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Multi-sensory data fusion for high performance attitude estimation

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Abstract. In this paper, attitude angles estimation utilizing low power consumption and efficient approaches will be focused on. The trade-off between power consumption and efficiency is a leading factor in enhancing the overall performance of the navigation system in most of the autonomous system applications, so Complementary and Mahony filters as accelerometer, gyro, and magnetometer data fusion algorithms with high performance and less computation complexity are utilized. A real time implementation for Complementary and Mahony filters was achieved using raw data from Vector NAV VN-100 IMU. Estimated Euler angels using each filter were compared with Euler angels from Vector NAV VN-100 which are estimated using Kalman filter. A comparative study was carried out for analyzing the performance of each algorithm. The study presented that the Complementary filter introduces better efficiency than Mahony filter in case of stationary situations and steady flight. On the other hand, Mahony filter presents better efficiency than Complementary filter in case of motion and high dynamics.

1. Introduction

Power management is one of the most important keys in designing and implementation of an efficient embedded system. The motivation behind power management is to enhance battery life, achieving lower heat dissipation to increase system stability, reducing cooling requirements, reducing operating cost for energy and cooling, and reducing noise. One approach for power management is to reduce the complexity of the software to reduce the processing power. So in this work, less computations and efficient algorithms for attitude angels estimation were utilized to improve the overall performance and reduce cost. Attitude angels estimation or data fusion is to integrate multisensory data such as accelerometer, gyroscope and magnetometer to get accurate Euler angels[1] (Yaw, Pitch and Roll). Accurate attitude estimation plays an important role in development of autonomous systems in military and civilian fields such as robotics, aerospace and unmanned aerial vehicles. The most widely used approaches for data fusion are Kalman filter[2], Extended Kalman filter[3], Madgwick filter[4], Mahony filter[5] and Complementary filter[6]. Although Extended Kalman filter introduces the best performance, it shares drawbacks of high computational complexity and difficulty of tuning which requires more processing power and more power consumption[7], so the approaches such as Madgwick filter, Mahony filter and Complementary filter arise as a suitable alternative for applications applied on embedded systems with limited computing power.



In this work, Vector NAV VN100 was utilized. Vector NAV VN100 has 3 accelerometers, 3 gyros and 3 magnetometers. Accelerometers can measure the orientation of a stationary body and this can be used to estimate Euler angles (pitch and roll). The Euler angles estimation is highly depending on the order of rotations that are applied for estimating the rotation matrix. The most common used order in aerospace applications is the sequence of yaw then pitch and finally a roll rotation(ZYX order),so Roll and Pitch angles can be calculated from accelerometer measurements (ax,ay,az) as in equations (1 and 2)[8].

$$\text{Roll}=\left(\frac{180}{\text{pi}}\right) * \tan^{-1} \frac{ay}{az} \quad (1)$$

$$\text{Pitch}=\left(\frac{180}{\text{pi}}\right) * \tan^{-1} \frac{-ax}{\sqrt{ay^2+az^2}} \quad (2)$$

Gyroscopes measure angular velocity. Gyro measurements (gx,gy,gz) can be also used to estimate Euler angles in ZYX order using quaternion mathematics[9]. The procedure for calculating the Euler angles from gyros measurements is as shown in figure 1.

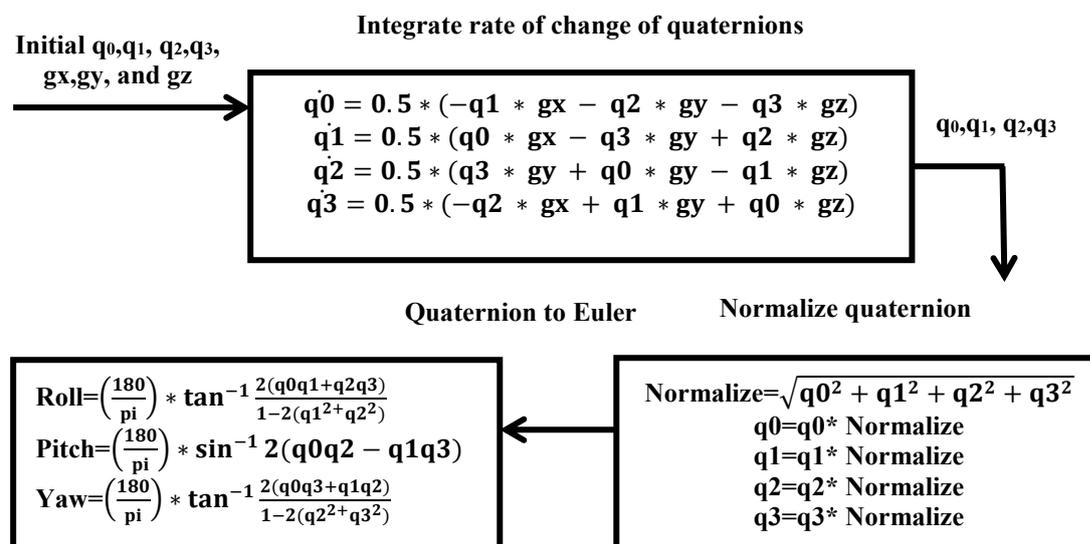


Figure 1. Calculating Euler angles from gyro measurements using quaternions.

Magnetometers measure the strength of magnetic field (He) which can be represented by $H_x, H_y,$ and H_z . The H_x and H_y can be used to estimate heading with respect to the magnetic poles. Magnetometer must be leveled to the earth's surface, there should not be any steely materials that interfere with the earth's field and the declination angle must be known. The formula of compass heading (yaw) angle is as in equation (3), where m_x, m_y, m_z are magnetometer measurements.

$$\text{Yaw}=\left(\frac{180}{\text{pi}}\right) * \tan^{-1} \frac{m_y}{m_x} \quad (3)$$

However, when the magnetometer is slanted, an algorithm for tilt compensation must be used[10]. Tilt compensation algorithm requires a magnetometer and an accelerometer. The accelerometer is to estimate the pitch and roll tilt angles for tilt compensation and the magnetometer is to measure the earth magnetic field and then the algorithm can estimate the yaw angle according to the magnetic north as shown in figure 2. For calculating the heading according to the geographic north, the declination angle should be added or subtracted from the magnetic heading (according to the location).

Magnetometer must be calibrated to compensate hard and soft iron effects[11]. In this work, hard iron calibration was applied, so hard iron calibration vector (v_x, v_y, v_z) should be subtracted from magnetometer measurements vector (m_x, m_y, m_z).

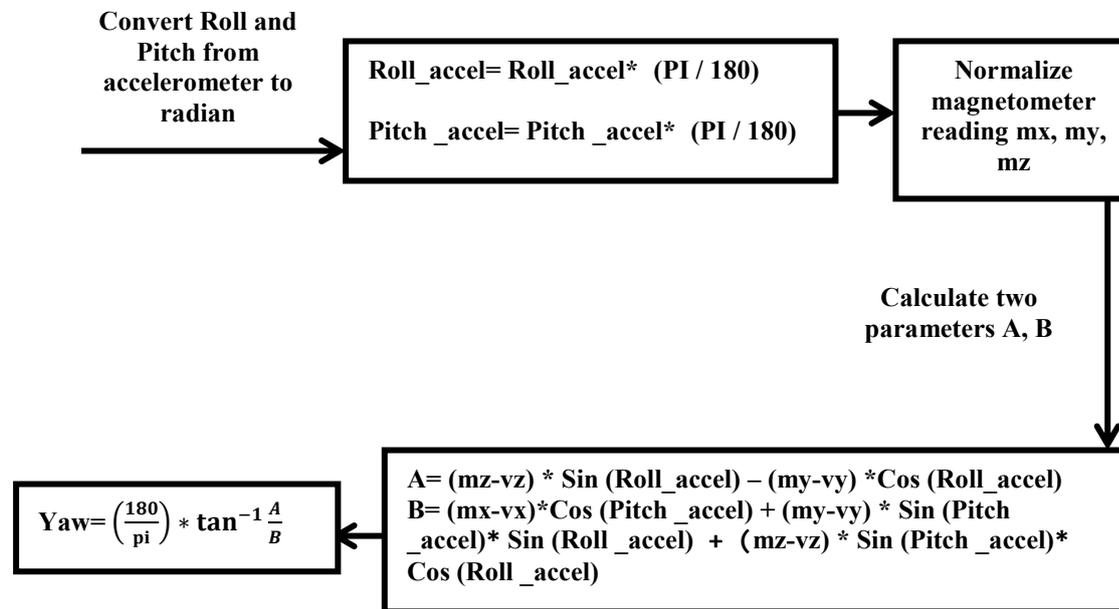


Figure 2. Tilt compensation algorithm.

This paper has three parts and a conclusion. Part 2 provides a detailed description of Complementary filter. Part 3 provides a detailed description of Mahony filter. Part 4 includes results of both filters implementation.

2. Complementary filter

As illustrated in the previous section, the accelerometer and gyroscope can be used to estimate Euler angles. However, the accuracy is rapidly degraded with time especially with high dynamics applications. So, filtering techniques must be used to enhance the accuracy by multi-sensory data fusion. The reasons for degrading the performance can be summarized as follows; the accelerometer senses additional centrifugal forces beside the actual vehicle acceleration, so, the accelerometer data is reliable only on the long term and in low dynamics or steady flight situations. Gyros can be used to obtain an accurate measurement which is not susceptible to external forces. However, integration over time leads to rapidly increasing in drift errors over time which makes the gyroscope data more reliable for short term navigation and maneuvering situations. The complementary filter takes the advantage of each sensor and compensates for the disadvantages of the other. In this work, the tuned values for complementing the gyros and accelerometers (or magnetometer) is 30% and 70% respectively, as the accelerometer measurements are more stable and do not drift with time for low dynamics, steady flight or stationary situations. The usage of 30% from gyro data is to attenuate higher frequencies of accelerometer (magnetometer) data and as the gyro measurements are efficiently capture the vehicle dynamics but rapidly drift with time due to integration errors and sensor drift error.

The filter formula is as in equation (4), Where, HP_weight (high-pass weight) and LP_weight (low-pass weight) must equal 1. The procedure of the proposed filtering scheme is as shown in figure 3.

$$\text{Angle} = \text{LP_weight} * (\text{gyro_angel}) + \text{HP_weight} * \text{acc_angel} (\text{magneto_angel for Yaw}) \quad (4)$$

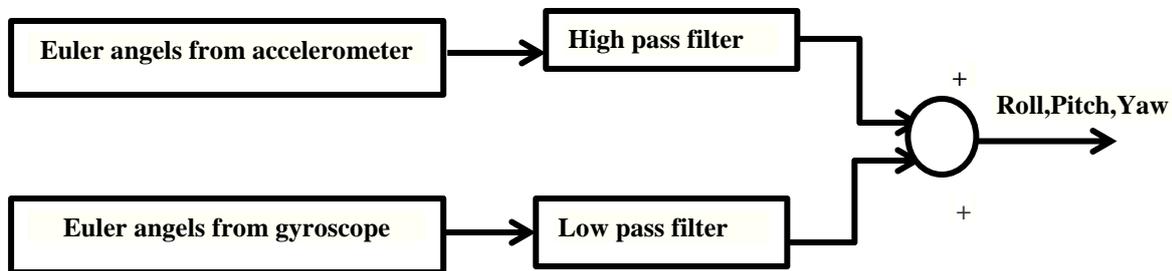


Figure 3. Complementary Filter Algorithm.

3. Mahony filter

This filter corrects the measured angular velocity using a correction step. This correction step is based on the measurements of the accelerometer and magnetometer and a Proportional-Integral (PI) compensator. Firstly the filter estimates the error between the reference direction of earth's magnetic field and estimated (measured) direction of gravity and magnetic field, then it multiplies this error by a proportional gain and multiplies the integration of this error with respect to time by an integral gain, after that, the previous two terms are added to the measured angular velocity to get the corrected measurement. The filter formula is as in equation (5), Where W_b is the angular velocity in body frame, K_p , K_I are proportional and integral gains (tuning parameters), e is the error between reference direction of earth's magnetic field and estimated (measured) direction of gravity and magnetic field.

$$W_b = W_b + K_p e + K_I \int e \quad (5)$$

The procedure for calculating the reference direction of earth's magnetic field is shown in figure 4.

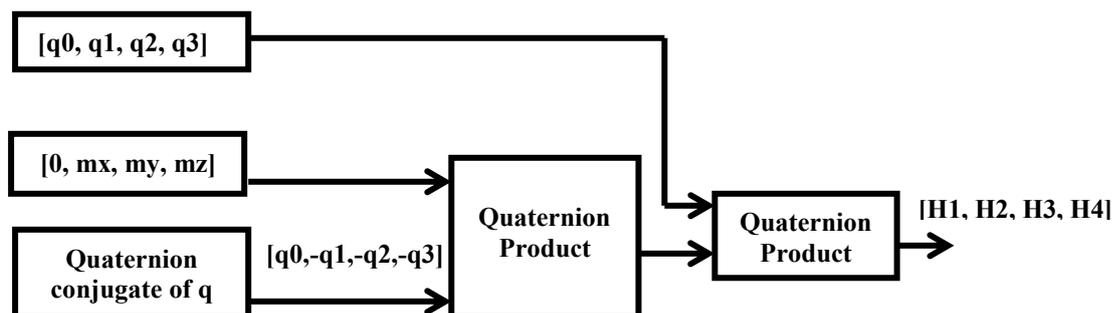


Figure 4. Calculating reference direction of Earth's magnetic field.

The output of the previous block diagram is a vector of four elements H_1 , H_2 , H_3 , and H_4 . H_2 and H_3 are represented by H_x and H_y respectively, the norm of H_x and H_y is calculated and represented by $b_x = \sqrt{H_x^2 + H_y^2}$ and H_4 is represented by b_z . The estimated (measured) direction of gravity and magnetic field can be calculated using two vectors, vector $v = [v_x, v_y, v_z]$ and vector $w = [w_x, w_y, w_z]$ as in equations (6, 7, 8, 9, 10 and 11).

$$v_x = q_1 * q_3 - q_0 * q_2 \quad (6)$$

$$v_y = q_0 * q_1 + q_2 * q_3 \quad (7)$$

$$v_z = q_0 * q_0 - 0.5 + q_3 * q_3 \quad (8)$$

$$w_x = b_x * (0.5 - q_2 * q_2 - q_3 * q_3) + b_z * (q_1 * q_3 - q_0 * q_2) \quad (9)$$

$$w_y = b_x * (q_1 * q_2 - q_0 * q_3) + b_z * (q_0 * q_1 + q_2 * q_3) \quad (10)$$

$$w_z = b_x * (q_0 * q_2 + q_1 * q_3) + b_z * (0.5 - q_1 * q_1 - q_2 * q_2) \quad (11)$$

The error between reference direction of earth's magnetic field and estimated (measured) direction of gravity and magnetic field can be calculated as shown in figure 5.

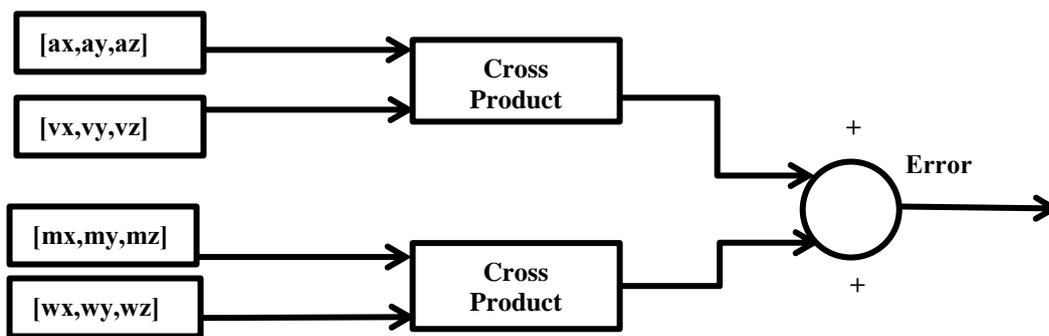


Figure 5. Calculating error between reference direction of earth's magnetic field and estimated (measured) direction of gravity and magnetic field.

The corrected gyro measurement can be estimated using the error calculated in figure 5, where this error is multiplied by proportional gain and the integration of this error with respect to time is multiplied by integral gain, and then the previous two terms are added to the gyro measurement to get the corrected measurement. Then the integration of quaternion propagation and quaternion normalization is carried out to estimate Euler angles as shown in figure 1.

The tuning parameters K_p and K_I (in rad/sec) are tuned to reduce the noise. In typical flight regimes, K_p would be tuned up to (from 4 to 8). The relationship between K_p and K_I is as in equation (12). In this work, K_p was set to 4.5 (rad/sec) and K_I was set to 0.45 (rad/sec).

$$K_I = 0.1 * K_p \quad (12)$$

4. Experimental results

A series of experiments were carried out to evaluate the performance of Mahony and Complementary filters in static and moving scenarios. The experiments were carried out utilizing Vector NAV VN-100 which its output frame is (Yaw, Pitch, Roll, Magnetic, Acceleration, and Angular Rates). Vector NAV VN-100 Euler angles (Yaw, Pitch and Roll) are estimated using Kalman filter, so, they were used as reference to compare the results of the proposed algorithms. Interfacing Vector NAV VN-100 was performed using C# program to receive its output frame serially, extracting Euler angles, magnetic,

acceleration and angular rates from the frame and applying Mahony and complementary filters to get Euler angels, then comparing estimated Euler angels with the reference from Vector NAV VN-100 using Matlab.

4.1. Stationary (static) scenario

Vector NAV VN100 was fixed. The results of estimating roll, pitch, and yaw angles and their related errors are demonstrated in figures (6, 7 and 8) for Complementary filter and figures (9, 10 and 11) for Mahony filter. The statistical analysis for the results of both filters is performed and summarized in table 1 using the maximum, minimum, mean, and standard deviation to analyze the performance of each algorithm.

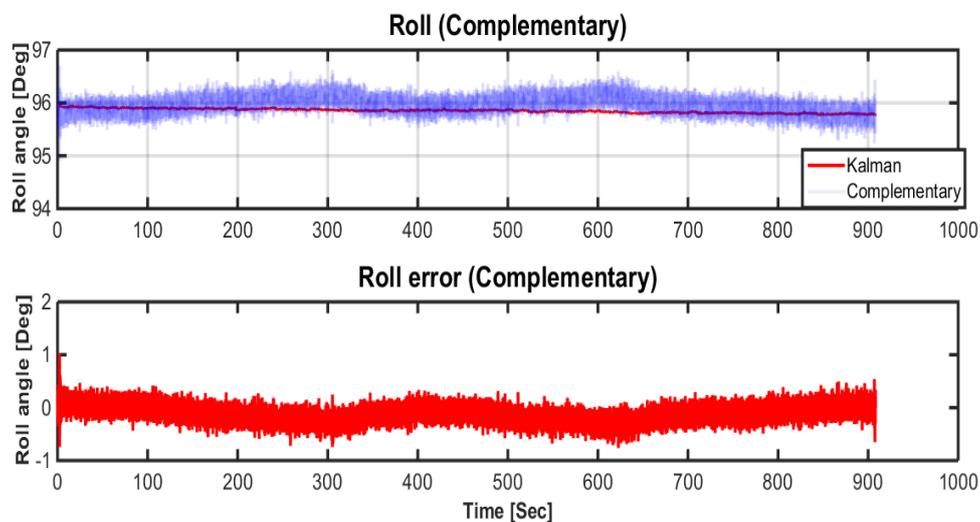


Figure 6. Roll using Complementary (static scenario)

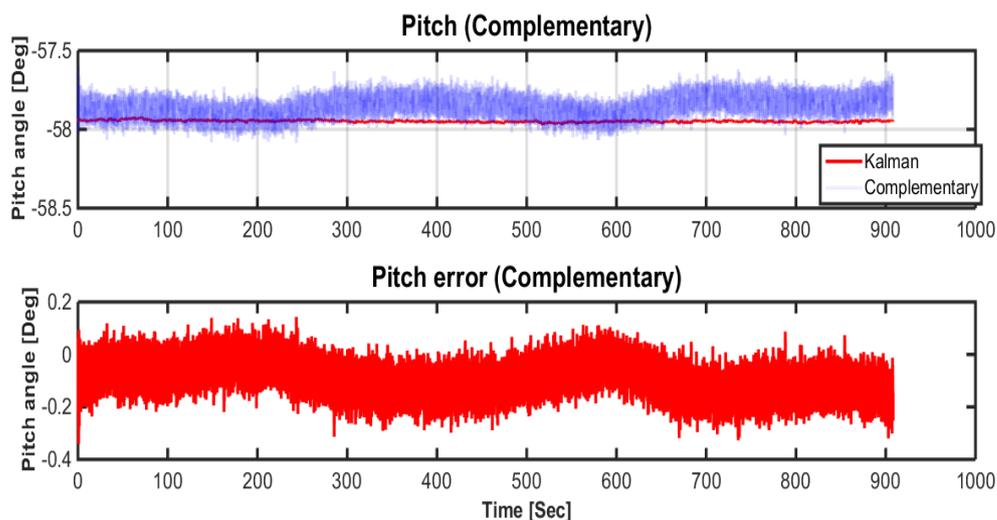


Figure 7. Pitch using Complementary (static scenario)

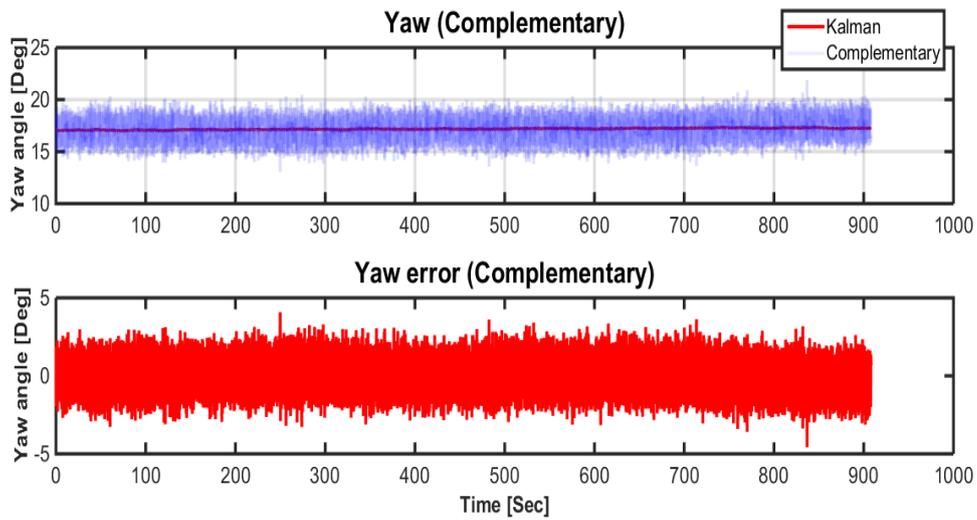


Figure 8. Yaw using Complementary (static scenario)

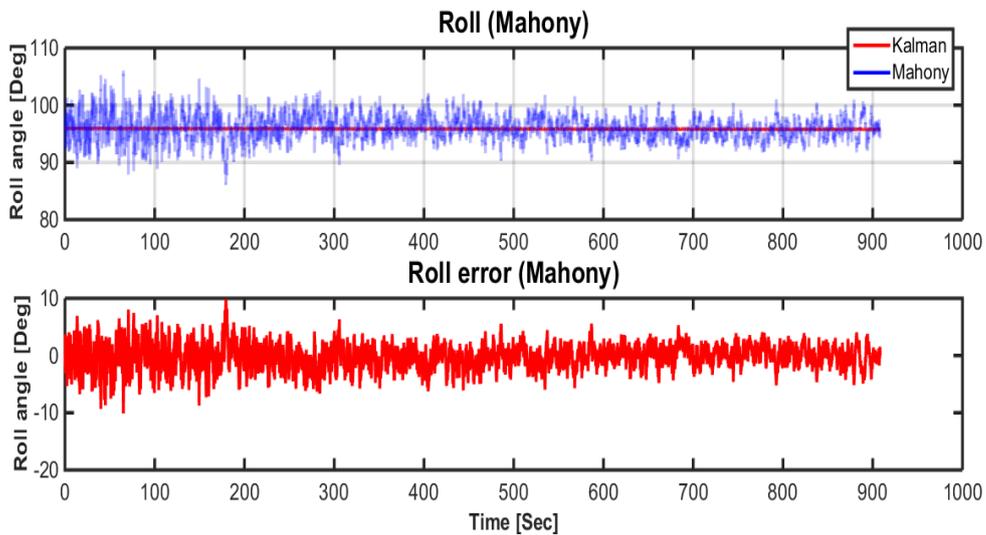


Figure 9. Roll using Mahony (static scenario)

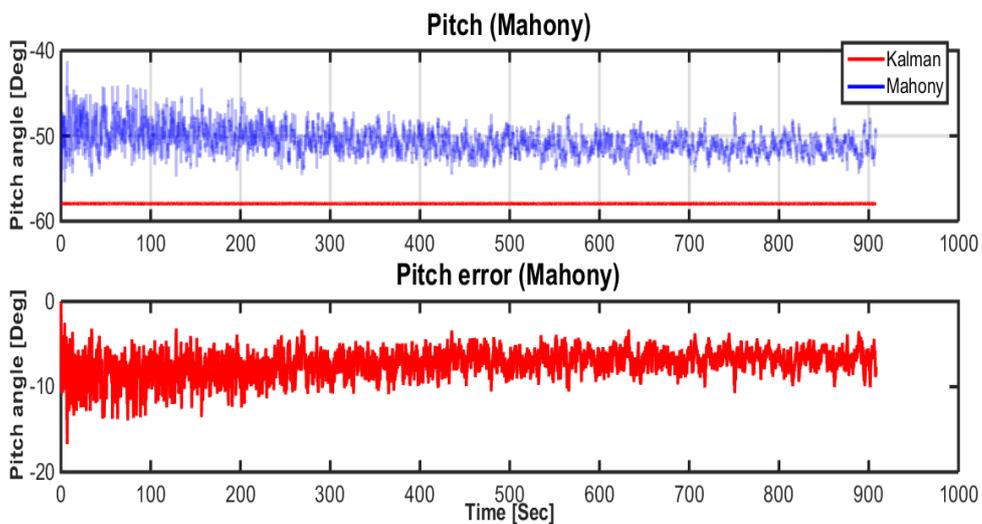


Figure 10. Pitch using Mahony (static scenario)

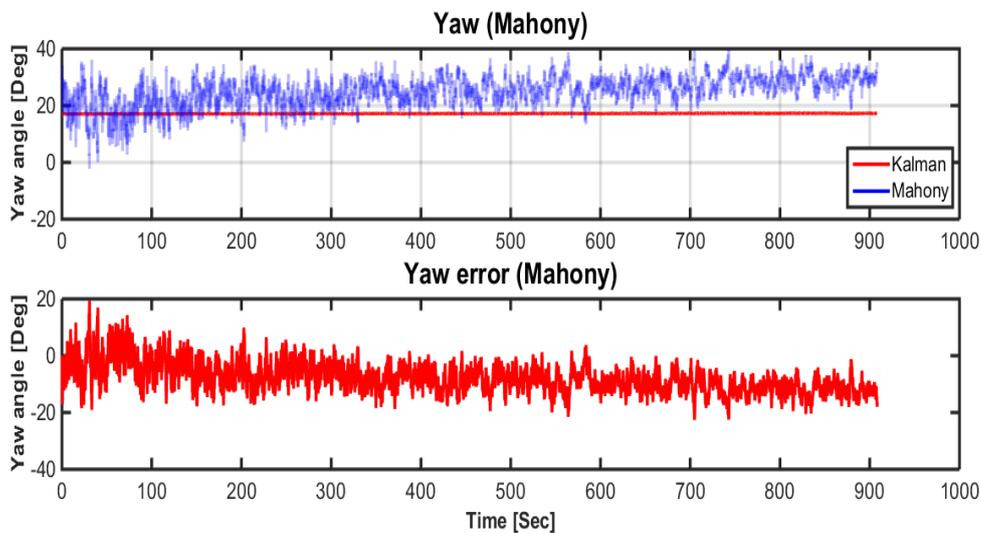


Figure 11. Yaw using Mahony (static scenario)

Table 1. Data analysis of Complementary and Mahony filters in static scenario

	Complementary			Mahony		
	yaw	pitch	roll	yaw	pitch	roll
Maximum Error (deg)	4.571	0.341	1.032	22.595	16.733	10.129
Minimum Error (deg)	0.00003	0	0	0.0015	0.0789	0.00007
Error Mean (deg)	0.738	0.0956	0.158	8.372	7.250	1.615
Error Standard deviation(deg)	0.559	0.055	0.114	4.230	1.447	1.277

Data analysis in table 1 shows that Complementary filter presented better efficiency than Mahony filter in yaw, pitch and roll channels, where maximum error, minimum error, error mean value and standard deviation for Complementary for yaw are 4.571, 0.00003, 0.738 and 0.559 respectively, for pitch are 0.341, 0, 0.0956 and 0.055 respectively and for roll are 1.032, 0, 0.158 and 0.114 respectively, where maximum error, minimum error, error mean value and standard deviation for Mahony for yaw are 22.595, 0.0015, 8.372 and 4.230 respectively, for pitch are 16.733, 0.0789, 7.250 and 1.447 respectively and for roll are 10.129, 0.00007, 1.615 and 1.277 respectively, which means that Complementary filter presents better efficiency than Mahony filter in steady flight and stationary situations in yaw, pitch and roll channels.

4.2. Moving scenario

The results of estimating roll and pitch angles and their related errors are demonstrated in figures (12 and 13) for Complementary filter and figures (14 and 15) for Mahony filter. The statistical analysis for the results of both filters is performed and summarized in table 2 using the maximum, minimum, mean, and standard deviation to analyse the performance of each algorithm.

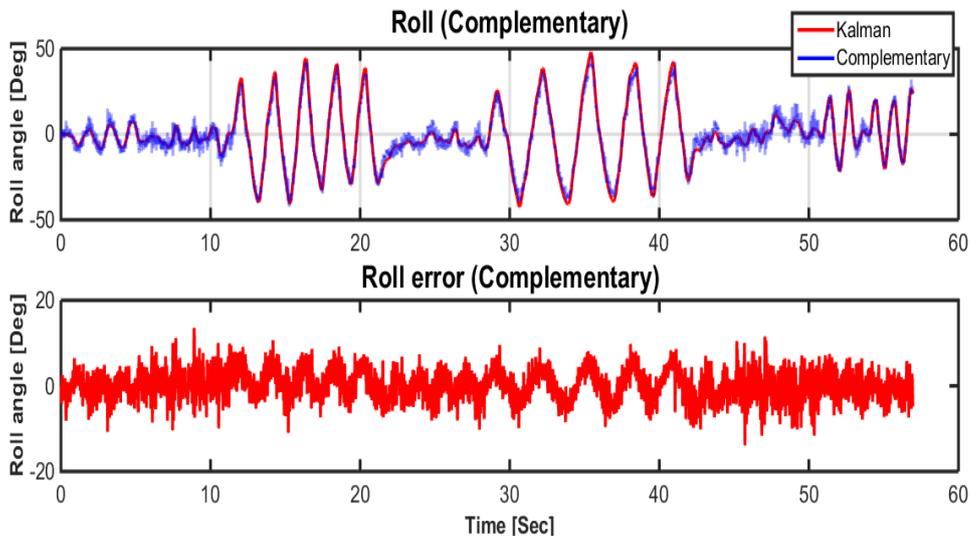


Figure 12. Roll using Complementary (Moving scenario)

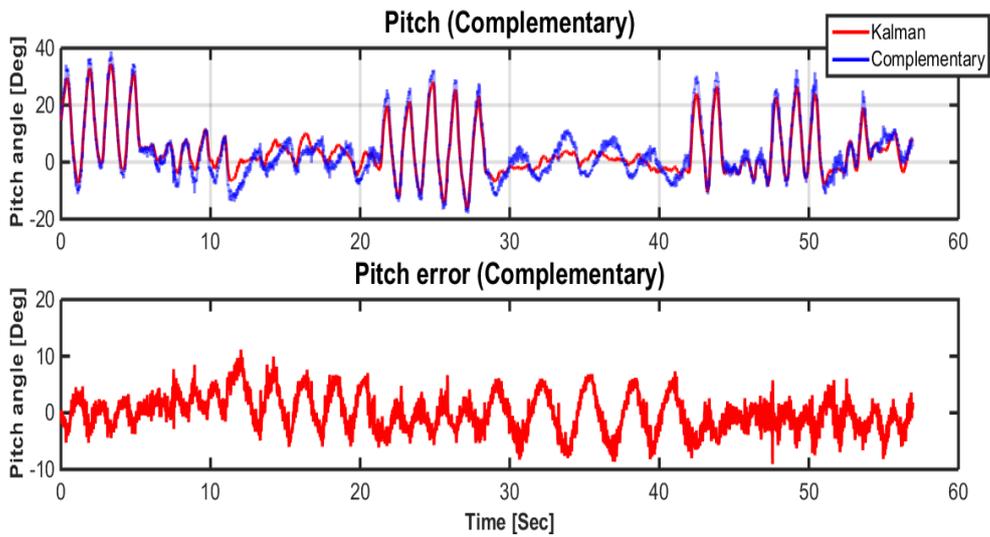


Figure 13. Pitch using Complementary (Moving scenario)

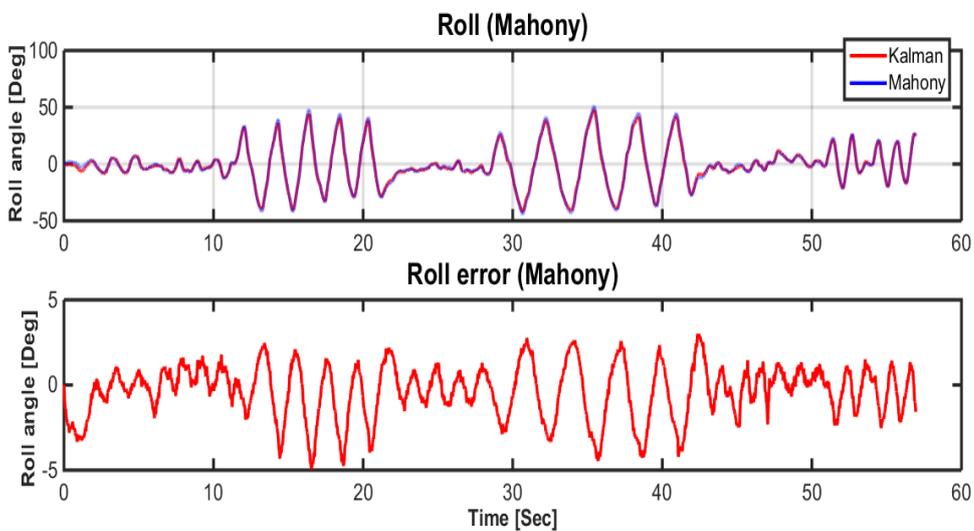


Figure 14. Roll using Mahony (Moving scenario)

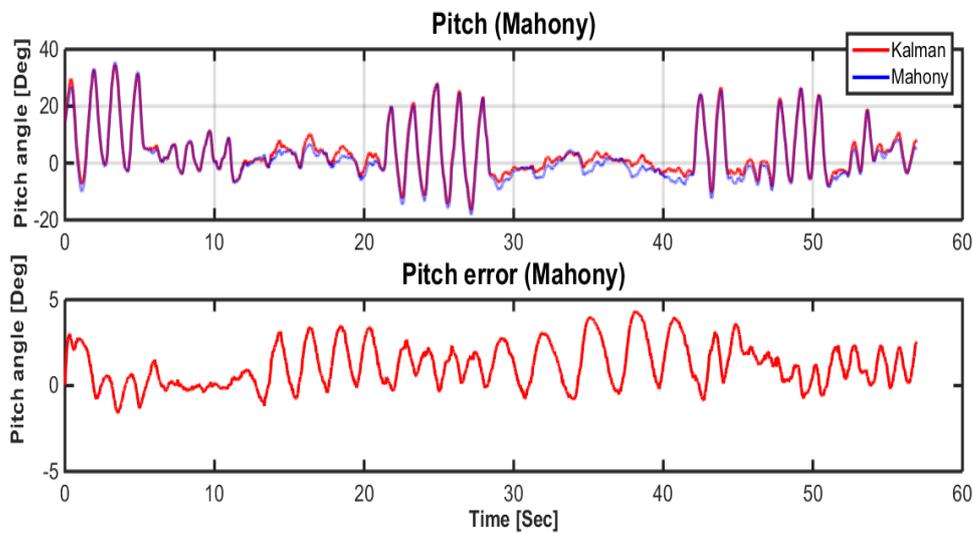


Figure 15. Pitch using Mahony (Moving scenario)

Table 2. Data analysis of Complementary and Mahony filters in Moving scenario

	Complementary		Mahony	
	Pitch	Roll	Pitch	Roll
Maximum Error (deg)	11.157	13.918	4.316	4.954
Minimum Error (deg)	0.0002	0.0002	0.0001	0.0003
Error Mean (deg)	2.642	2.679	1.311	1.250
Error Standard deviation(deg)	1.914	2	1.093	1.024

Data analysis in table 2 shows that Mahony filter presented better efficiency than Complementary filter in pitch and roll channels, where maximum error, minimum error, error mean value and standard deviation for Mahony for pitch are 4.316, 0.0001, 1.311 and 1.093 respectively and for roll are 4.954, 0.0003, 1.250 and 1.024 respectively, where maximum error, minimum error, error mean value and standard deviation for Complementary for pitch are 11.157, 0.0002, 2.642 and 1.914 respectively and for roll are 13.918, 0.0002, 2.679 and 2 respectively, which means that Mahony filter presents better efficiency than Complementary filter in maneuverable motion and high dynamics situations in both pitch and roll channels.

5. Conclusion

Power management is one of the most important keys in designing and implementation of an efficient embedded system to enhance stability and reduce noise and cost. One of the most utilized approaches for power management is reducing the software complexity, so in this work, low power consumption and efficient algorithms (Complementary and Mahony filters) for attitude angles estimation were utilized. From the result analysis, Complementary filter presented better efficiency than Mahony filter in steady flight and stationary situations in yaw, pitch and roll channels. On the other hand, Mahony filter presented better efficiency than Complementary filter in maneuverable motion and high dynamics situations in both pitch and roll channels.

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