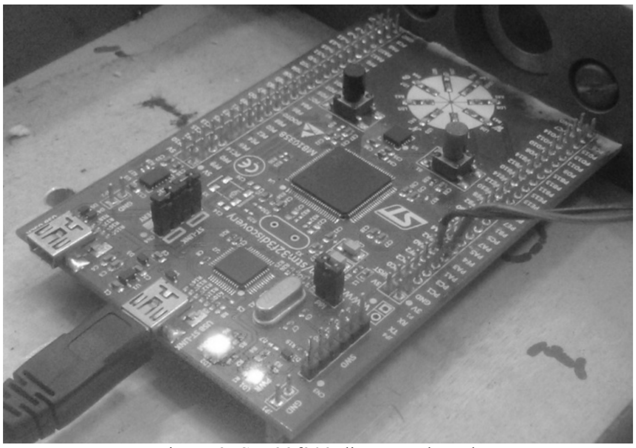

Figure 3. Stm32f303 discovery board

$$\omega(T) = 0.03 \cdot T \tag{20}$$

III. EXPERIMENTATION

The experimentation of this paper was carried out on Gauss-Newton method firstly. A development board based on stm32f303 was used for the experiments. A 3-axial gyro, 3-axial accelerometer, 3-axial magnetometer, temperature sensor are embedded on the board as shown in figure 3.

The results in figure 4 show that the rotation quaternion tends to be stable after 3 times of iteration. The accuracy and stability of system is tested under quasi-static conditions. The static tests shows on drift. The stability of row and pitch is about 0.1º root means square as shown in figure 5 and 6 respectively. And the stability of yaw is about 0.3º root means square as shown in figure 7. Because there is no direction drift so we ignore time influence on direction. We rotate the turntable and then write down angles as shown in upper computer. Range of measurement of row and pitch is set from -85° to 85°, with step of 5°. As for yaw, it is from -170° to 170° and 10°. It shows that 3%, 0.6% and 6% error of row, pitch and yaw in figure 8, 9 and 10 respectively. The red line represents real angle and the green line represents measurement value.

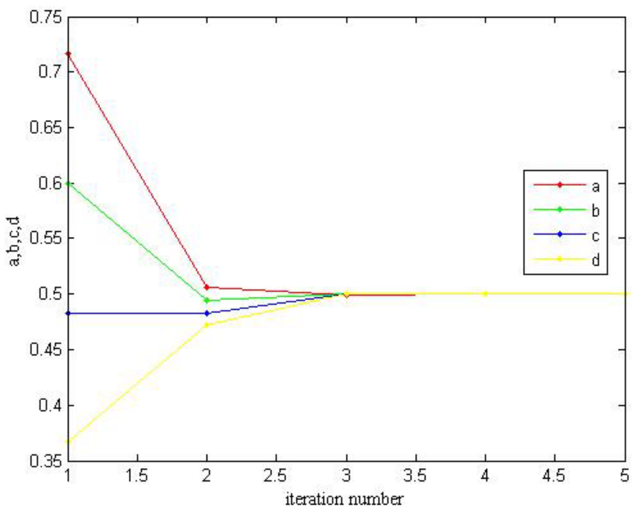

Figure 4. Convergence rate of Gauss-Newton method

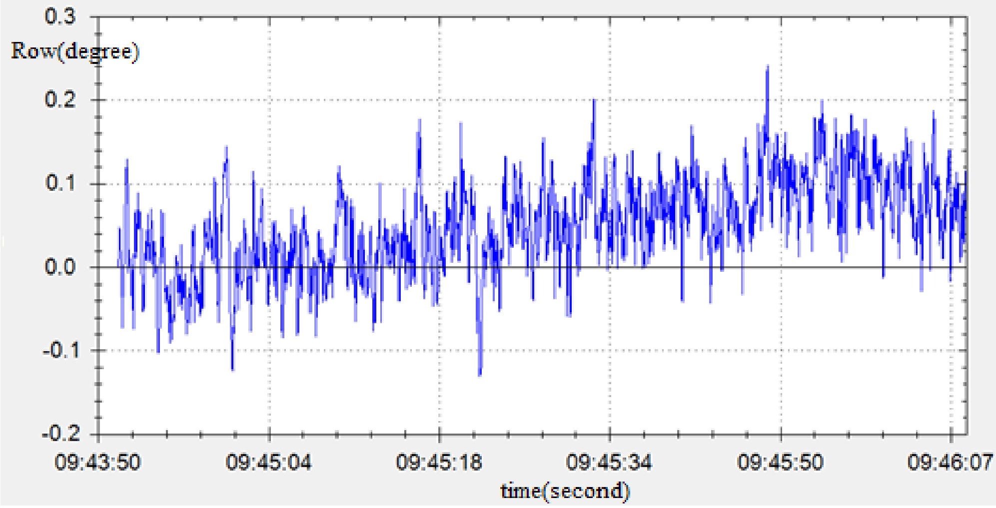

Figure 5. Stability of Row under quasi-static conditions

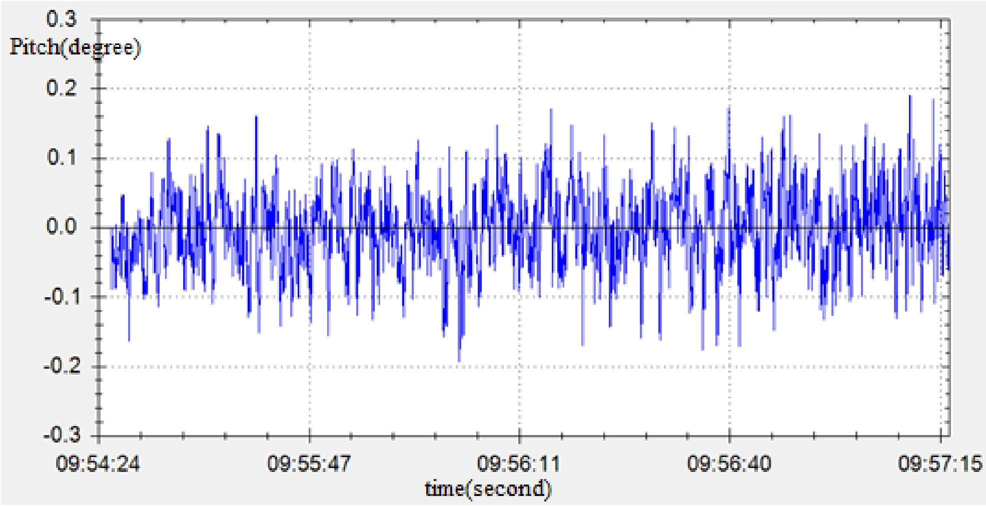

Figure 6. Stability of Pitch under quasi-static conditions

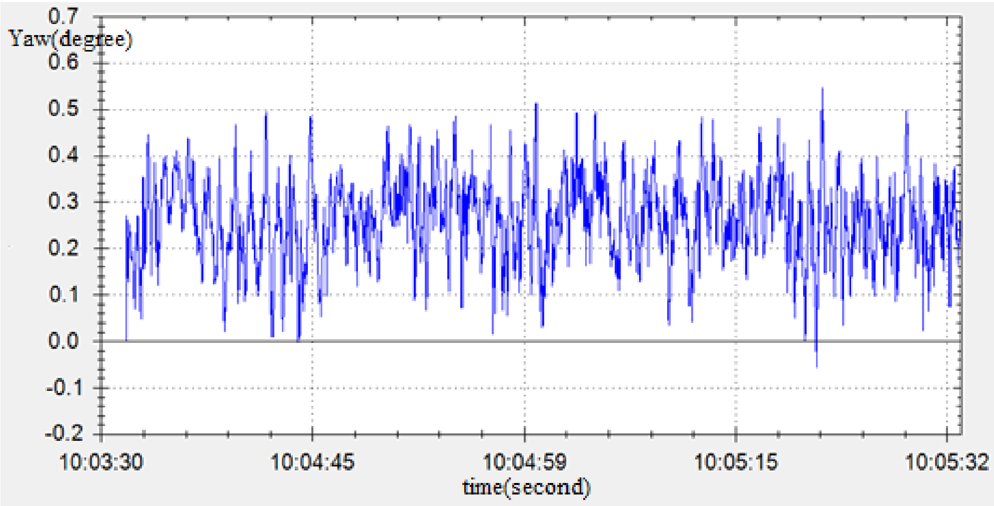

Figure 7. Stability of Yaw under quasi-static conditions

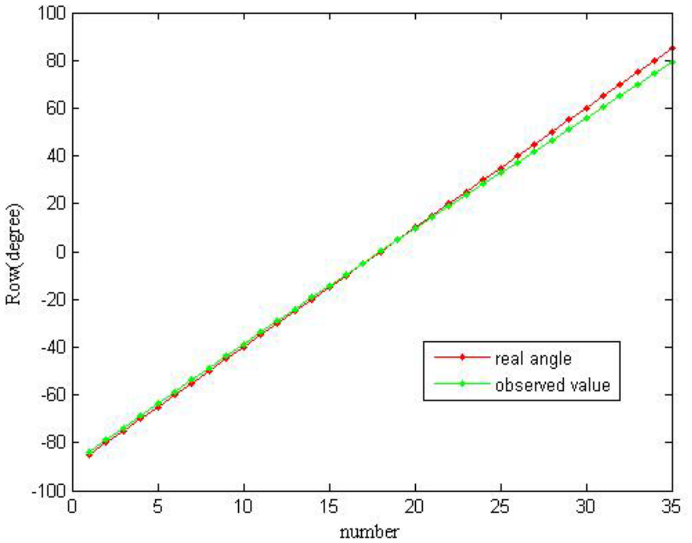

Figure 8. Observed value compared to real angle(row)

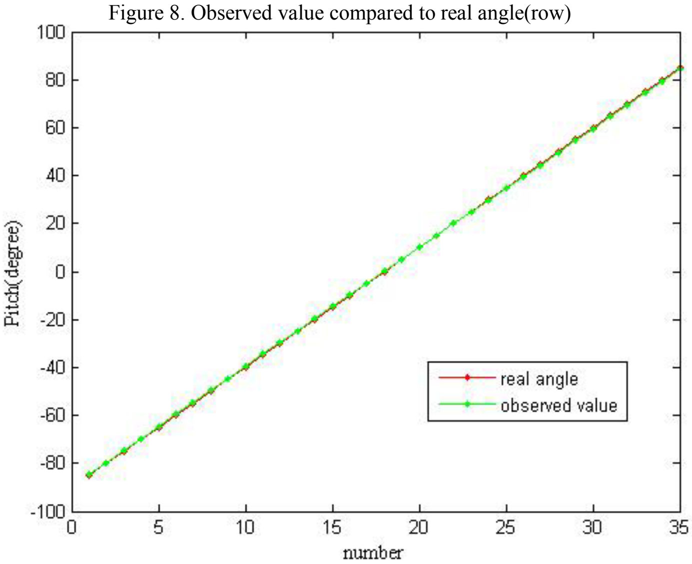

Figure 9. Observed value compared to real angle(pitch)

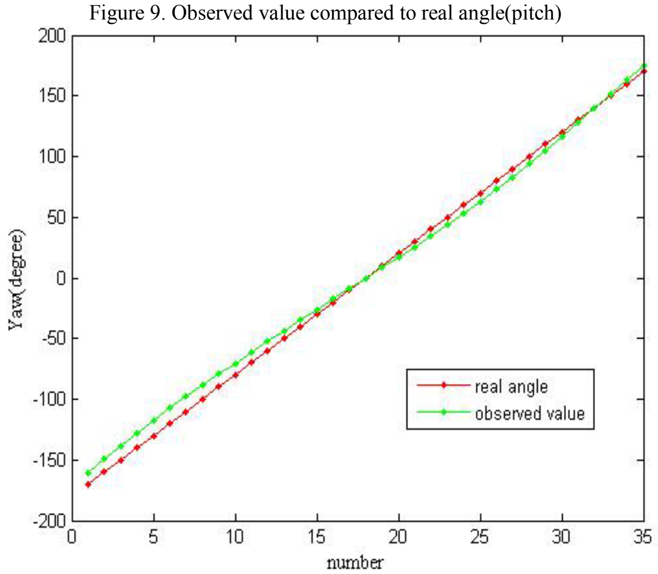

Figure 10. Observed value compared to real angle(yaw)

IV. CONCLUSION

This paper introduced a 10-DoF AHRS design by fusing data from gyro, accelerometer, magnetometer and temperature sensor to estimate attitude and heading information. This AHRS system was designed to be applied to many occasions,esspecially for underwater vehicles or buoys where need the orientation measurement system to be small, low power consumption and lowcost. The only things have to be known are the specifications of the sensors, like noise and drift.

However, the system are tested in the non-magnetic laboratory instead of in underwater conditions. It can be found that the AHRS is sensitive to the ferromagnetism, so that internal or external ferrous material may disturb the orientation of AHRS. Further work should be built on the calibration of intrinsic magnetism. Besides, if the system is moving with acceleration, accelerometer model has to be modified.

REFERENCES

[1] R. E. KALMAN, A New Approach to Linear Filtering and Prediction Problems. Research Institute for Advanced Study, Baltimore, Md. April 1960.

[2] Daniel Roetenberg, Henk J. Luinge, Chris T. M. Baten, and Peter H. Veltink, Member, IEEE, Compensation of Magnetic Disturbances Improves Inertial and Magnetic Sensing of Human Body Segment Orientation, IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITATION ENGINEERING, VOL. 13, NO. 3, September 2005.

[3] James Diebel. Representing Attitude: Euler Angles, Unit Quaternions, and Rotation Vectors. Stanford, California 94301–9010, Stanford University, 20 October 2006.

[4] Paul Berner. Technical Concepts Orientation, Rotation, Velocity and Acceleration, and the SRM, Copyright © 2008 SEDRIS,20 June 2008.

[5] João Luís Marins, Xiaoping Yun, Eric R. Bachmann, Robert B. McGhee, and Michael J. Zyda. An Extended Kalman Filter for Quaternion-Based Orientation Estimation Using MARG Sensors, Proceedings of the 2001 IEEE/RSJ,International Conference on Intelligent Robots and Systems,Maui, Hawaii, USA, Oct. 29 - Nov. 03, 2001.