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Tariqul Islam, Md. Saiful Islam, Md. Shajid-Ul-Mahmud, and Md Hossam-E-Haider

Comparison of Complementary and Kalman Filter Based Data Fusion for Attitude Heading Reference System

Tariqul Islam[1], Md.Saiful Islam[2], Md.Shajid-Ul-Mahmud[3], Md Hossam-E-Haider[4]

[123]Aeronautical Engineering Department
[4]Electrical, Electronic and Communication Engineering Department
[1234]Military Institute of Science and Technology
[1234]Dhaka, Bangladesh

[1]tariqulae@gmail.com, [2]tarekislm39@gmail.com, [3]sumahmud19@gmail.com
[4]haider8400@yahoo.com

Abstract. An Attitude Heading Reference System (AHRS) provides 3D orientation of an aircraft (roll, pitch, and yaw) with instantaneous position and also heading information. For implementation of a low cost AHRS system Micro-electrical-Mechanical system (MEMS) based sensors are used such as accelerometer, gyroscope, and magnetometer. Accelerometers suffer from errors caused by external accelerations that sums to gravity and make accelerometers based rotation inaccurate. Gyroscopes can remove such errors but create drifting problems. So for getting the precise data additionally two very common and well known filters Complementary and Kalman are introduced to the system. In this paper a comparison of system performance using these two filters is shown separately so that one would be able to select filter with better performance for his/her system.

INTRODUCTION

In aspects of geometry the rigid body orientation means how a substance or a system is placed in the space. Heading and Orientation or attitude of a system is a measure Roll, Pitch and Yaw is obtained. Longitudinal, Lateral and Vertical axis are the Principle axes of Roll-pitch-yaw which are represented by x, y and z [1]. In Fig.1 the Rotational angle Roll-pitch-yaw about the axis x, y and z is shown. Orientation is measured in various way. In this paper Quaternion is used for representing orientation. To provide 3D orientation of the aircraft the basic sensors always used were gyroscope and accelerometer [3], [4]. One sensor cannot be used as a standalone device which mea-sure orientation because of many limitations. Accelerometer gives acceleration of a stationary object moving up or downs.

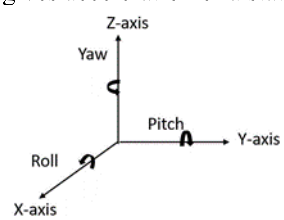

FIGURE 1. Orientation of Roll, Pitch and Yaw

Gyroscope uses earth gravity to measure the rotation about the 3 axis using the famous principle of angular momentum. But gyroscope is subjected to drift. This drifting value can be corrected using magnetometer. So a data fusion algorithm is needed in which all this sensors are integrated. In terms of Inertial Measurement Unit (IMU) data fusion algorithm, the complementary filter and Kalman filter are the most widely used algorithms. Each has its unique

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advantages and disadvantages [5], [6], [7]. In this paper the research first studied both Complementary and Kalman filter in IMU data fusion separately. A comparison was made on the experiment results obtained using the two algorithms. The analysis and outcome showed that there is a small difference between these two filter.

LITERATURE REVIEW

Rotation of a flying object can be described in many ways such as Direction Cosine Matrix (DCM), Euler angles, Quaternions. DCM having nine parameters is very difficult to implement. Euler angle suffers from gimble lock. However Quaternion has less parameters and it has advantages over 3-D rotation [2]. MEMS sensors are very cheap with having errors in measurements. Accelerometer is designed to measure the acceleration with respect to earth axis but it will show zero accleration of falling freely object. As it cannot sense the 3D rotation of the moving object, so to measure the rotation orientation of the object gyroscope was introduced to the system. But when the spinning axis is aligned with any other axis of freedom it will create gimbal lock. For these problems different sensor fusion methods have been implemented. The basic concept is to remove one's weakness using other's strengths. Several filters such as low pass filter, Complementary filter, Kalman filter, Extended Kalman filter are used for sensor fusion in last few decades. The complementary filter uses relatively easy algorithm, which only requires less computation and easy to implement. Such a feature makes it preferred for embedded systems.Using high pass filter and low pass filter it removes accelerometer spike and Gyroscopic drift relatively. Kalman filter is an iterative filter, which is efficient but high computational complexity [14]. The advantage of Kalman filter is that having very low memory. It works by correlating between current and predicted states.

QUATERNION MEASUREMENT

The quaternions, also called as versors, give an effective mathematical notation for representing orientations and rotations of any objects for every dimensions [8], [9]. To measure the orientation frame M relative to N it is required to have the rotational angle b and the rotation axis using a unit vector v (2). Thus the rotation quaternion can be written as (1) [15]

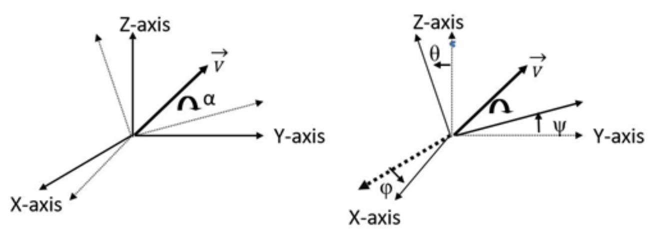

FIGURE 2. Frame rotation M before and after rotation (Roll-Pitch-Yaw)

$$S\frac{M}{N} = cos\frac{b}{2} + vsin\frac{b}{2} \qquad 1$$

$$v = v_x + v_y + vz \qquad 2$$

$$S\frac{M}{N} = cos\frac{b}{2} - v_x sin\frac{b}{2} v_y sin\frac{b}{2} - v_z sin\frac{b}{2} \qquad 3$$

$$S\frac{M}{N} = S_1 S_2 S_3 S_4 \qquad 4$$

Then rotating a vector V_p in a frame M around v by an angle. So resultant S in frame N is –

$$V_S = S\frac{M}{N} * V_P * S\frac{\vec{M}}{N} \tag{5}$$

Here ’*’ is Hamilton Product that if P1 and P2 are defined as two quaternion then the Hamilton Product will be followed as,

$$P1 * P2 = \begin{matrix} a_1a_2 - b_1b_2 - c_1c_2 - d_1d_2 \\ a_1b_2 + b_1a_2 + c_1d_2 - d_1c_2 \\ a_1c_2 - b_1d_2 - c_1b_2 + d_1b_2 \\ a_1d_2 + b_1b_2 - c_1b_2 + d_1a_2 \end{matrix} \tag{6}$$

The following representation of the rotational matrix $R\frac{M}{N}$ is derived from quaternion $S\frac{M}{N}$,

$$\mathrm{R}\frac{\mathrm{M}}{\mathrm{N}} = \begin{bmatrix} -2\mathrm{S}_3{}^2 - 2\mathrm{S}_4{}^2 & 2\mathrm{S}_2\mathrm{S}_3 - 2\mathrm{S}_4\mathrm{S}_1 & 2\mathrm{S}_2\mathrm{S}_4 + 2\mathrm{S}_3\mathrm{S}_1 \\ 2\mathrm{S}_2\mathrm{S}_3 + 2\mathrm{S}_4\mathrm{S}_1 & 1 - 2\mathrm{S}_2{}^2 - 2\mathrm{S}_4{}^2 & 2\mathrm{S}_3\mathrm{S}_4 - 2\mathrm{S}_2\mathrm{S}_1 \\ 2\mathrm{S}_2\mathrm{S}_4 + 2\mathrm{S}_3\mathrm{S}_1 & 2\mathrm{S}_3\mathrm{S}_4 + 2\mathrm{S}_2\mathrm{S}_1 & 1 - 2\mathrm{S}_2{}^2 - 2\mathrm{S}_4{}^2 \end{bmatrix} \tag{7}$$

The angle Roll-Pitch-Yaw (ψ, θ, φ) of an aerospace vehicle can be achieved then,

$$\begin{bmatrix} \psi \\ \theta \\ \varphi \end{bmatrix} = \begin{bmatrix} \mathrm{atan2}(\mathrm{S}_1\mathrm{S}_2 + \mathrm{S}_3\mathrm{S}_4), 1 - 2(\mathrm{S}_2{}^2 + \mathrm{S}_4{}^2) \\ \arcsin(2(\mathrm{S}_1\mathrm{S}_3 + \mathrm{S}_2\mathrm{S}_4) \\ \mathrm{atan2}(\mathrm{S}_1\mathrm{S}_4 + \mathrm{S}_2\mathrm{S}_3), 1 - 2(\mathrm{S}_3{}^2 + \mathrm{S}_4{}^2) \end{bmatrix} \tag{8}$$

COMPLEMENTARY FILTER

In the Inertial Measurement Unit (IMU) accelerometer, gyroscope and magnetometer is integrated. Accelerometer and the gyroscope are the main sensor and magnetometer is the correction sensor. 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 period of time the value starts to drift in the long term, so high pass filter is needed for gyroscopic data correction[5], [10]. The complementary filter consists of both low and high pass filter and as it is easier to implement this filter was implemented for getting precise data.

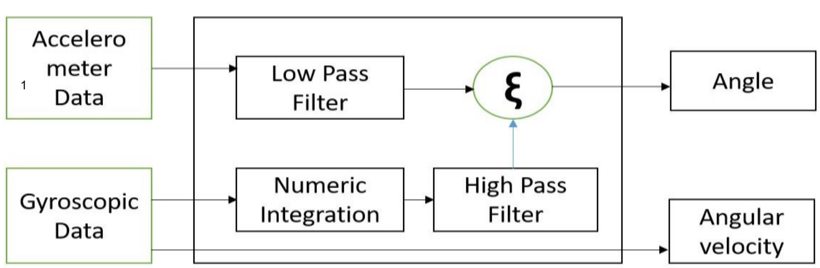

FIGURE 3. Block Diagram of Complementary filter.

The transfer function for the input passing through the low pass filter = $\frac{1}{1+T_S}$

The transfer function for the input passing through the high pass filter = $\frac{T_S}{1+T_S}$

In terms of transfer function we can write the complementary filter as,

Total $= \frac{\alpha}{1+T_S} + \left[\frac{T_S}{S(1+T_{S)}} + \frac{1}{S}\right] * \beta$

The total gain of the two filter is 1

Gain1(s) + Gain2(s) = 1

Here, α = accelerometer data input, β/s = calculated angle from gyroscope passing through an integrator
Total T = filter cutoff frequency
Only if the nature of data is complementary to each other then they can be improved by removing noise using data fusion Total of high pass and low pass filter.

W(s) = Final output signal

U(s) = Output gain

V(s) = True signal

N1, N2 = the noise signal which needs to be suppressed

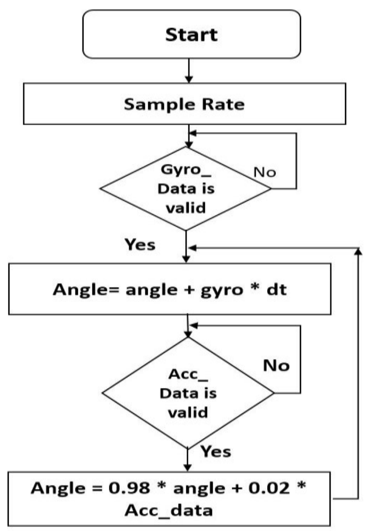

FIGURE 4. Complementary filter flow chart

W(s) = [1 - U(s)] × [V (s) + N1(s)] + U(s) × [V(s) + N2(s)] 9

W(s) = [1 - U(s)] ×V (s) + [1 - U(s)] × N1(s) + U(s)(V (s)) 10

W(s) = V (s) × U(s)V (s) + [1 - U(s)] ×N1(s) + U(s)V 2(s) + U(s)N2(s) 11

W(s) = V (s) + [1 - U(s)] × N1(s) + U(s)N2(s) 12

So the equations above are showed that only the noise signals are affected by complementary filter gain. If the noises are removed then the desired data will be obtained. But most of the cases it is impossible [11]. But if the N2 signal is of very low frequency, then the multiplication of U(s) N2(s) will be very low and can be removed by high pass filter. Again [1-U(s)] will be very high then if N1 is of high frequency then the multiplication of this two will be very high and can be removed by using low pass filter. Our complementary filter is the fusion of high pass filter and low pass filter and so it is very efficient specially in this case as here the sensors are accelerometer and gyroscope. So the output will be the $W(s) = V(s)$

KALMAN FILTER

The AHRS design here provides the measurements for the low speed aircraft which is a dynamic system as the condition of aircraft changes simultaneously with respect to time. For a dynamic system by predicting the future value from the previous data the situation of the system can be guessed. For this type of system which are continuously changing the Kalman filter is the perfect to make an educated guess of what happened. As this filter predict future from previous data so some initial value is considered in the beginning [10]. In this implementation the filter starts working after the IMU is on and measures the initial value. Then the value is transmitted to the filter and thus the filter starts computing. Kalman filter uses correlation between prediction and what actually happened to make the prediction error. An advantage of Kalman filter is its memory is low, so it cannot save nothing but the previous value. The procedure is divided into four steps. Firstly the initial value is given, then the prediction step, computing gain of the filter and then estimation is done. At last it calculates the error covariance [14]. If the initial value is a_0, B_0.

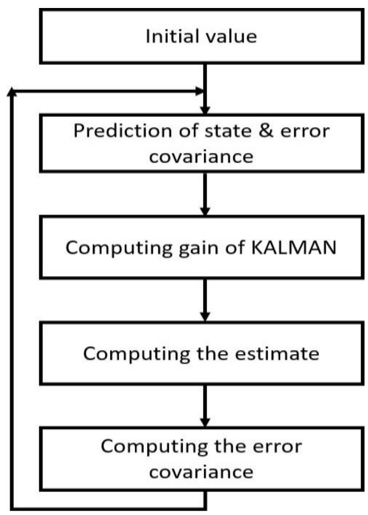

FIGURE 5. Kalman filter flow chart

Then the prediction state is,

$$a_{kp=}\ Aa_{k-1} \tag{13}$$

$$b_{kp=}\ AB_{k-1}A^T + C \tag{14}$$

The kalman gain $K_{g=}\ B_{kp}J^T(JB_{kp}J^T + M)^{-1}$

The computation of state $a_{k=}\ a_{kp} + (z_k - Ja_{kp})$

Finally the covariance $B_{k=}\ B_{kp} + K_gJB_{kp})$

Here,

Z_k = Measurement provided

a_k = Final Output (estimation)

A, J, M, C = System model and $a_{kp}, B_{kp}, B_k,\ K_g$= Internal computation variable

In the initial step the value of a_0 and error covariance b_0 for the computation to start. In the second step the prediction of state for the next step B_{kp} is calculated from the previous value given. The system parameters that used in this prediction process A, C are calculated before. The subscript a_{kp} used for a means the predicted value of a. In the estimation process, the computation of state

$$a_{k=}\ a_{kp} + K_g(Z_k - Ja_{kp}) \quad 15$$
$$a_{k=}\ a_{kp} + K_g(Z_k - Ja_{kp}) \quad 16$$

$$a_{k=}\ a_{kp} + K_gZ_k - K_gJa_{kp} \quad 17$$

$$a_{k=}\ a_{kp}(I - K_gJ) + K_gZ_k \quad 18$$

Here, Z_k is the value of measurement and a_{kp} is the predicted value used as input for the estimation. Let us assume that J is an identity matrix as I

The working principle of 1st order low pass filter and Kalman filter is almost same. The only difference is that the

$$a_{k=}\ a_{kp}(I - K_gJ) + K_gZ_k \quad 19$$
$$a_{k=}\ a_{kp}(I - K_g) + K_gZ_k \quad 20$$

Kalman filter is not using the previous estimate but prediction. At last the error covariance is calculated and the value is sent to the prediction process to determine the efficiency of the filter.

HARDWARE SETUP

To do our experiment 9-degree of freedom (9-DOF) MEMS sensor MPU-9150 has been used. It integrates the ADXL345 accelerometer, the HMC5883L magnetometer, the ITG-3205 gyroscope. The algorithm was implemented in Arduino plat-form. We build an AHRS and save the output rotation using two filters (Complementary and Kalman). Then from the data their performance have been analyzed through Matlab.

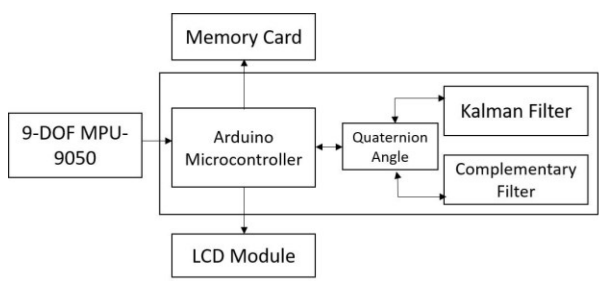

FIGURE 6. Hardware block diagram

FIGURE 7. Implementation of AHRS

ACCELEROMETER, GYROSCOPIC AND MAGNETOMETER ANGLE

The MEMS sensors usually give raw data which needs to be converted. The output of raw data from the Acclerometer, Gyroscope and Magnetometer have shown in Figure 9. Then the converted quaternion angles have been calculated for further sensor fusion. Accelerometer does not give z-axis angle. So the yaw of it measured from magnetometer. Roll and Pitch angle of each sensor are also plotted in Figure 8 and 10.

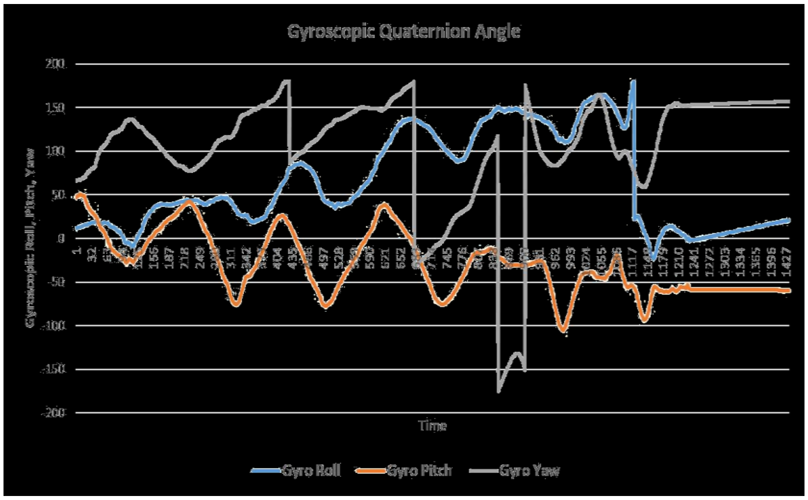

FIGURE 8. Gyroscope Rotation Angle

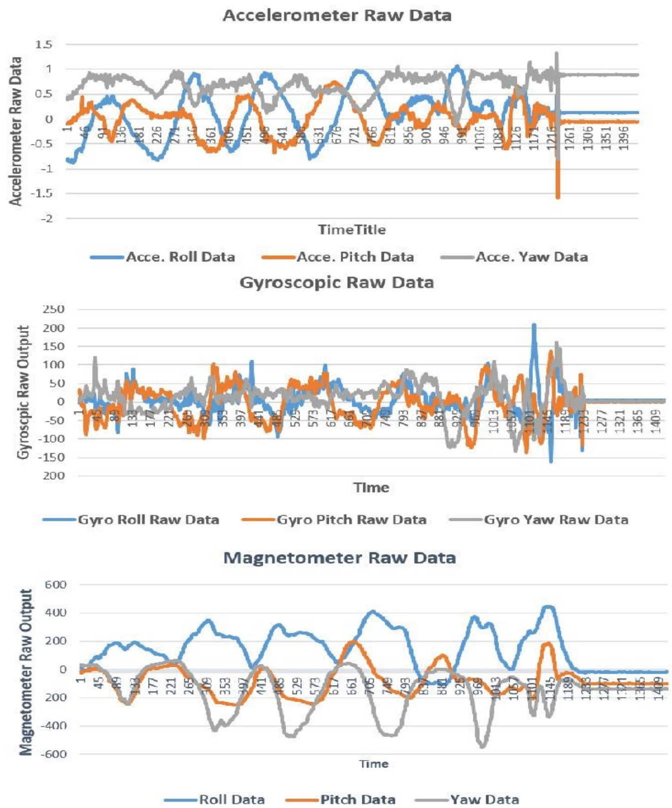

FIGURE 9. Sensors Raw Data

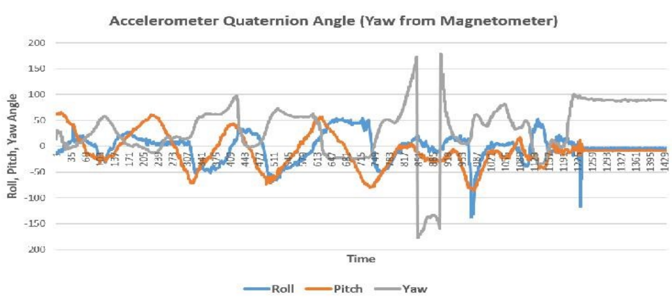

FIGURE 10: Accelerometer Rotation Angle

EXPERIMENT RESULT

Result: Complementary Filter

In case of complementary filter, the time constant is 0.75(s) and program loop-time is 0.03(s). The coefficient of complementary filter value is = 0.98. During study, the output angle of the complementary filter is compared with accelerometer, gyroscope, Kalman filter value. The Angle is divided into three sections: single rotation about x-axis (roll), single rotation about y-axis (pitch) and rotation about z-axis is Yaw. In Figure. 11, the experiment result is shown. It is clear that the accelerometer Pitch angle and Roll angle is comprises of noises and baises. Another thing is that complementary filter has no information about the output filtered data. Nevertheless, the resulted angles from the complementary filter are much more accurate and with less errors .When the IMU rotates about only one single axis, there is about no vibration on the other axes. That means no signal coupling is happening on both axes (pitch and roll). So the complementary filter is effective, stable and reliable in IMU data fusion once the filter coefficient is well tuned.

Result: Kalman Filter

In case of the Kalman Filter IMU data fusion experiment, the values of filter Parameters A, C are set at 0.001, 0.003 accordingly. The program loop time is chosen 0.04s. In order to determine the effectiveness of the Kalman algorithm, the Acce.Pitch and Acce.Roll are used as the references. From Figure 11, during test the signal filtered by Kalman filter is more stable than that outcome from the accelerometer. However, the final filtered roll data is more accurate than the filtered pitch signal. Since Kalman filter is a more complex and considerate algorithm, it should have been more accurate than the complementary filter. It is a process of iteration which consistently tries to find the statistically most optimal value. Nevertheless, the Kalman filter discussed in this study has A, C basic parameters that need to be well tuned. Thus the difficulty of the Kalman filter to achieve a more optimal result increases. Moreover, the usefulness of a Kalman filter requires computational complexity which demands for more powerful microcontroller. In case of the sample rate could be increased, the Kalman filter would get a better output.

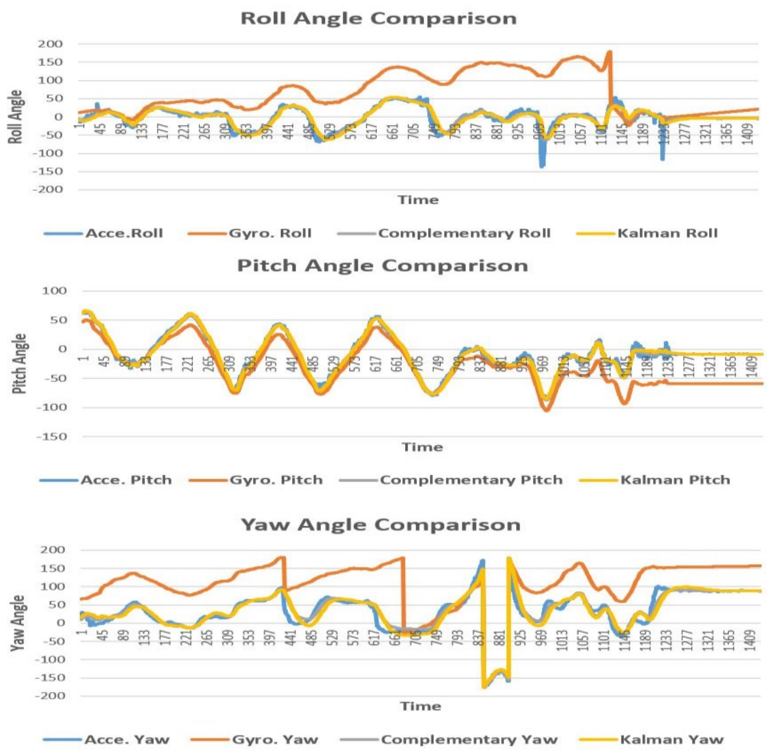

FIGURE 11: Comparison of Roll, Pitch, Yaw Angle

CONCLUSION

The ultimate aim is to implement a low cost AHRS using Complementary and Kalman filter respectively and compare their performance. Kalman filter is well known for its accuracy. As the device AHRS is a dynamic system so Kalman filter is an ideal filter for getting precise value. In the graphs given above firstly there is so much ups and downs but after introducing the Kalman filter the curve is stable and the value is much more precise. As the implementation of Kalman filter is a bit tough and hard to understand then the second choice is complementary filter. The value provided by the complementary filter is not so accurate as the Kalman filter. But this filter is much simple to implement and easy to understand. However as for accuracy is concern the Kalman filter is the ideal choice.

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