ICSE 2010

PROCEEDINGS OF THE SECOND INTERNATIONAL CONFERENCE ON SCIENCE AND ENGINEERING

Volume - 1

Electronics
Electrical Power
Information Technology
Engg: Physics

Sedona Hotel, Yangon, Myanmar
December 2-3, 2010

PROCEEDINGS OF THE SECOND INTERNATIONAL CONFERENCE ON SCIENCE AND ENGINEERING

Organized by
Ministry of Science and Technology

DECEMBER 2-3, 2010
SEDONA HOTEL, YANGON, MYANMAR

Attitude Estimation System Using MEMS Inertial Sensors and Kalman Filter

Htoo Maung Maung#1, Zaw Min Naing*2, Hla Myo Tun#3

Department of Electronic Engineering, Mandalay Technological University
Mandalay, Myanmar

1hmaungmaung@gmail.com

3hlamyotun.mtu@gmail.com

**Technological University (Maubin)*
Maubin, Myanmar

2zawminnaing@pmail.ntu.edu.sg

***Abstract*— This paper focuses on the attitude estimation problem for a moving object using two MEMS sensors: accelerometer and gyroscope. These two sensors have different noise characteristics and are combined using the Kalman filter so that accurate attitude estimation is obtained. The process noises of two MEMS sensors are selected as the nominal values of actual sensors. The gyroscope output is used for time update portion of the filter and the accelerometer output is utilized the measurement update portion of the filter. The performance of the attitude estimation system is demonstrated through numerical simulations.**

***Keywords*—attitude estimation, accelerometer, gyroscope, Kalman filter, MEMS inertial sensor, sensor data fusion**

I. Introduction

The estimation of the "tilt" of vehicles has been of much interest, especially in the areas such as aerospace [5] or control system [3],[6]. For instance, controlling autonomous flight vehicle is the practical issue related with tilt estimation. They have been utilized in applications such as forest fire perimeter tracking, military tactical reconnaissance, and rural search and rescue where rapid area searches are desired.

Guidance and navigation are the key technologies for the autonomous flight vehicle wherein the attitude information is indispensable. Inertial sensors fabricated by micro electromechanical system (MEMS) technology offer revolutionary improvements in cost, size, and ruggedness relative to fiber optic and spinning mass technologies. MEMS gyroscopes and accelerometers are ideal as components of a compact and affordable attitude determination system.

Gyroscopes measure the body's angular velocity and, by integrating this angular velocity, they can calculate the attitude angle. Accelerometers measure the body's translational acceleration. If they measure only the acceleration of gravity, they provide the body's absolute attitude in the navigational frame of reference.

One drawback of the accelerometer is that its sensitiveness to vibration of bodies; vibration contains a lot of acceleration components. To reduce high frequency vibration noises, a low pass filter is required. This limits the bandwidth of the accelerometer and a phase delay is introduced in the filtered result. However, calculating the attitude angle using the integrating gyroscope's output causes divergence in the attitude's error.

In this paper, a Kalman filter is proposed to compensate this error by fusing two sensor's data. The Kalman filter provides an optimal sensor fusion method for linear systems and is divided into two main parts: the time update and the measurement update.

This paper presents only the first step of developing the attitude estimation system for autonomous flight vehicle and there are still many things left to do, for example, adding the gyro bias to the filter states and expanding the algorithm for high frequency acceleration. Although it is not well tuned, it can be seen that the filter works well.

II. Attitude Determination Algorithm

The problem of attitude estimation is to determine the orientation of the vehicle's body reference frame with respect to a navigational reference frame. The two low-cost MEMS inertial sensors, accelerometer and gyroscope, are used in this problem. Because the values of these two sensors are defined in the body frame of reference, it is necessary to transform the sensors output in the body frame into the rate of attitude angle in the navigation frame.

The gyroscope's output is related to the rate of attitude angle as

$$\begin{bmatrix} \omega_x \\ \omega_y \\ \omega_z \end{bmatrix} = \begin{bmatrix} 1 & 0 & -\sin\theta \\ 0 & \cos\gamma & \sin\gamma\cos\theta \\ 0 & -\sin\gamma & \cos\gamma\cos\theta \end{bmatrix} \begin{bmatrix} \dot{\gamma} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} \tag{1}$$

where γ, θ and ψ are the roll, pitch and azimuth (yaw) angle respectively. ω_x, ω_y and ω_z represent the body's angular velocity. This equation can also be expressed as

$$\begin{bmatrix} \dot{\gamma} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} 1 & \sin\gamma\tan\theta & \cos\gamma\tan\theta \\ 0 & \cos\gamma & -\sin\gamma \\ 0 & \sin\gamma\sec\theta & \cos\gamma\sec\theta \end{bmatrix} \begin{bmatrix} \omega_x \\ \omega_y \\ \omega_z \end{bmatrix} \tag{2}$$

Accelerometer can also be utilized to calculate attitude by using the acceleration due to gravity. The relationship between the acceleration of gravity in the navigational frame of reference and translational acceleration in the body frame of reference can be written as

$$\begin{bmatrix} u_x \\ u_y \\ u_z \end{bmatrix} = \begin{bmatrix} 1 & 0 & -\sin\theta \\ 0 & \cos\gamma & \sin\gamma\cos\theta \\ 0 & -\sin\gamma & \cos\gamma\cos\theta \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ g \end{bmatrix} \tag{3}$$

$$\begin{bmatrix} u_x \\ u_y \\ u_z \end{bmatrix} = \begin{bmatrix} -g\sin\theta \\ g\sin\gamma\cos\theta \\ g\cos\gamma\cos\theta \end{bmatrix} \tag{4}$$

where u_x,u_y, and u_z represent the translational acceleration of each axis in the body frame of reference and g is the acceleration due to gravity.

III. DESIGN OF KALMAN FILTER

The Kalman filter is a good tool that estimates the state of the system including measurement noise. It is useful to combine two sensor data containing measurement noise. Designing a Kalman filter requires a linear dynamic system model [1],[2],[4]-[6], like equation (5).

$$\begin{aligned} \dot{x} &= Ax + w \\ y &= Cx + v \end{aligned} \tag{5}$$

The state variable is defined as

$$x = \begin{bmatrix} -\sin\theta \\ \cos\theta\sin\gamma \\ \cos\theta\cos\gamma \end{bmatrix} \tag{6}$$

The system model using a gyroscope model is

$$\dot{x} = \begin{bmatrix} 0 & \omega_z & -\omega_y \\ -\omega_z & 0 & \omega_x \\ \omega_y & -\omega_x & 0 \end{bmatrix} x + w \tag{7}$$

The measurement model using an accelerometer model is

$$y = \begin{bmatrix} u_x \\ u_y \\ u_z \end{bmatrix} = \begin{bmatrix} g & 0 & 0 \\ 0 & g & 0 \\ 0 & 0 & g \end{bmatrix} x + v \tag{8}$$

The system using the sensors which have the sampling time is naturally a discrete one. Thus, the discrete processing model is needed to implement the designed Kalman filter.

$$\begin{aligned} x_{k+1} &= \Phi_k x_k + w_k \\ y_k &= H_k x_k + v_k \end{aligned} \tag{9}$$

Equation (9) is the discrete time system model. Φ_k is the state transition matrix and it can be obtained by Taylor series expansion method where T_s is the sampling time.

$$\begin{aligned} \Phi_k &= \exp(A(kT_s)T_s) = I + T_s.A(kT_s) + \ldots \\ &= \begin{bmatrix} 1 & \omega_z.T_s & -\omega_y.T \\ -\omega_z.T & 1 & \omega_x.T \\ \omega_y.T & -\omega_x.T & 1 \end{bmatrix} \end{aligned} \tag{10}$$

The process noise w and the measurement noise v are assumed to be Gaussian white noises, and their continuous and discrete covariance matrices are given as

$$Q = \begin{bmatrix} q_1 & 0 & 0 \\ 0 & q_1 & 0 \\ 0 & 0 & q_1 \end{bmatrix} = E\{w.w'\} \tag{11}$$

$$R = \begin{bmatrix} r_1 & 0 & 0 \\ 0 & r_1 & 0 \\ 0 & 0 & r_1 \end{bmatrix} = E\{v.v'\} \tag{12}$$

$$\begin{aligned} Q_k &= \int_0^{T_s} \Phi(t) Q \Phi^T(t) dt \\ &\approx \begin{bmatrix} q_1.T_s & 0 & 0 \\ 0 & q_1.T_s & 0 \\ 0 & 0 & q_1.T_s \end{bmatrix} \end{aligned} \tag{13}$$

$$R_k = R \tag{14}$$

Using the discrete Kalman filter, the values of the sensors are updated, and the state variables are newly estimated by every sampling time. Also, the attitude angles are calculated from the estimated state variables as

$$\begin{aligned} \theta &= \sin^{-1}(-x_1) \\ \gamma &= \sin^{-1}(x_2 / \cos\theta) \end{aligned} \tag{15}$$

A. Kalman Filter Time Update

The time update equation for discrete kalman filter is written as

$$\hat{x}_k^- = \Phi_{k-1}\hat{x}_{k-1} \tag{16}$$

The equation for the covariance matrix, P, is written as

$$P_k^- = \Phi_{k-1} P_{k-1} \Phi_{k-1}^T + Q \tag{17}$$

where Q is the covariance of the stationary, zero-mean process noise w(t).

B. Kalman Filter Measurement Update

The measurement update portion is divided into three parts: calculation the Kalman gain, updating the covariance matrix, and estimating the new system state. The key relationship for the Kalman filter measurement update step is the measurement output matrix, H_k. The equation for calculating the Kalman gain matrix can be written as

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1} \tag{18}$$

where R represents the applicable sensor noise covariance.

The covariance matrix, P, is updated by using Kalman gain, K, according to the equation

$$P_k = (I - K_k H) P_k^- \tag{19}$$

In the final step, the Kalman filter gain is used to scale the state error prior to summation with the previous state estimate to determine the new state estimate, according to

$$\hat{x}_k = \hat{x}_k^- + K_k (y_k - H\hat{x}_k^-) \tag{20}$$

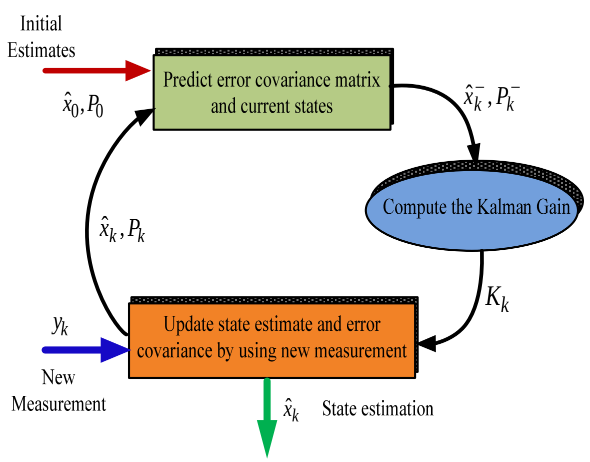

Fig. 1 Principle of Kalman filtering

The principle of Kalman filtering is described in Fig. 1. There are two main portions: time update and measurement update. The states are firstly predicted in time update portion and then they are corrected in measurement update portion. New state estimation is obtied by using previous state estimation, new measurement values and the Kalman gain.

IV. Numerical Simulation

The performance of the filter has been verified by numerical simulations. For specific noisy characteristics of the inertial sensors, the nominal values of ADXRS 150 gyroscope and ADXL210 accelerometer from Analog Device are chosen to use. The sampling frequency of the simulation is 100Hz. The simulation is run over 50 second.

A. Noise Covariance Matrix

The process noises q_{acc} and q_{gyro} are adopted from Analog Device's ADXRS150 MEMS gyro and ADXL210 MEMS accelerometer.

$$q_{acc} = \begin{bmatrix} 2.2\times10^{-2} \\ 2.2\times10^{-2} \\ 2.2\times10^{-2} \end{bmatrix} \left[m/s^2 \right] \tag{21}$$

$$q_{gyro} = \begin{bmatrix} 2.8\times10^{-1} \\ 2.8\times10^{-1} \\ 2.8\times10^{-1} \end{bmatrix} \left[\mathrm{deg}/s \right] \tag{22}$$

B. Simulations Results

Reference signals are assumed as sine waves with different phase angles. Accelerometer outputs are obtained by adding zero mean white Gaussian noises. Gyroscopes sense angular velocities, which are the time derivatives of reference signals. By integrating these gyroscopes outputs, measured values of angles are obtained. These data are sampled with a sampling period of T_s = 0.01 sec. After that the Kalman filter is used to estimate the actual signal.

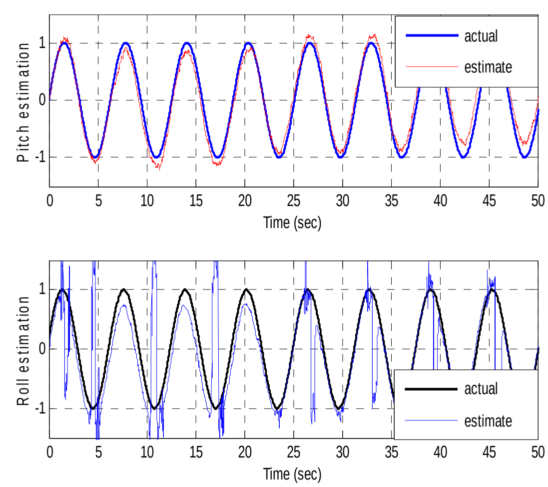

Fig. 2 Actual and estimate signals

As shown in Fig. 2, the estimated values for pitch angles are very close to the actual values. But for roll angles estimation, there are errors in peak values.

According to the results of simulation, the estimation of pitch angle is pretty good but the estimation error in roll estimation is often quite large. This shows that it is necessary to consider the gyro bias in the system states. By adding gyro bias values into the state variables of filter, the errors in roll error estimation will be elimiated.

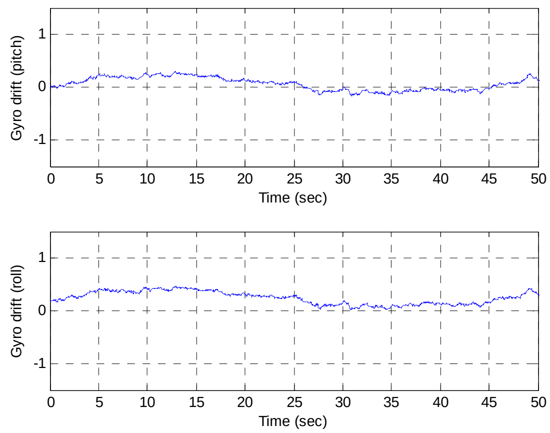

Fig. 3 Gyroscope drift

The gyroscope drifts are shown in Fig. 3. Due to this drift term, attitude estimation by integrating the gyroscope output over time is practically useless.

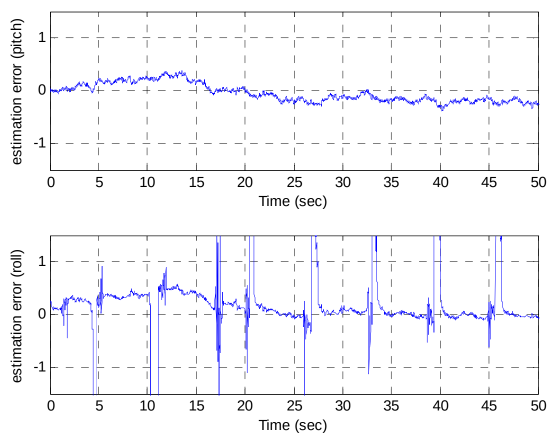

Fig. 4 Attitude estimation error

The estimation errors for both pitch angle estimation and roll angle estimation can be found in Fig. 4. The estimation error is the error which can be calculated by subtracting estimated values from the actual values.

IV. Conclusions

In this paper, the attitude estimation system using MEMS inertial sensors was developed. A Kalman filter is designed to fuse the information from accelerometer and gyroscope. Simulation results show that the proposed algorithm can obtain reliable pitch angle estimation and acceptable roll angle estimation. Even though many problems remain, the performance of the proposed filter in this paper is quite satisfactory. But for more reliable performance, it is necessary to add the gyro bias as the system state.

Acknowledgment

The authors would like to express respectful thanks to his supervisor Prof. Dr. Zaw Min Naing, Pro-Rector, Technological University (Maubin) for his valuable suggestions and guidance. The authors gratefully acknowledge many colleagues at Mandalay Technological University who have assisted for accomplishment of this paper.

References

[1] B. D. O. Anderson and J. B. Moore, *Optimal Filtering*, Englewood Cliffs, NJ, Prentice-Hall, Inc. 1979.

[2] M. S. Grewal and A. P. Andrews, *Kalman Filtering: Theory and Practice Using MATLAB*, 2nd ed., John Wiley & Sons, Inc. 2001.

[3] H. Rehbinder and X. Hu, “Drift-free attitude estimation for accelerated rigid bodies”, in *Proc.IEEE, 2001. International Conference on Robotics & Automation, Seoul, Korea*, pp 4244-4249.

[4] Y. S. Suh, “Attitude Estimation Using Low Cost Accelerometer and Gyroscope”, in *Proc. IEEE, 2003, Korea-Russia International Symposium*, pp 423-427.

[5] J. Yun, C.K. Ryoo and T.L. Song, “Strapdown Sensors and Seeker Based Guidance Filter Design”, in *Proc. IEEE, 2008, International Conference on Control, Automation and Systems, COEX, Seoul, Korea*, pp 468-472.

[6] J.K. Hall, N.B. Knoebel and T.W. McLain, “Quaternion Attitude Estimation for Miniature Air Vehicles Using a Multiplicative Extended Kalman Filter”, in *Proc. IEEE, 2008, Position, Location and Navigation Symposium*, pp 1230-1237.

[7] X. Liang, Y. Weizheng, C Honglong and J. Chengyu, ”MEMS-based Multi-sensor Integrated Attitude Estimation Technology for MAV Applications”, in *Proc. IEEE, 2009, International Conference on Nano/Micro Engineered and Molecular Systems, Shenzhen, China*, pp 1031-1035.

[8] O. C. Heo and K. Park, “Estimating Accelerated Body’s Attitude Using an Inertial Sensor”, in *Proc. IEEE, 2009, ICROS-SICE International Joint Conference, Fukuoka International Congress Center, Japan*, pp 5474-5478.

[9] Z. Zhen, Z.Wang and Y. Hu, “Multi-Sensor Information Fusion for Aircraft Attitude Determination System”, in *Proc. IEEE, 2009, World Congress on Computer Science and Information Engineering*, pp 474-478.

[10] M. Romanovas, L. Klingbeil, M. Trachtler and Y. Manoli, “Efficient Orientation Estimation Algorithm for Low Cost Inertial and Magnetic Sensor Systems”, in *Proc. IEEE, 2009, 15th Workshop on Statistical Signal Processing*, pp586-589.