Attitude Estimation Algorithms Using Low Cost IMU

Dung Duong Quoc[1, 3], Jinwei Sun[1*] and Van Nhu Le [2,3]

[1]*Dept. of Automatic test and control, Harbin Institute of Technology, Harbin 150001, China*
[2]*Research center for Space Optics Engineering, Harbin Institute of Technology, China*
[3] *Le Qui Don Technical University, Cau Giay, Ha Noi, Viet Nam*
Corresponding author: Jinwei Sun, Email: jwsun@hit.edu.cn

Abstract

Attitude estimation has a wide range of applications including aerial (UAVs for example), underwater (ROVs for instance), navigation systems, robotics, games, augmented reality system, industrial and so on. Extensive research over decades in this field resulted in a number of powerful estimators; complex like Kalman based algorithms as well as simple such as complementary filters & the kinds. For applications where computational simplicity is of prime concern, complementary filters have proven efficiency. This paper presents a comparative study of computationally simple algorithms naming Explicit Complementary Filter (ECF) and Gradient Descent based Complementary Filter (GDCF) along with computationally demanding extended Kalman filter-a de-facto standard for attitude estimation so far, regarding attitude estimation based on MEMS IMU. An alternative would be the variants of complementary filter; sufficiently efficient and simple scheme to avoid computational complexity.Performance of these estimators is evaluated for Euler angle estimation using both simulated data from Matlab and experimental data from MPU6050 IMU. The assessment is based on the root mean square error computation for these algorithms. Moreover, the algorithms adjustable parameters were exploited for a range of values in the hunt for perfection

Keywords: Attitude Estimation, IMU, Data Fusion, INS

1. Introduction

In theory, simple integration of gyroscope data will suffice to keep track of body's orientation or attitude. The alternative would be to use accelerometer measuring specific force. However, due to high bias and thus drift problem associated with gyro and high disturbance associated with accelerometer (due to body/platform movement, as accelerometer do not measure gravity alone in such situation), none of them can be used as standalone system for attitude estimation [1-2]. Hence some algorithm needs to be devised to account for the problem stated. Due to its vast applications and as a prerequisite requirement in fields such as UAVs, ROVs navigation systems, surgical aid, robotics, games, and industrial quality control, attitude estimation is a well researched area [3-9]. Research in this regard resulted many sensor fusion and attitude estimating algorithms; highly accurate but computationally complex as well as adequately accurate but simple [10]. Kalman filter and its nonlinear variants like Extended Kalman filter, Unscented Kalman filter; and particle filter have been successfully implemented and researched for attitude estimation. The UKF and particle filter as attitude estimators are, however, computationally demanding. EKF, although may have linearization problems in some applications, may not be an optimal estimator and may not be robustly applied, is still seen as the de facto standard in navigation system [5]. In

parallel, some computationally simpler single input single output linear complementary filters have been implemented for limited applications [11]. As most of the practical estimation problems are nonlinear in nature, the nonlinear complementary filters have been devised and implemented recently [12-16]. A number of attitude representations have been formulated and remained in use; the easily interconvertable Euler angles (roll, pitch and yaw) and quaternion (a four parameters representation) being the mostly exploited. Whereas the Euler angles encounter the problem of singularity or gimbal lock, quaternion resolves the issue with extra storage requirement [19].

For navigation system, sensory system in use falls in two categories; internal (or dead reckoning such as IMU) and external (or sometimes aided as GPS/SONAR). Dead reckoning sensor accumulate error with time whereas aided sensor system output at low frequency the sensor fusion algorithm ,hence, resolve the matter [20-21]. The internal sensor system-Inertial Measurement Unit (IMU) consists of mutually orthogonal tri-gyroscopes and tri-accelerometers. Recently, MEMS (Micro-Electro-Mechanical Systems) technology emerged with the benefits of a low cost, low power miniature size IMU at the cost of associated noise [2]. Attitude estimators are applied on IMU data for orientation tracking and the aided system provide the reference parameters. Thus a number of interesting aided-INS systems have been proposed and researched including; GPS aided INS, APS aided INS, Vision based INS, LVS aided IMU and DVL-IMU for UAV, robots and underwater UUV/ROV using variants of Kalman filter as sensor fusion algorithm [22-29].

In the context of attitude estimation, the estimator first debias the high bandwidth gyro rate with the aid of stable low bandwidth accelerometer and then integrate the de-biased gyro rate. This is true for roll and pitch Euler angle, estimated solely from IMU with velocity reference. However yaw estimate being not observable by accelerometer, needs aided system like magnetometer. The constant gain based schemes like Complementary algorithms exploit inertial measurement unit (IMU) data where the accelerometer output estimates the gravitational direction [17-18]. The Explicit Complementary Filter (ECF) and Gradient Descent based Complementary Filter (GDCF) are both equipped with filter gain and can fully estimate orientation from IMU data only. However the algorithms fail in situation where the object dynamics are high as the assumption of negligible translational acceleration is no more valid.

The organization of this paper is as follows. The paper consists of five sections followed by a conclusion. Section 2 provides an overview in the context of attitude estimation and the MEMS IMU triad of gyros and accelerometer models. Section 3 briefs the three algorithms; the Extended Kalman Filter, Explicit and Gradient Descent based Complementary Filters and the MATLAB implementation steps. Section 4 compares the performance of the three techniques for roll and pitch angles estimation based on simulation data. Section 5 includes the results obtained by applying the algorithms on the MEMS IMU data, the discussion and comparison part followed by the conclusion.

2. Mems IMU

The problem of tilt, orientation and attitude estimation need a sensory set along with a proper estimation scheme/algorithm. The sensor set may include gyrometer, accelerometer, magnetometer and so on. For the second part, feedback controller, complementary filters and Extended Kalman Filters have been devised and successfully implemented. MEMS based IMU, a triplets of accelerometers and triplets gyros is an increasingly popular choice recently. As this paper focuses on MEMS IMU data without aided sensors, the mandate is limited to roll and pitch

angles estimation for performance evaluation of the complex and simple estimators under consideration.

2.1. Accelerometer Model

Accelerometer do not capture the high frequency dynamics, are usually noisy (especially MEMS-based) and also have some bias. The specific force measured by MEMS triplet accelerometers can be represented by:

$$\bar{f}^b_{accel} = \begin{bmatrix} f_{x,accel} \\ f_{y,accel} \\ f_{z,accel} \end{bmatrix} = \bar{f} + \begin{bmatrix} n_{a_x} + b_{a_x} \\ n_{a_y} + b_{a_y} \\ n_{a_z} + b_{a_z} \end{bmatrix} \tag{1}$$

Here, n_a and b_a represent accelerometer noise and bias respectively. Accelerometer measure total acceleration relative to free fall, also called specific force ($\bar{f}^b$). Life would have been very easy if accelerometer measured acceleration due to gravity only. When accelerometer is a part of a moving system (like AUV, ROV, robots), it measure translation acceleration, rotational acceleration and acceleration due to gravity. The problem is it cannot distinguish between them. An ideal accelerometer aligned with body coordinates measure

$$\bar{f}^b = \dot{\bar{V}}^b + \bar{\Omega}^b \times \bar{V}^b - \bar{g}^b \tag{2}$$

Here, $\dot{\bar{V}}^b$ is translational acceleration w.r.t body coordinates, $\bar{\Omega}^b \times \bar{V}^b$ is rotational acceleration and $\bar{g}^b$ is gravity in body coordinates. For a steady state case ($\dot{\bar{V}}^b = 0$), the specific force measured by accelerometer reduces to

$$\bar{f}^b_{steady\,state} = \bar{\Omega}^b \times \bar{V}^b - \bar{g}^b = \bar{\Omega}^b \times \bar{V}^b - g \begin{bmatrix} -\sin\theta \\ \sin\phi\cos\theta \\ \cos\phi\cos\theta \end{bmatrix} \tag{3}$$

Where ϕ and θ represent roll and pitch in radian respectively. For orientation problem in some situation where rotation acceleration can be neglected, it can further be simplified as

$$\bar{f}^b = \begin{bmatrix} f_{x,accel} \\ f_{y,accel} \\ f_{z,accel} \end{bmatrix} \approx -g \begin{bmatrix} -\sin\theta \\ \sin\phi\cos\theta \\ \cos\phi\cos\theta \end{bmatrix} \tag{4}$$

2.2. Gyroscope Model

Gyroscopes compute the angular velocity but the main concern is the bias issue. For MEMS based IMU, three gyroscopes orthogonally installed measure angular velocity in x, y, z directions. Like all the sensors measuring a specific quantity, the gyroscope measurements include noises and biases. Hence a gyroscope can be modeled as:

$$\bar{\Omega}^b_{gyro} = \begin{bmatrix} \Omega_x \\ \Omega_y \\ \Omega_z \end{bmatrix} = \bar{\Omega}^b + \begin{bmatrix} n_{\Omega_x} + b_{\Omega_x} \\ n_{\Omega_y} + b_{\Omega_y} \\ n_{\Omega_z} + b_{\Omega_z} \end{bmatrix} \tag{5}$$

Where, b_Ω and n_Ω represent the gyro bias and the associated noise respectively.
The relationship between gyro measurement and Euler angle rate is given by [3]:

$$\begin{bmatrix} \Omega_x \\ \Omega_y \\ \Omega_z \end{bmatrix} = (I_1 + R_x(\phi)I_2 + R_x(\phi)R_y(\theta)I_3) \begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} \tag{6}$$

Where,

$$I_1 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, I_2 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}, I_3 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$R_x(\phi) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\phi & \sin\phi \\ 0 & -\sin\phi & \cos\phi \end{bmatrix}, R_y(\theta) = \begin{bmatrix} \cos\theta & 0 & -\sin\theta \\ 0 & 1 & 0 \\ \sin\theta & 0 & \cos\theta \end{bmatrix}$$

Thus, Eq. (6) can also be written as

$$\begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} 1 & \sin\phi\tan\theta & \cos\phi\tan\theta \\ 0 & \cos\phi & -\sin\phi \\ 0 & \sin\phi\sec\theta & \cos\phi\sec\theta \end{bmatrix} \begin{bmatrix} \Omega_x \\ \Omega_y \\ \Omega_z \end{bmatrix} \tag{7}$$

Attitude can be estimated with noise and bias –free gyros with known initial orientation of the test object by integrating the Euler rate estimated from gyro data as given in Eq. (7). However, error accumulation with time due to gyro bias makes it practically impossible to rely on gyro data alone for Euler angle estimation. Hence accelerometers are used to compensate for the gyro's drifts in pitch and roll estimation while yaw estimation drift can be mitigated by magnetometers.

3. Estimators/Algorithms

3.1. Extended Kalman Filter

Extended Kalman Filter (EKF) is a nonlinear extension of Kalman filter consisting of nonlinear process and nonlinear measurement model. The state vector can be defined as

$$\hat{\bar{x}} = \begin{bmatrix} \hat{S}_1 & \hat{S}_2 & \hat{S}_3 \end{bmatrix}^T \tag{8}$$

Where,

$$\left. \begin{array}{l} S_1 = -\sin\theta \\ S_2 = \sin\phi\cos\theta \\ S_3 = \cos\phi\cos\theta \end{array} \right\} \tag{9}$$

Hence the dynamic model is as

$$\frac{d}{dt}\hat{\overline{x}} = f(\hat{\overline{x}}, \overline{\Omega}^b_{gyro}) + \overline{w}(t)$$

$$\begin{bmatrix} \dot{S}_1 \\ \dot{S}_2 \\ \dot{S}_3 \end{bmatrix} = \begin{bmatrix} 0 & \Omega_z & \Omega_y \\ -\Omega_z & 0 & \Omega_x \\ \Omega_y & -\Omega_x & 0 \end{bmatrix} \begin{bmatrix} S_1 \\ S_2 \\ S_3 \end{bmatrix} + \overline{w}(t) \qquad (10)$$

And the measurement model is given by

$$\overline{z} = h(\hat{\overline{x}}) + \overline{r}(t) = \begin{bmatrix} g\sin\hat{\theta} \\ -g\sin\hat{\phi}\cos\hat{\theta} \\ -g\cos\hat{\phi}\cos\hat{\theta} \\ (\sin\hat{\theta})^2 + (\sin\hat{\phi}\cos\hat{\theta})^2 + (\cos\hat{\phi}\cos\hat{\theta})^2 \end{bmatrix} + \overline{r}(t))$$

$$\begin{bmatrix} f_{x,accel} \\ f_{y,accel} \\ f_{z,accel} \\ 1 \end{bmatrix} = \begin{bmatrix} -g\hat{S}_1 \\ -g\hat{S}_2 \\ -g\hat{S}_3 \\ \hat{S}_1^2 + \hat{S}_2^2 + \hat{S}_3^2 \end{bmatrix} + \overline{r}(t) \qquad (11)$$

Here, $\overline{w}(t)$ and $\overline{r}(t)$ are zero mean Gaussian process and sensor measurement noise respectively. Note that, this measurement equation assumes zero translational and zero rotational acceleration.

The algorithm developed for Euler angels (Roll and pitch) estimation in MATLAB works as follow:

Initialization: Define initial values for state estimate (3×1 vector), error covariance matrix and process noise matrix.

Data acquisition: Load MEMS gyros and accelerometers data iteratively and implement Eq (11) for first iteration. Initialize measurement noise matrix R on the base of measurements dynamics.

EKF implementation: With all required parameters in hand, EKF is now performed iteratively. The matrix H is given as:

$$H = \frac{\partial h}{\partial x} = \begin{bmatrix} -g & 0 & 0 \\ 0 & -g & 0 \\ 0 & 0 & -g \\ 2S_1 & 2S_2 & 2S_3 \end{bmatrix} \qquad (12)$$

Euler angle estimation: Pitch and roll angles are given by Eq.9.

3.2. Explicit Complementary Filter

Algorithms based on complementary filtering combine accelerometer and gyroscope measurements for orientation estimation in a way so that estimation based on accelerometer measurements are low passed where as high-pass filtering is applied on estimation based on gyroscope output [15]. Explicit Complementary Filter (ECF) algorithm is a nonlinear fixed gain complementary filter employing quaternion. ECF algorithm in quaternion form combines inertial direction measurement ($\overline{v}$, provided by accelerometers) and angular velocity (Ω^b, measured from gyroscopes). The filter is

equipped with two adjustable parameters like proportional (K_p) and integral gain (K_i) for fine tuning. Detailed algorithm can be found in [17]. The algorithm can be summarized as following:

Initialization: At this stage, parameters like sampling rate, proportional and integral gain and initial value of attitude as $\begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix}$ in quaternion form are defined.

Data preprocessing: MEMS based IMU tri-accelerometers data is normalized

Estimating Gravity direction: At this stage, to debias gyro data, error is to be worked out by cross multiplying measured inertial gravitational direction ($\bar{v}$, as provided by tri-accelerometers) and estimated gravitational direction ($\hat{v}$). The estimated gravitational direction is computed at this stage as:

$$\hat{v} = \begin{bmatrix} 2(\hat{q}_2\hat{q}_4 + \hat{q}_1\hat{q}_3) \\ 2(\hat{q}_3\hat{q}_4 + \hat{q}_1\hat{q}_2) \\ \hat{q}_1^2 - \hat{q}_2^2 - \hat{q}_3^2 + \hat{q}_4^2 \end{bmatrix} \tag{13}$$

Here, $\hat{q}_x$ shows quaternion parameters.

Cross multiplication: At cross multiplication stage, error is calculated by cross multiplying normalized accelerometer data and estimated direction of gravity (as provided by previous step) as:

$$e = \bar{v} \times \hat{v} \tag{14}$$

Debias gyroscope rate: Now is the time to debias gyroscope measurements so that gyro rate can be employed for attitude estimation by simple integration by applying feedback terms as:

$$\bar{\Omega}^b = \Omega^b + K_p e + K_i \int e \tag{15}$$

Some suitable values of adjustable parameters K_p and K_i are provided here.

Update rate: compute rate of change of quaternion as:

$$\dot{\hat{q}} = \frac{1}{2}\hat{q} \otimes p(\bar{\Omega}^b) \tag{16}$$

Where

$\hat{q}$ is Estimated normalized quaternion at one step previous time (t-1), $p(\bar{\Omega}^b) = (0, \bar{\Omega}^b)$ and $\otimes$ is quaternion product operator.

Estimate updated attitude: Integrate to yield estimated attitude in quaternion and normalize. At this stage, attitude in Euler angles can also be computed.

For the next iteration, the algorithm is repeated from Data Processing stage

3.3. Gradient Decent Based Complementary Filter

GDCF is also nonlinear complementary filtering scheme with single adjustable parameter *β*. IMU tri-gyroscopes measuring angular rate can be shown as:

$$\Omega^b = \begin{bmatrix} 0 & \Omega_x^b & \Omega_y^b & \Omega_z^b \end{bmatrix} \tag{17}$$

The rate of change of angular rate in quaternion representation can be represented as:

$$\dot{q}_{(\omega,t)}^b = \frac{1}{2}\hat{q}^b \otimes \Omega^b \tag{18}$$

For orientation estimation, accelerometer measurement is used to debias estimation based on gyroscope data. Orientation estimation is performed using equation (8) and (one step) previous estimation in quaternion as below [16]:

$$q^b_{(est,t)} = \hat{q}^b_{(est,t-1)} + \dot{q}^b_{(est,t)} \Delta t \qquad (19)$$

Here,

$$\dot{q}^b_{(est,t)} = \dot{q}^b_{(\omega,t)} - \beta \frac{\nabla f}{\|\nabla f\|} \qquad (20)$$

$$\nabla f = J_g^T(\hat{q}^b) f_g(\hat{q}^b, \hat{a}^b) \qquad (21)$$

$$f_g(\hat{q}^b, \hat{a}^b) = \begin{bmatrix} 2(q_2 q_4 - q_1 q_3) - a_x \\ 2(q_1 q_2 + q_3 q_4) - a_y \\ 2(0.5 - q_2^2 - q_3^2) - a_z \end{bmatrix} \qquad (22)$$

$$J_g(\hat{q}^b) = \begin{bmatrix} -2q_3 & 2q_4 & -2q_1 & 2q_2 \\ 2q_2 & 2q_1 & 2q_4 & 2q_3 \\ 0 & -4q_2 & -4q_3 & 0 \end{bmatrix} \qquad (23)$$

The terms are explained in the following stepwise detailed algorithm:

Initialization: Assume initial quaternion as $q = \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix}$, specify sampling time and the adjustable gain β value.

Normalization step: Normalize IMU tri-accelerometer measurements

G.D. Algorithm: gradient descent algorithm to compute $\dfrac{\nabla f}{\|\nabla f\|}$ using equation (21)

Rate quaternion correction: At this stage, correction is made in rate quaternion using equation (20).

Final orientation estimation: Finally Integration is done to estimate orientation in quaternion by equation (19) where $\hat{q}^b_{est,t-1}$ is the normalize quaternion estimated at time $t-1, q^b_{(est,t)}$ from previous step and Δt is sampling time.

Quaternion Normalization: Finally, Normalize the estimated quaternion is normalized and can then be interchanged to Euler angles representation.

Next Iteration: Algorithm is repeated from stage two (Normalization step) for next iteration

4. Simulation Results

MATLAB simulated data was used to compare the performance of EKF, ECF and GDCF based on RMSE in attitude estimation. For tunable parameters (K_p, K_i for ECF and β for GDCF), suitable values were first selected using monticarlo simulation. The proportional gain (K_p) is usually 10 to 100 times integral gain (K_i) where as β for GDCF is well below unity (in the range of 0.03 to 0.05) [19]. In this research, 0.3 for K_p, 0.02 for K_i and 0.045 for β were selected.

Figure 1a shows simulation data for the reference values of roll variations with respect to time where as Figure 1b shows the same for pitch Euler angle for a total time of 620 seconds. As shown, roll Euler angle varies between ± 80 degrees as per set pattern and pitch Euler angle varies between ± 35 degrees. Figure 2a depicts the result of the three

estimators for roll estimation against the reference values. Similarly, Figure 2b shows the same for pitch estimation where as Figure 3a,b provide comparison in terms of error in estimation. It is evident from these results that for the attitude estimation problem, computationally less expensive algorithms like ECF and GDCF are comparably efficient and powerful like the much expensive EKF. Furthermore, for the simple algorithms, ECF is better than GDCF in terms of accuracy. Table-1 further verifies this on the base of RMSE (root mean square error) of roll and pitch for simulated data case. Values of adjustable filter gains, $K_p = 0.3$, $K_i = 0.02$ (for ECF) and $\beta=0.045$ (for GDCF) were selected whereas EKF was tuned using adoptable R based on IMU data dynamics. Also, simulation shows that with higher values of GDCF filter gain, the resultant estimations by GDCF are much noisier with large errors in comparison with ECF.
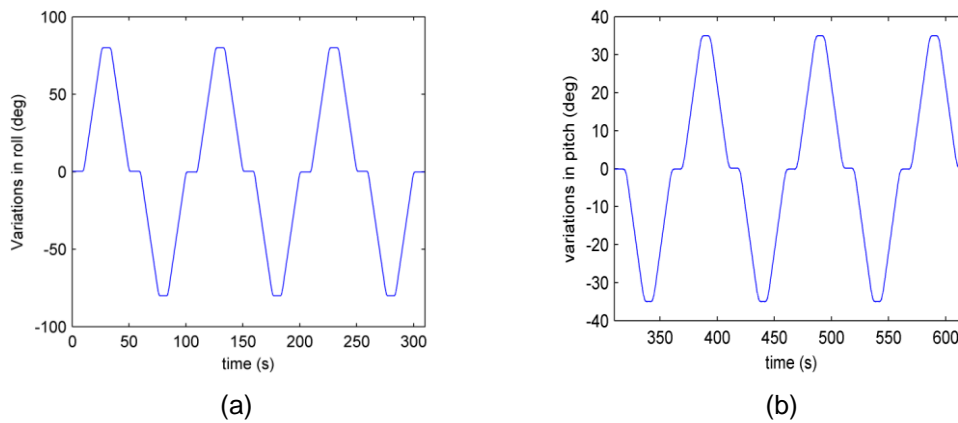

Figure 1. Actual Variations in Attitude-Simulation Data

(a) Variations in Roll Euler Angle. (b) Variations in Pitch Euler Angle
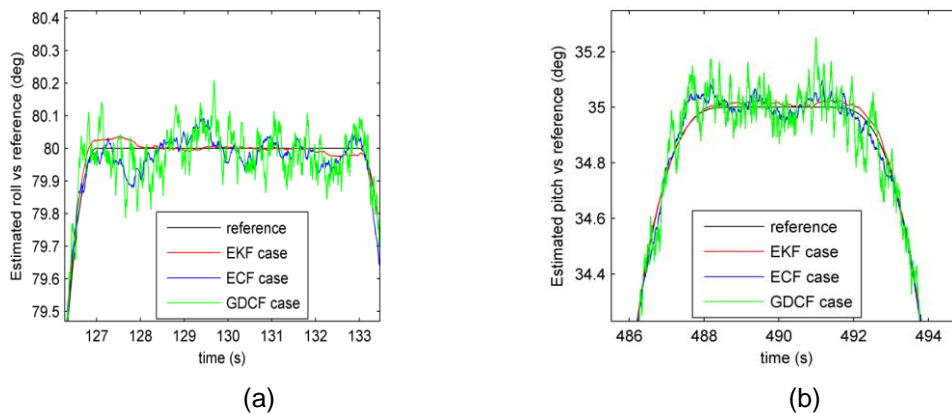

Figure 2. Attitude Estimation in Terms of Roll and Pitch

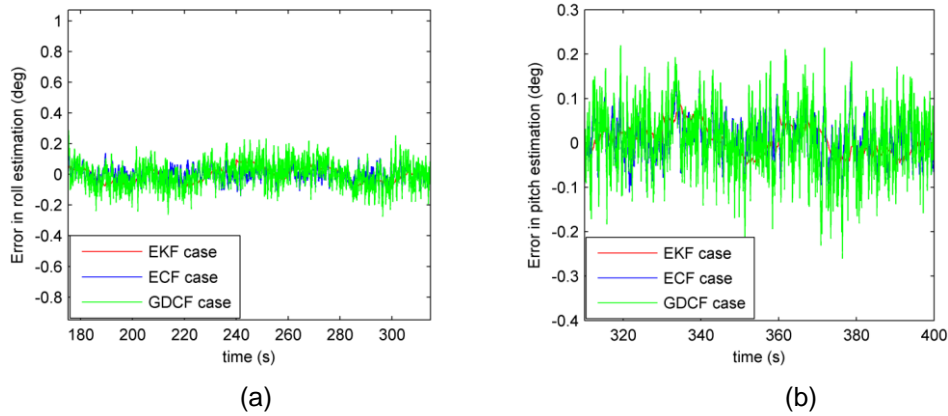(A) Roll Euler Angle Estimation By EKF, ECF & GDCF. (B) Pitch Euler Angle Estimation By EKF, ECF & GDCF

(a)   (b)

Figure 3. Error in Attitude Estimation

(A) Error In Roll Euler Angle Estimation By EKF, ECF & GDCF. (B) Error In Pitch
Euler Angle Estimation By EKF, ECF & GDCF

Table 1. RMSE Comparison of EKF, ECF and GDCF

Euler angles (deg)	EKF	ECF	GDCF	Simulated Data
RMSE roll	0.01	0.03	0.04	Noise free
RMSE pitch	0.01	0.05	0.05	Noise free
RMSE roll	0.21	0.54	0.55	Noisy
RMSE pitch	0.32	0.62	0.62	Noisy

5. Experimental Results

EKF and variants of complementary filters were tested for attitude estimation on experimental data obtained from MEMS based MPU-6050 IMU at 100 Hz. Only IMU was used without external sensors, so only the roll and pitch were considered for comparison. As only comparison and variation of the three algorithms was intended, so no need of measuring the true attitude was necessary. Hence, the IMU was rotated around X and Y-axis with hand. All the settings of fixed filter gains (for complimentary case) and other tunable parameters were kept the same as used in simulation case.

Figure 4 depicts the IMU 3-D accelerometers measurement for the case under consideration (as in Figure 6, 7) for a 550 second time where as Figure 5 shows the corresponding gyroscopes measurement for the same case.
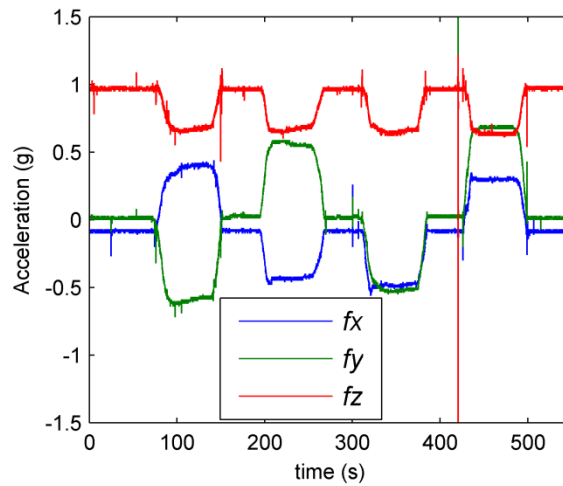
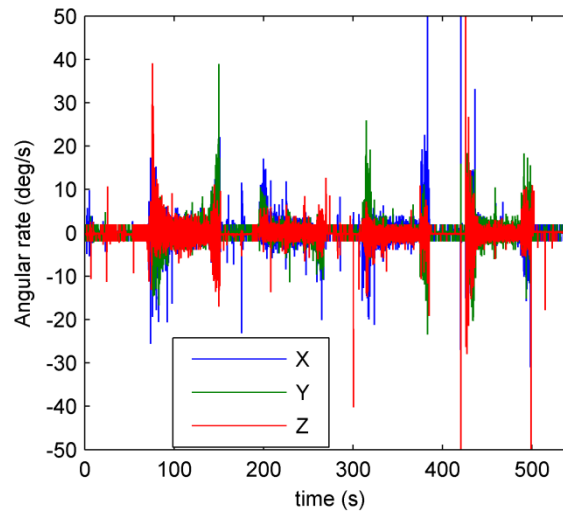**Figure 4. MPU-6050 3-D Accelerometers Measurements**

Figure 5. MPU-6050 3-D Gyroscope Measurements

Figure 6 a depicts comparison of the roll estimated by EKF, ECF and GDCF for experimental case where as a zoom-in view is depicted in Figure 6b. The pattern is selected such that variations in roll Euler angle are in the vicinity of ±40 with repeated null time. For the same experiment, the pitch estimated by the three algorithms under consideration is shown in Figure 7
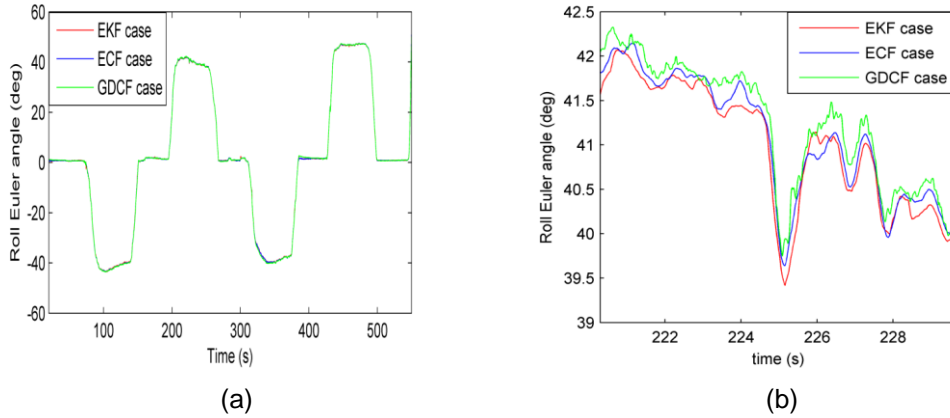
Figure 6. Roll Estimation

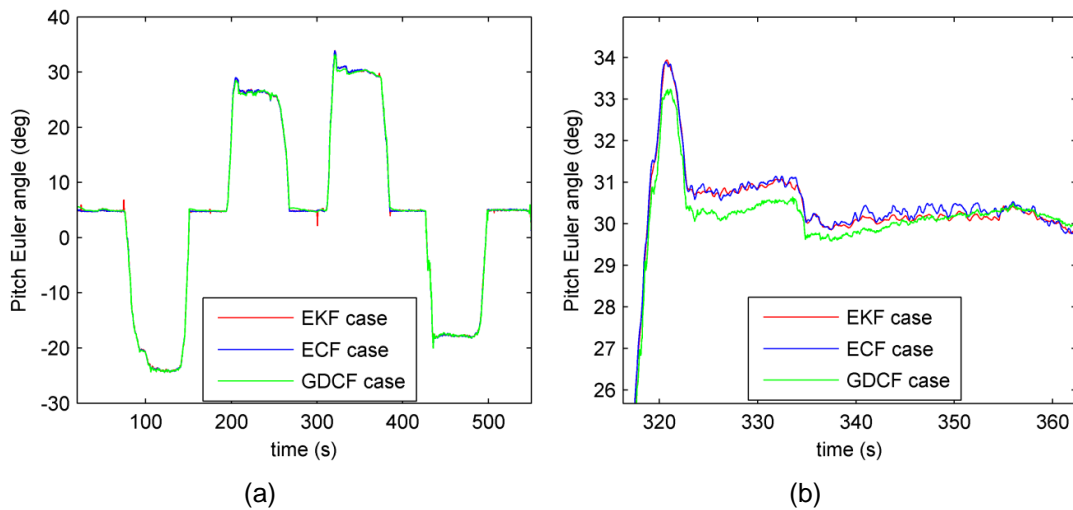(a)   Roll estimated by EKF, ECF and GDCF, (b) Zoom-in view

Figure 7. Pitch Estimation

(a) Pitch estimated by EKF, ECF and GDCF, (b) Zoom-in view

As obvious from these results, attitude estimation in terms of roll and pitch Euler angles by the three algorithms namely EKF, ECF and GDCF are in close proximity (within ±1 limit). This is sufficient for most of the attitude estimating applications and so the computationally less expensive Complementary filters can be readily used. This shows that the recent development in complimentary filters provide greater accuracy while keeping the simplicity and computational inexpensive feature in place. Moreover, as depicted in the zoom-in view, ECF is closely following EKF in comparison with GDCF case which further strengthens the argument that ECF is more accurate when it comes to complimentary case.

6. Conclusion

In this paper, a comparative performance analysis was presented in for computationally complex and simple schemes regarding the attitude estimation problem using MEMS IMU. In situation where computation burden are detrimental, Kalman filter and its variants-the benchmark for the problem of position and attitude estimation, Complementary filters can be an alternative in such situation. Both ECF and GDCF are

effective and novel approaches in this regard. With the power of adjustable gain, these techniques find places in most of the real world applications. The evaluation of these filter results in an obvious win for EKF, however, the execution time was noticeably larger in comparison with Complementary filters. On the other hand, ECF may have a bit edge over GDCF partly because of the two adjustable gains resulting in extra choices. Both techniques can be efficiently used in aided-INS system where less computation burden is of prime importance.

References

[1] D. Titterton and J. Weston, "Strap-down Inertial Navigation Technology", The American Institute of Aeronautics and Astronautics, 2nd Ed. 2004.

[2] O. J. Woodman, "An Introduction to Inertial Navigation", UCAM-CL-TR-696, University of Cambridge, 2007

[3] H.G. de Marina and F. J. Pereda, "UAV Attitude Estimation Using Unscented Kalman Filter and TRIAD", IEEE Transaction on Industrial Electronics, vol. 59, no. 11, 2012.

[4] R. Munguía and A. Grau, " Attitude and Heading System based on EKF total state configuration", IEEE International Symposium on Industrial Electronics, 2011.

[5] R. Munguia and A. Grau, "A Practical Method for Implementing an Attitude and Heading Reference System", International Journal of Advanced Robotic Systems, 2014.

[6] J. Wang and M. Garratt "Integration of GPS/INS/Vison Sensors to Navigate Unmanned Aerial Vehicles", The I.A. of the Phot., Remote Sen and Spat I.S. Vol. XXXVII. Part B1. Beijing 2008.

[7] E. Lefferts, F. Markley and M. Shuster, "Kalman filtering for spacecraft attitude estimation", AIAA J. Guidance, Control, Navig., vol. 5, no. 5, pp. 417–429, Sep, 1982.

[8] S.-G. Kim, J. L. Crassidis and Y. Cheng, "Kalman Filtering for Relative spacecraft Attitude and Position Estimation", American Institute of Aeronautics and Astronautics, 2007.

[9] EH. Shin, "Accuracy improvement of low cost INS/GPS for land applications", PhD Thesis, Dept of Geomatics Engineering University of Calgary, 2001.

[10] J. L. Crassidis, F. L. Markley and Y. Cheng, "Survey of Nonlinear Attitude Estimation Methods", JOURNAL OF GUIDANCE, CONTROL AND DYNAMICS, Vol. 30, No. 1, January–February 2007.

[11] P. Corke, "An inertial and visual sensing system for a small autonomous Helicopter", Journal of Robotic Systems. Volume 21, Issue 2, pages 43–51, 2004.

[12] C. Coopmans, A.M. Jensen and Y. Chen, "Fractional-Order Complementary Filters for Small Unmanned Aerial System Navigation", Journal of Intelligent & Robotic Systems, Volume 73, Issue 1-4, pp 429-453, Jan 2014.

[13] A.-J. Baerveldt and R. Klang, "A low-cost and low-weight attitude estimation system for an autonomous helicopter", Proc. IEEE Int. Conf. Intell. Eng. Syst., 1997, pp. 391–395.

[14] T. Hamel and R. Mahony, "Attitude estimation on SO(3) based on direct inertial measurements", in Proc. Int. Conf. Robotics Automation (ICRA), Orlando, FL, 2006, pp. 2170–2175.

[15] R. Mahony, T. Hamel and J. Michel, "Non-linear complementary filters on the special orthogonal group", IEEE Transactions on Automatic Control, 2007.

[16] B. Vik and T. Fossen, "A nonlinear observer for GPS and ins integration", Proc. IEEE Conf. Decision and Control, Orlando, FL, Dec. 2001, pp. 2956–2961.

[17] M. Euston, P. Coote and R. Mahony, "A Complementary Filter for Attitude Estimation of a Fixed-Wing UAV", IEEE Int. conf. on intelligent robots & system, 2008.

[18] M.D. Shuster, "A survey of attitude representations", The Journal of the Astronautical Sciences, 41(4), 439-517, (1993)

[19] S.O.H. Madgwick, A.J.L. Harrison and R. V., "Estimation of IMU and MARG orientation using a gradient descent algorithm", 2011 IEEE Int. Conf on Rehabilitation Robotics, Zurich, Switzerland, 2011.

[20] E. Nebot and H. Durrant-Whyte, "Initial calibration and alignment of low cost inertial navigation units for land vehicle applications", J. of Robotics Sys 16 (2), 1999.

[21] X. Kong, "INS algorithm using quaternion model for low cost IMU", Robotics and Autonomous Systems 46 (2004) 221–246.

[22] F. Caron, E. Duflos and D. Pomorski, "GPS/IMU data fusion using multisensor Kalman filtering: introduction of contextual aspects", Information Fusion 7, p.221 230, 2004.

[23] S. Sukkarieh, "Low cost, high integrity, aided inertial navigation systems for autonomous land vehicles", PhD Thesis, Australian Center for Fields Robotics, University of Sydney, 2000.

[24] Chong-moo Lee, Seok-Won Hong and Woo-Jae Seong, "An Integrated DVL/IMU System for Precise Navigation of an Autonomous Underwater Vehicle", OCEANS 2003 Conference Proceedings.

[25] C.-M. Lee, P.-M. Lee, S.-W. Hong and S.-M. Kim, "Underwater Navigation System Based on Inertial Sensor and Doppler Velocity Log Using Indirect Feedback Kalman Filter", International Journal of Offshore and Polar Engineering, Vol. 15, No. 2, June 2005, p. 8895.

[26] A. Hanai, S.K. Choi and J. Yuh, "A new approach to a laser ranger for underwater robots", Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems, 2003, Vol. 1, pp. 824-829, October 2003.

[27] P.M Lee and B.H. Jun, "Pseudo long base line navigation algorithm for underwater vehicles with inertial sensors and two acoustic range measurements", Ocean Engineering 34 (2007) 416–425.

[28] C.K. George, G.L. Savvas and J.K. Kostas, "Visual-Servoing Scheme for Semi-Autonomous Operation of an Underwater Robotic Vehicle Using an IMU and a Laser Vision System", 2010 IEEE Int Conf on Robo and Auto, 2010, Anchorage, Alaska, USA.

[29] R. Garcia and T. Nicosevici, "Towards a Real-Time Vision-Based Navigation System for a Small-Class UUV", Pro. of the 2003 IEEURSJ Intl. Conf on Intell Robo and Syst Las Vegas, Nevada ' Oct 2003.

[30] C.W. Kang and C.G. Park, "Attitude Estimation with Accelerometers and Gyros using Fuzzy Tuned Kalman filter", proc. Of EU cont. conf, Hungary, 2009.

Authors

Dung Duong Quoc was born in 1981. He received the B.S., M.S. degrees from the Le Qui Don Technical University, Hanoi, Vietnam, in 2007 and 2010, respectively. Now he is pursuing Ph.D. degree in Harbin Institute of Technology (HIT), Harbin, China. His research interests include sensor technology, testing instruments, and signal processing.

Jin Wei Sun (M'09) was born in 1964. He received the M.S. degree in electrical engineering from Harbin Institude of Technology (HIT), Harbin, China, in 1990 and the Ph.D. degree in advanced system control and production from Saga University, Saga, japan, in 2000. He is currently a Professor with HIT. His research interests include sensor technology, testing instruments, and signal processing.

Van Nhu Le e, was born in 1982. He received the B.S degrees from the Le Quy Don Technical University, Hanoi, Vietnam, in 2007 and M.S dgree from Harbin Institute of Technology in 2012. Now he is pursuing Ph.D. degree in Harbin Institute of Technology, Harbin, China. He currently focuses image processing, optic image processing and design optic system.