Quadcopter Attitude Estimation using filters for Sensor Fusion in 6D Inertial Measurement Unit

Jackson O. Oloo and Stanley I. Kamau

Abstract— Orientation tracking of a quadcopter Unmanned Aerial Vehicle (UAV) involves monitoring the Roll, Pitch and Yaw angles. These angles provide feedback information that is then used to give appropriate angling and heading orientation. Measurements of these Euler angles is accomplished by use of an Inertial Measurement Unit (IMU) consisting of either a gyroscope, accelerometer or both. The IMU created with the gyroscope is less sensitive to vibrations and is not affected by earth's gravity. One of the problems that a gyro based IMU encounters is the drifting of the angles. Another problem occurs when the IMU is started at an angled surface. This is because the IMU has no reference to what is level. In static or slow movement, the accelerometer measures roll and pitch by leveling to correct the gyro-unbounded error. This is due to the trustworthiness of the gravitational measurement. While the accelerometer gives absolute measurement of the quadcopter attitude, the motors on the quadcopter produce a lot of vibrations introducing significant noise into the accelerometer reading. Therefore, a proper fusion of IMU data is needed to overcome the shortcomings of each sensor. Kalman filter is therefore proposed to merge the two sensor measurements to achieve better estimates, redundancy and drift compensation. In conclusion, the performance of the Kalman filter is then compared with that of the unfiltered sensor data and Complimentary filter.

Keywords— Accelerometer, Complimentary filter, Gyroscope, Kalman filter,

I. Introduction

A quadrotor is a helicopter lifted and propelled by four rotors. Small sized quadrotors are often used as Unmanned Aerial Vehicles (UAVs) in research and amateur projects, because of the simple symmetric structure and relatively easy control law with respect to traditional helicopters.

Quadrotors have a set of sensors that provide the information needed by the attitude, altitude and the navigation control systems. This set of sensors is usually called an Inertial Measurement Unit (IMU). The IMU of a quadrotor contains the following sensors: an accelerometer, a gyroscope, a magnetometer and a barometer. During flight, the motors in the quadrotor introduces noise into the data read from the sensors. This brings divergence from the intended orientation and trajectory.

Filtering involves seeking for the best values of the system states via new measurements and updating of the new measurements [1]. Kalman filter has become popular and is used in almost every sensor processing applications. Some extensions of Kalman filter are adaptive Kalman filtering [2], unscented Kalman filtering [3] ,extended Kalman filtering [4]. The most and widely used filtering techniques are based on extended Kalman filter [5], [6]. Some other techniques have also been developed like the nonlinear observer given in [7], or based on unscented filter [8]. Most of these methods are computationally demanding. Estimation of Quadrotor attitude using Extended Kalman Filter (EKF) has been discussed in [9] while [10] compares the performance of the quadrotor with both the EKF and the Kalman Filter with the conclusion that EKF gives the best performance theoretically. However, attitude estimation using EKF has been found inapplicable to embedded systems.

The use of Kalman filters to estimate the attitude continues to attract many researchers. In [11], Kalman filter is designed to estimate the noisy states of the system. However, it is computationally demanding and difficult to understand. An alternative, the Complementary filters, which are not so computationally demanding are used for attitude estimation in [12], [13] and its performance is compared with that of Kalman filter in [14]. Accelerometer and gyroscope measurements are fused using Complimentary filter in [15] to estimate the orientation.

In this scheme, the Kalman filter and complementary filter is applied to estimate the attitude states of the quadrotor from the noisy measurements of on board Microelectromechanical sensors (MEMS). The estimated state is intended to be used by a control algorithm (not discussed in this work) to maintain the desired attitude during various maneuvers. In conclusion, the performance of the Kalman filter is then compared with that of the unfiltered sensor data and Complimentary filter.

II. MicroElectroMechanical Sensor (MEMs)

A. Accelerometer Model

Accelerometer measures total acceleration relative to free fall, also called specific force $\bar{f}^b$ [16]
However, Accelerometer do not capture the high frequency dynamics. When an accelerometer is part of a moving system like UAVs and robots, it not only measures acceleration due to gravity but also translational and rotational accelerations. Therefore, an ideal accelerometer aligned with the body measures specific force as shown in (1). A detailed derivation is given in [17].

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$$\overline{f}^b = \begin{bmatrix} f_{x,accel} \\ f_{y,accel} \\ f_{z,accel} \end{bmatrix} = -g \begin{bmatrix} -\sin\theta \\ \sin\phi\cos\theta \\ \cos\phi\cos\theta \end{bmatrix} \tag{1}$$

Where, $\bar{g}^b$ is gravity in body coordinates, $\emptyset$ and θ represent roll and pitch in radian respectively.

B. Gyroscope model

Gyro sensors measure angular velocity in x, y, z directions although its measurements include biases. It is modeled as follows:

$$\overline{\Omega}^b_{gyro} = \begin{bmatrix} \Omega_x \\ \Omega_y \\ \Omega_z \end{bmatrix} = \overline{\Omega}^b + \begin{bmatrix} n_{\Omega_x} + b_{\Omega_x} \\ n_{\Omega_y} + b_{\Omega_y} \\ n_{\Omega_z} + b_{\Omega_z} \end{bmatrix} \tag{2}$$

Where, b_Ω and n_Ω represent the gyro bias and the associated noise respectively. Gyro measurement and Euler angle rate are related as shown [17]:

$$\begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\varphi} \end{bmatrix} = \begin{bmatrix} 1 & \sin\phi\tan\theta & \cos\phi\tan\theta \\ 0 & \cos\phi & -\sin\phi \\ 0 & \sin\phi\sec\theta & \cos\phi\sec\theta \end{bmatrix} \begin{bmatrix} \Omega_x \\ \Omega_y \\ \Omega_z \end{bmatrix} \tag{3}$$

Where, $\emptyset$ and θ represent roll and pitch in radian respectively and Ω is the propeller angular velocity.

Errors accumulate with time due to gyro bias making 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. (Yaw estimation is not covered in this work).

III. MATHEMATICAL FORMULATION OF KALMAN FILTER

Kalman filter is a recursive filter that estimates the states of the dynamics of a system by noisy measurement.

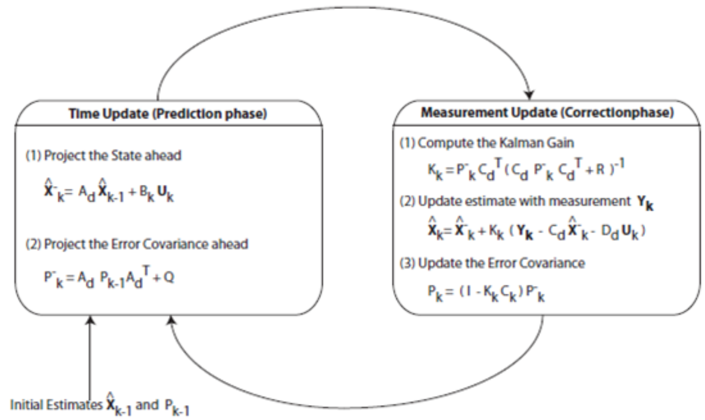

Fig. 1 Kalman model

The Kalman filter is based on a two-step process: First, the system acts as a Predictor; i.e. it uses the model of the system, the current state and the input vector to predict the future state considering the covariance error. In application, the filter takes the gyroscope measurements and calculates attitude estimations based on the gyroscope rates, and makes a prediction estimate of the error covariance.

The Measurement update phase, which is the second phase, corrects the predicted state and the estimated covariance error according to the measurements and its noise covariance. These are then used to calculate the Kalman gain. The accelerometer data is incorporated to aid the gyroscope measurement. These two values are multiplied by the Kalman gain to use a percentage of each measurement based on their noise characteristics.

Therefore, a model for the prediction of the angular velocity (without the model noise) is given by [18]:

$$\dot{\theta}_k = \dot{\theta}_{k-1} + \frac{k}{j}(u_1 - u_2) \tag{4}$$

Where $\dot{\theta}_k$ is the angular velocity, k is a constant for the linear relationship between the force generated by the motor and the input, j is the inertia and u is the input to the motors. To make (4) complete, the model noise $w_k \sim N(0, Q)$ is introduced to take model errors into consideration. Q is the covariance matrix of the noise given. The predicted state is then updated according to the steps described in [18].

IV. COMPLIMENTARY FILTER

When measuring the body angle with the accelerometer, it is affected by translation and vibrations of the motors, but the errors are not accumulated. When measuring with the gyro sensor, the errors are accumulated, but vibrations do not affect its operation. These two sensors measure the same physical quantities, and the properties are complementary, so the weaknesses of each sensor can be supplemented through convergence.

Generally, all the forces working on the object are measured by accelerometer and as the small forces creates disturbance in measurement, long-term measurement is reliable. So for accelerometer low pass filter is needed for correction. In the gyroscopic sensor the integration is done over a period of time and the value starts to drift in the long term, so high pass filter is needed for gyroscopic data correction[19], [20]. Therefore, the complementary filter consists of both low and high pass filter as shown in Fig. 2.

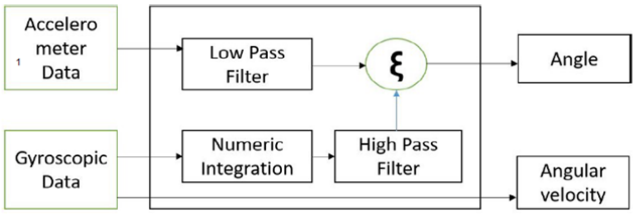

Fig. 2 Complimentary filter block diagram

The complimentary filter is a unity filter i.e. $Gain1(s) + Gain2(s) = 1$ and is based on time constant to produce desired gains [21]

$$\alpha = \frac{\tau}{\tau + dt} \quad (5)$$

τ is calculated from examining the gyroscope drift rate.

The complimentary filter angle is therefore calculated by summing weighted portions of the gyroscope and accelerometer angles to create a more accurate combined attitude angle.

$$\theta_k = gyro\_gain * (\theta_{k-1} + gyro * dt) + (0.020) * (accel) \quad (6)$$

V. Implementation

In this scheme, a 6-degree of freedom (6-DOF) MEMS sensor MPU-6050 has been used. It combines a 3-axis gyroscope, 3-axis accelerometer, and a Digital Motion Processor™ (DMP) all in a small 4x4x0.9mm package.

The fusion algorithms were implemented in Arduino platform.

The test was performed as follows:

- First the IMU GY-521breakoutboard was tilted smoothly.
- Next, the board was then continually tilted with some vibrations, i.e. by tapping and shaking the board quickly

The data was received on the Arduino Uno serial monitor. A program was written on the Arduino environment to prompt for inputs from the IMU sensor. The received inputs are then processed using the Kalman and Complimentary libraries.

Then from the data, their performance was analyzed using Matlab.

VI. Simulation Results

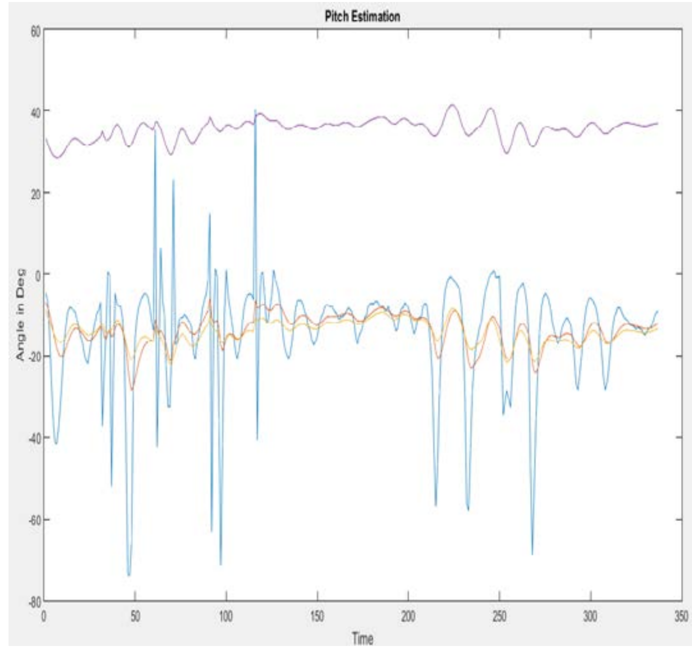

Fig. 3 Pitch angle estimation using Kalman Filter, Complimentary filter and MEMs sensors raw data

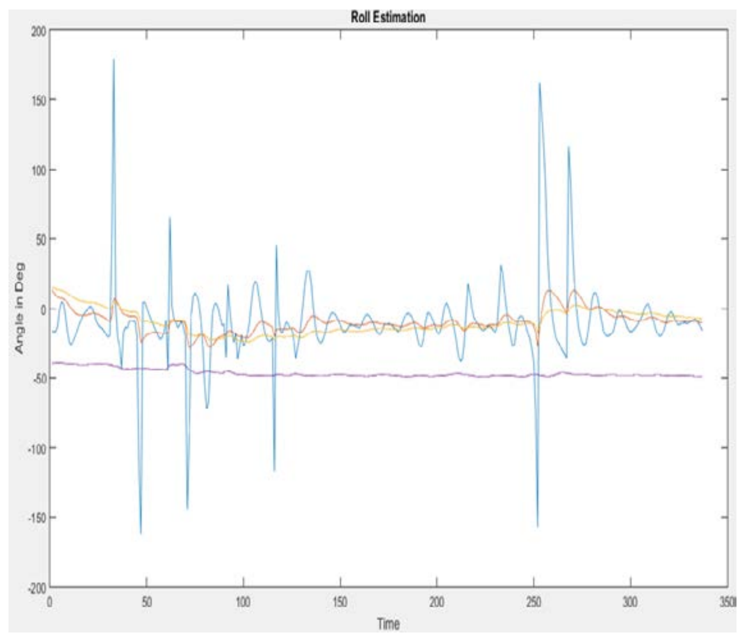

Fig. 4 Raw angle estimation using Kalman Filter, Complimentary filter and MEMs sensors raw data

From the Figs. 3 and 4, gyro data is represented by the purple line, Accelerometer by the blue line, the yellow line is the filtered data by Kalman filter and the red line is the complimentary filtered data. The filtered signal was obtained by combining the Accelerometer and Gyroscope data using the two fusion algorithms.

The purple line clearly shows how the gyro data drifts slowly with time from the zero level while the blue line shows the effect of vibrations (shaking) on the accelerometer data. The gyro data is however not affected by vibrations while the accelerometer data has no bias.

It can be observed that even with much vibration, the Kalman and Complimentary Filtered data is not much affected and the noise pronounced in the MEMs sensor raw data is eliminated with these two filters.

VII. Conclusion

From the results, the Kalman filter is more precise than the Complementary Filter, especially during vibrations. The Kalman filter is however mathematically involving and difficult to understand as compared to the complimentary filter which is easy to implement. Future work would involve application of Extended Kalman filter to perform the fusion of the two sensor signals and compare its performance with that of linear Kalman Filter studied in this work and to implement these Filter attributes in a physical Quadcopter system.

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