

Performance Comparison of Experimental-based Kalman Filter and Complementary Filter for IMU Sensor Fusion by applying Quadrature Encoder

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Abstract- In this work, Kalman filter is designed with the help of C programming language and compared experimentally based on the actual Encoder values with Complementary estimation for Inertial Measurement Unit (IMU) sensor fusion. As IMU sensor, ADXL345 accelerometer and L3G4200D gyroscope are utilized in this analysis. For the actual rotation, the Quadrature encoder is applied with Arduino UNO by interrupt reading. Complementary filter is intended for human arm movement and Kalman filter is emphasized derived from the experimental covariance such as Q_{angle} for accelerometer trust level, Q_{bias} for gyroscope and R_{measure} for the measurement. The sable solution to this system is obtained via a chart display and root mean square error checking method. For the various changing to Kalman coefficient, the experimental test is performed and optimal estimation could be founded out at 0.001, 0.1 and 0.0001 for Q_{angle} , Q_{bias} and R_{measure} for Kalman filter.

Index Terms- Accelerometer, Complementary filter, Gyroscope, IMU sensor fusion, Kalman filter, Quadrature Encoder

I. INTRODUCTION

Remote manipulation of a robot by a human control at a safe distance becomes essential for various environment. Mobile robot can replicate human arm movement by applying inertial measurement units (IMU). IMU sensors dramatically reduced size along with decrease in cost and power utilization over decades. Development of reducing noise heads to get complete solution for applications of orientation estimation. Orientation and attitude estimation are extensively researched for several years. The angles computation of inclined device and its angular velocity can be used for many applications for aeronautics, distance travelled checking, transportation systems, human motion tracking, games, unmanned vehicle and virtual reality. IMU sensor fusion has been extensively adopted in many areas. Error and noise analysis in an IMU was studied for several years too [1]. Moreover IMU and magnetic sensing based yaw angle estimation was also done in [2]. In that work, gyroscope and compass data were used with Kalman filter for smoothness.

Recently, sensor fusion has been well developed so far that consequently generates many products. But checking error with actual tilt angle is still needed to carry out precisely. Particularly

in condition of significant lack of computational resources, complementary filter is used more than Kalman filter [3]. The explicit and gradient descent based orientation filter has been discussed in [4].

Except complementary filter, Kalman filter can also be applied to fuse accelerometer and gyroscope [5]. With the study of a relation between estimation accuracy and time consumption, the complementary filter has much less convergence speed than other filters.

In most case, mission time is important. According to the reference papers, Kalman filter shows a noisier output than the complementary filter. In the case of quad-rotor, the mission's time are not longer than 15 minutes, and with initial calibration the bias is not an issue for stabilization purposes. In reference [5] the algorithmic applied simplicity makes that the complementary is more suitable for embedded applications that were not much computational burden is available.

The publication in [6] pointed out that the complementary filter just operates on the noise (i.e it is constructed based on accelerometer noise and gyroscope bias) and is not affected by actual signals to be estimated. After discussing the basic equations, the two examples of the previous section are reworked using the steady-state Kalman filter approach [6].

The goal of this research work is to develop a new quadrature encoder based comparison for Kalman and complementary using accelerometer and gyroscope.

II. RELATED WORKS

In this study, to reduce calculation burden for microcontroller fast complementary filter is used with Kalman filter. Related research work on IMU fusion have been successfully done in [7], [8], [9] and [10]. But if there is no angle feedback from observer frame, the performance of the comparison cannot be done distinctly. The quadrature encoder can easily accomplish this requirement, and that can be done by using several microcontroller-based interrupt watching.

As the brains of the system, Arduino UNO is applied using its

- 1) Inter-integrated Communication (I2C) for sensor data reading
- 2) Two interrupt channels for Quadrature Encoder

3) Serial communication for serial data display.
 Fig. 1 represents the comparison model applied in this research work.

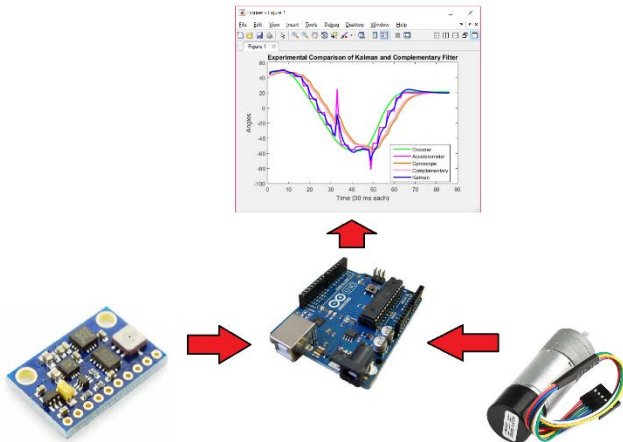


Fig. 1 Comparison Model using IMU, Encoder, Arduino and Chart Display

III. ENCODER-BASED ROBOTIC ARM DESIGN

In Rotary encoder is a shaft encoder that can convert the angular position to analog or digital signal. They are used in so many applications such as industrial control, robotics, rotating radar and high precision angle movement control etc.

The YFRobot motor is used for this comparison. This is shown in Fig. 2. Hall-effect sensor based quadrature encoder channels are attached to interrupt pins of Arduino. Fig. 3 shows internal pull-up resistor for maximum supply voltage 20V.



Fig. 2 YFRobot GM25-13CPR JGA25 Gear Motor

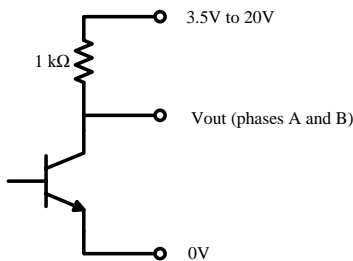


Fig. 3 Internal pull-up resistor connection of encoder

These types of motor have up to 8 kg.cm stall torque and 352 rpm at gear reduced 34:1 side. Experimentally 1 pulse of encoder is equal to $30/34 = 0.8823529$ degrees. That motor give only incremental or relative, it cannot give absolute angle.

For clockwise direction, Phase B leads than A. The interrupt watching attached to Phase B will check Phase A condition whenever it changes state LOW to HIGH or HIGH to LOW condition. After Phase A is changed LOW to HIGH condition,

the second interrupt will check Phase B condition. If it noticed Phase B stands at LOW condition, the rotation takes clockwise direction could be determined. This condition is represented as Fig. 4.

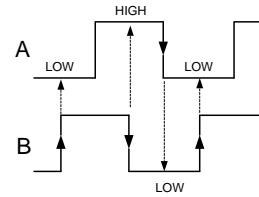


Fig. 4 Phase Condition for Clockwise Direction

For counter clockwise direction, Phase A leads than B. The interrupt watching attached to Phase B will also check Phase A condition whenever it changes state LOW to HIGH or HIGH to LOW condition.

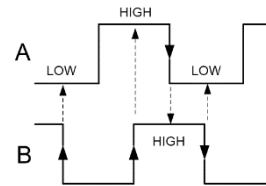


Fig. 5 Phase Condition for Counter Clockwise Direction

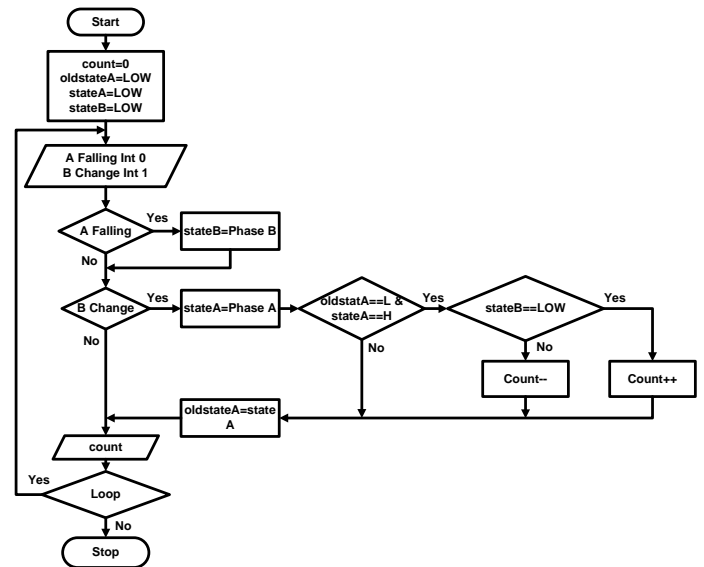


Fig. 6 Flowchart for Rotation Angle Sensing

After Phase A is changed LOW to HIGH condition, the second interrupt will also check Phase B condition. If it noticed Phase B stands at HIGH condition, we can surely determine that the rotation currently takes counter clockwise direction. This condition can be represented in Fig. 5. These above two consideration method can be represented as following flowchart of Fig. 6.

In this research work, pitch angle is applied using the encoder of DC motors. In this case, the encoders will give actual angular rotation angles instantly. This will reduce calculation burden and help for getting actual inclination compared to object reference frame. According to the type of encoder, each controller will read angle zero at program start. So we need to place arm position to original reference position before we start

data collecting. Fig. 7 mentions initialization program flow chart for this setup.

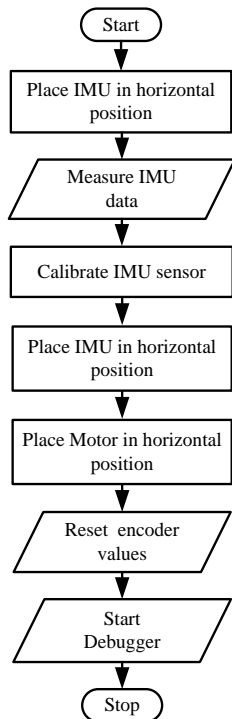


Fig. 7 flowchart for real-time debugger setup

IV. IMU SENSOR FUSION

A. IMU sensor

GY-80 module mounted with 3-axis accelerometer and 3-axis gyroscope is used to fuse sensing data using I2C protocol. This board combines five sensors into a single package and all sensors are all accessible using I2C communication. Among them ADXL345 accelerometer and L3G4200D gyroscope is used for this research work.

The ADXL345 is a small and it uses ultralow power. It can sense three axis with high resolution (13-bit) measurement at up to ± 16 g. Digital output data of ADXL345 is formatted as two 8-bits register and it is accessible through either a SPI (Serial Peripheral Interface) or I2C interface. This is well suited for mobile devices and portable conditions. It measures the static acceleration of gravity in inclination or declination sensing applications, as well as dynamic acceleration resulting from motion or shock. It has a high resolution (3.9 mg/LSB) for inclination changes less than 1.0° .

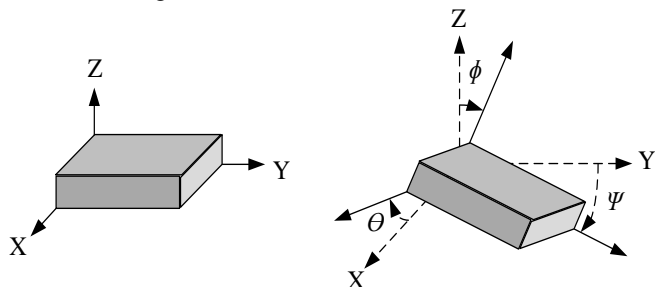


Fig. 8 Roll, Pitch and Yaw Angles of Inclined Object

The following equation can give

Roll (θ) - Angle of rotation along the X axis

Pitch (ψ) - Angle of rotation along the Y axis

Yaw (Φ)- Angle of rotation along the Z axis. Fig. 8 represents tilt angles of inclined object.

$$\theta = \text{atan} \left(\frac{Ax}{\sqrt{Ay^2 + Az^2}} \right) \quad (1)$$

$$\Psi = \text{atan} \left(\frac{Ay}{\sqrt{Ax^2 + Az^2}} \right) \quad (2)$$

$$\phi = \text{atan} \left(\frac{\sqrt{Ax^2 + Ay^2}}{Az} \right) \quad (3)$$

The L3G4200D is a three-axis angular rate sensor with I2C/SPI serial interface communication. The device has a full scale range of $\pm 250/\pm 500/\pm 2000$ degree per second. The device can be configured to generate interrupt signal to user by an independent wake-up condition. Gyroscope can detect only angular rate, so the new angle can be get from integrating rate and adding to old angle as follow.

$$\text{Angle}(n) = \text{Angle}(n-1) + \text{Rate} * dt \quad (4)$$

where dt= sampling period.

B. Complementary Filter

Accelerometer gives the acceleration with respect to the earth reference frame and gyroscope gives angular rate. The output of accelerometer is much nosier than that of gyroscope and gyroscope occurs non-return zero error due to integration. Acceleration can be converted into inclination angles using Euler's calculation and gyroscope rate can be integrated numerically. Control algorithm of complementary filter is shown in Fig. 9.

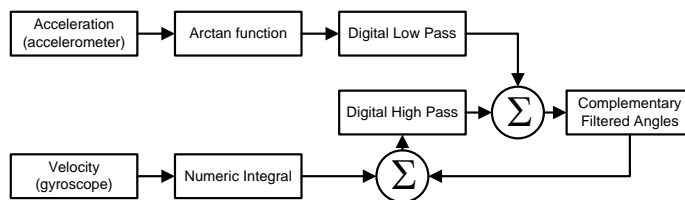


Fig. 9 Complementary Filter Representation Diagram

Complementary Filter coefficient α is can be calculated as

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

Where τ = Time Constant given by cutoff frequency and dt is sampling period.

According to the action of human arm, the speed of human arm and limbs fluctuates between 0 to 7 ms^{-1} . [10] Applying proportion to arm limb length and maximum reachable motion, the maximum angular rate of human arm is 0 to 5 degree per second. As an example, 7 meter up down movement for 0.5 meter limb gives $2 * \tan(3.5/1.5) = 0.08$ angle movement in one second.

For experimental analysis, the robotic arm is forced using human arm and the applied motor can rotate up to 352 rpm which is much faster than human arm movement speed. It means that motor speed is much enough to represent of human arm movement. For sensing and driving operation, complementary cutoff frequency is chosen 10 Hz which is much faster than human arm angular speed and much slower than motor maximum speed. Experimentally sampling rate of Arduino UNO for filter execution is 30 ms or 33.33 Hz. Coefficient α is now 0.769.

C. Kalman Filter

The Kalman filter could estimate the state of the system, based on current and previous states. It is more precise than the measurement alone. Generally the accelerometer is in general very noise when it is used to measure the gravitational acceleration since the arm is moving up and down. The problem with the gyroscope is that it drifts over time and it will start to fall down even it is losing movement speed. [12] It helps to determine that the gyroscope can only be trusted on a short term while the accelerometer on a long term.

The complimentary filter is easy to be used because it just consist of a digital low-pass filter for the accelerometer and digital high-pass filter for the gyroscope readings. But it is not as accurate as the Kalman filter. On the other hand, the complementary filter is less complicated and good for short observation time [3-4].

The Kalman filter operates by producing a optimal estimation of the state of the system based upon the measurements. There are two different noises: the noise of input to the filter called the measurement noise and the noise of the system itself called the process noise.

The Kalman filtering process was implemented for C programming using the following seven steps [12].

1. Estimation the current state based on previous states and gyroscope measurement

$$\hat{x}_{k|k-1} = F\hat{x}_{k-1|k-1} + B\dot{\theta}_k$$

In above expression, $\hat{x}_{k|k-1} = \begin{bmatrix} \theta \\ \theta_b \end{bmatrix}$ is priori state matrix containing accelerometer angle θ and gyroscope bias θ_b at the current time k based on the previous state.

$F = \begin{bmatrix} 1 & -\Delta t \\ 0 & 1 \end{bmatrix}$ is the state transition model.

The term $\hat{x}_{k|k-1}$ represents the previous state.

B is the control input model which is defined as $B = \begin{bmatrix} \Delta t \\ 0 \end{bmatrix}$ and multiply by gyroscope rate $\dot{\theta}_k$.

Simplify this stage give the following relation in C programming. At the program starts, rate and bias must be reset.

$$angle += rate(newrate - bias);$$

2. Estimation the priori error covariance matrix based on previous error covariance matrix

$$P_{k|k-1} = FP_{k-1|k-1}F^T + Q_k$$

In above expression, $P_{k|k-1}$ is a priori error covariance matrix which is calculated from $P_{k-1|k-1}$ previous state matrix. According to two type estimation, P is defined as $\begin{bmatrix} P_{00} & P_{01} \\ P_{10} & P_{11} \end{bmatrix}$. Q_k is the current process noise for accelerometer measurement. F and F^T are transport each other. After solving matrix equations, the following relations for C programming are got.

$$P00 += dt * (dt * P11 - P01 - P10 + Qangle);$$

$$P01 -= dt * P11;$$

$$P10 -= dt * P11;$$

$$P11 += Qbias * dt;$$

In above equation, Q-angle and Q-bias can be justified and experimentally implemented in this research work.

3. Computation the difference between the measurement and the priori state

$$\tilde{y}_k = Z_k - H\hat{x}_{k|k-1}$$

In this expression, \tilde{y}_k is the difference between measurement Z_k and priori state $\hat{x}_{k|k-1}$. The observation model $H = [1 \ 0]$ is applied for matrix multiplication. By C programming language it can be expressed as following. It is applied for Step 6.

$$y = newAngle - angle;$$

4. Calculation the innovation covariance S_k

$$S_k = HP_{k|k-1}H^T + R$$

After inserting previous equations, the following code can be written in C language. R or Rmeasure is the measurement covariance matrix which must be defined by user.

$$S = P00 + Rmeasure;$$

5. Calculation the Kalman gain

$$K_k = P_{k|k-1}H^T S_k^{-1}$$

$$K_k = \begin{bmatrix} K_0 \\ K_1 \end{bmatrix} \text{ Now the gains of Kalman began}$$

$$K0 = P00/S;$$

$$K1 = P10/S;$$

6. Updating the posteriori estimate of the current state

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \tilde{y}_k$$

By substitution above equations, new accelerometer and gyroscope angle can be calculated as follows.

$$angle += K0 * y;$$

$$bias += K1 * y;$$

7. Updating the posteriori error covariance matrix

$$P_{k|k} = (I - K_k H)P_{k|k-1}$$

For temporary usage and updated matrix will form as followings.

$$float P00_{temp} = P00;$$

$$float P01_{temp} = P01;$$

$$P00 -= K0 * P00_{temp};$$

$$P01 -= K0 * P01_{temp};$$

$$P10 -= K1 * P00_{temp};$$

$$P11 -= K1 * P01_{temp};$$

For most of IMU sensor such as ST L3FD20 3-axis digital output gyroscope, ST LSM303DLHC MEMS system, the following coefficients are used for Kalman filtering. Most of test used STM32 high performance microcontroller. [3]

$$Q_angle = 0.001$$

$$Q_gyroBias = 0.003$$

$$R_measure = 0.03$$

In this research work, low cost sensor and controller are used and it is not sure the above coefficients are still useful or not. So a practical observation on above coefficients will be discussed on coming section.

D. IMU Sensor Fusion

Functional block diagram is shown in Fig. 10. At first, program needs to check interrupt signal changes which is attached to A and B phase of Quadrature Encoder. Then, it is required to record time in milli-second. And then acceleration and gyroscope rate are measured. Moreover, the calculation using arctan function for acceleration and recording new milli-second time is preceded consequently. The time interval is calculated by subtracting old milli-second record from new one because the time stamp is increasing in every milli-second. For getting changes in one second rate, this time interval is divided by 1000 because gyroscope can give changes in one second only. Multiplying these rate and time interval gives the angle changes. By adding these angle changes to old angle, the inclination angle can be recorded. The complementary filtering will perform using predefined coefficient of 0.679 for low-pass and high-pass operations. According to the literature review, this coefficient is not different for experimental tests compared to design process [5-6]. So in this work, Kalman coefficients will be emphasized. After performing Kalman filtering, old angles are needed to replace with new angle for gyroscope rate calculation for next program sequence.

Fig. 10 Flowchart of Complementary Filter Process

As the heart of the system Arduino UNO board is used. 115200 baud rate is applied for serial communication to PC as shown in Fig. 11. The two interrupt channels are used for Quadrature encoder and I2C pins are applied for sensor board with respective address.

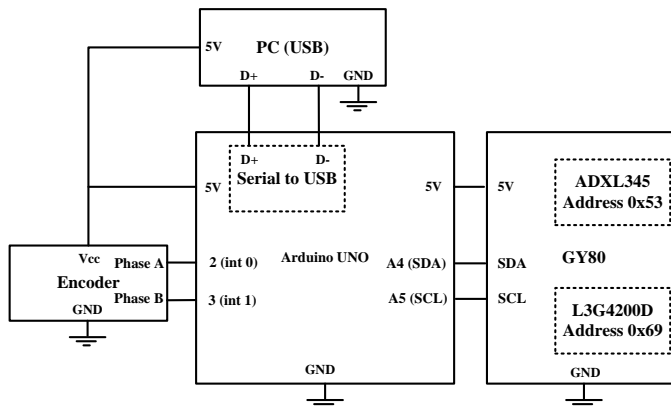


Fig. 11 Overall Block Diagram of the System

V. EXPERIMENTAL TEST AND RESULT

Experimental setup for the comparison process is shown in Fig. 12. The arm on which GY-80 board is attached and the rotation angle is cascaded with motor encoder. Real time pulses for both of encoder are measured using oscilloscope and precise measurement are displayed on PC.

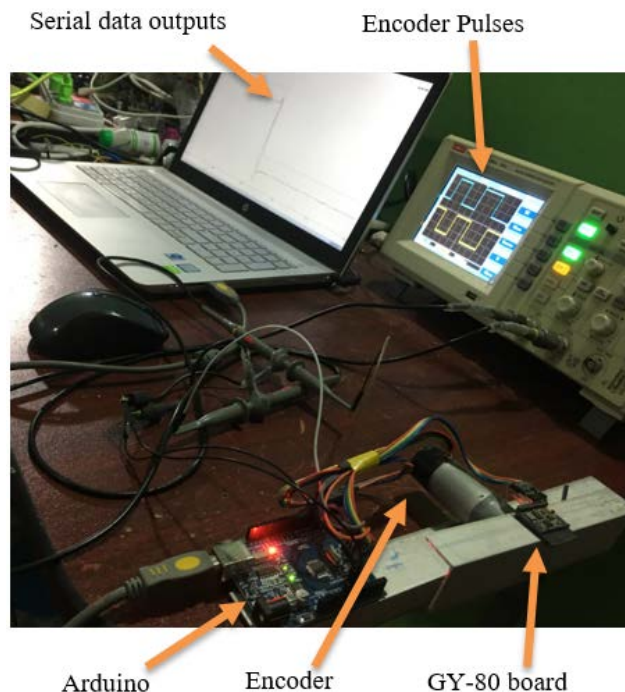
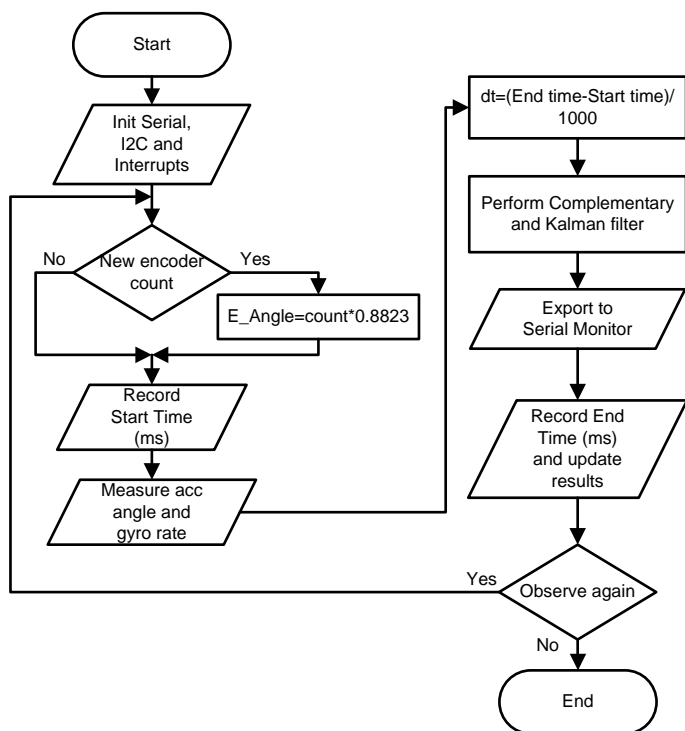


Fig. 12 Experimental Setup for Comparison Process

A. Experiment I

The first experiment is done using default Kalman setting. They are

float $Q_angle = 0.001$;
 float $Q_gyroBias = 0.003$;
 float $R_measure = 0.03$;

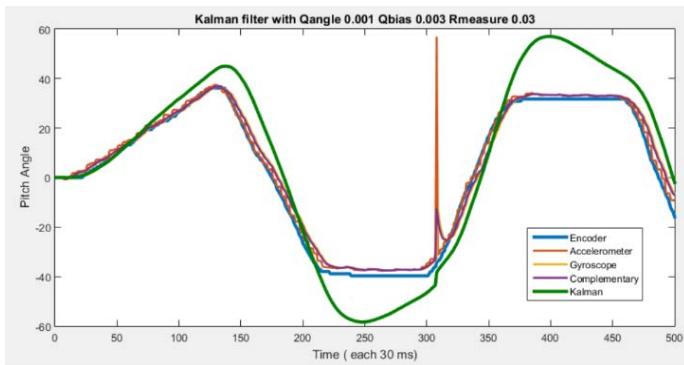


Fig. 13 Kalman Filter Test Using Default Setting

This experiment gives the result as shown in Fig. 13. Each interval of X-axis long for 30 milli-second which is Δt of program loop. Although Complementary outputs seem nearly equal to Encoder value, the Kalman outputs differ from Encoder values. It can be clearly seen that the difference between Encoder and Kalman filter is twenty degrees.

B. Experiment II

To reduce the difference between Encoder and Kalman filter, the trust level should be reduced. The measurement covariance matrix is reduced to 0.001 $R_measure$ value. The new result can be seen in Fig. 14.

At the beginning of the experiment II, the estimation of Kalman filter begins quite accurate. But it goes worse later. The measurement covariance value should be reduced less.

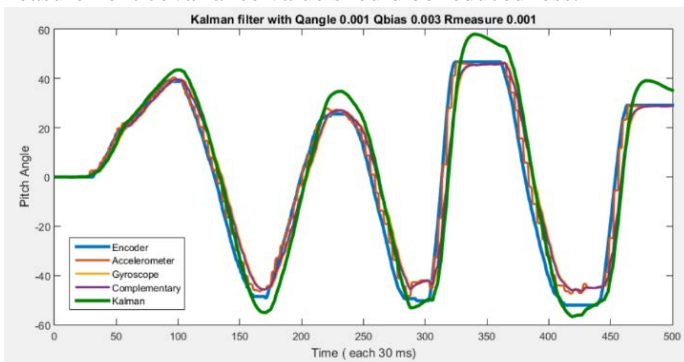


Fig. 14 Experimental Result for $R_measure$ Value of 0.001 Change

C. Experiment III

Now the $R_measure$ value is reduced to 0.001 and the result curve is shown in Fig. 15.

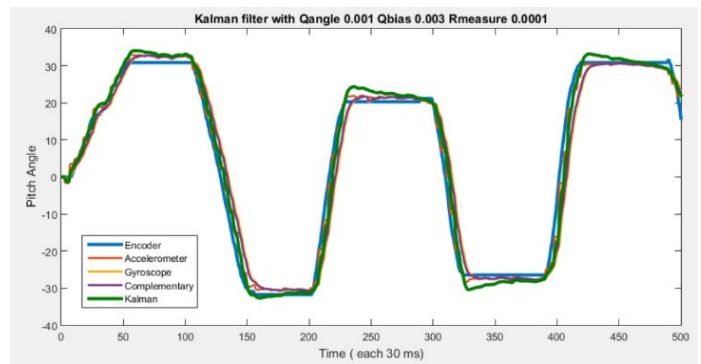


Fig. 15 Experimental result for $R_measure$ value of 0.0001 change
 Although the difference between Encoder and Kalman filter becomes narrow, the filter out is noisy as much as the output of accelerometer. It can be determined that the Q_bias should be increased for more trust in the value of gyroscope.

D. Experiment IV

Now the Q_bias is increased into the value of 0.1 and the result becomes as shown in Fig. 16.

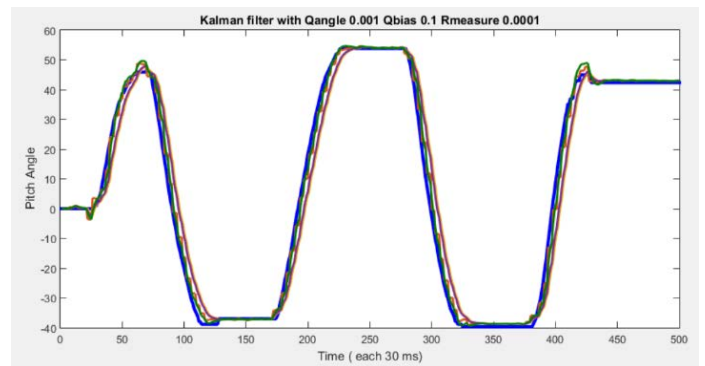


Fig. 16 Experimental result for Q_angle value of 0.1 change

Now, the value of Complementary filter and Kalman filter seem closely equal and the comparison should be started.

Now the curve in Fig. 16 are enlarged for X-axis values of 231 to 330 for the following figures. In Fig. 17, the Complementary filter output is closely to gyroscope value and it is big far from actual Encoder value. If its alpha value is decreased, its output would be look like accelerometer value and very noisy.

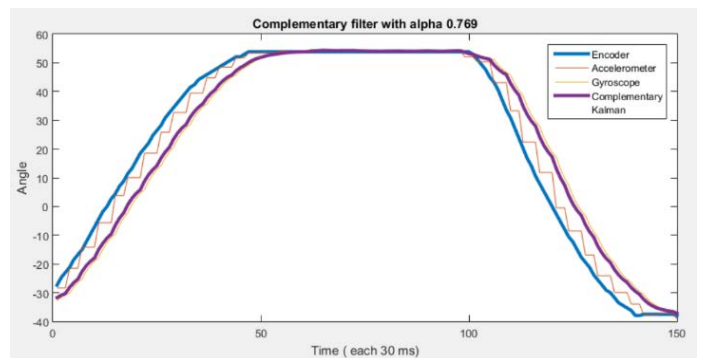


Fig. 17 Complementary filter output and IMU data

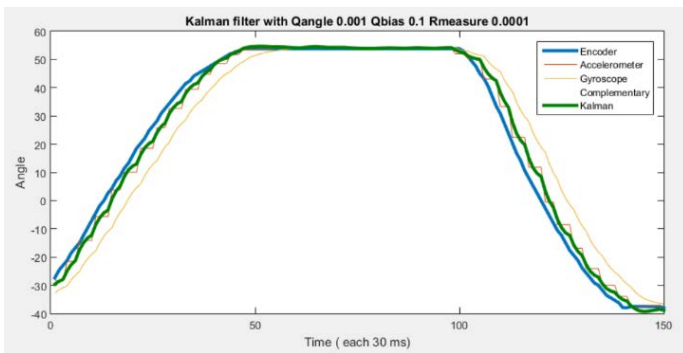


Fig. 18 Kalman filter output and IMU data

Fig. 18 shows the Kalman filter output is closely to accelerometer value and it is smooth like gyroscope value. There is small difference with actual Encoder value. It is much better than complementary filter output.

Fig. 19 shows the comparison of Complementary and Kalman filter outputs. There is small difference between Kalman filter and actual Encoder value. It is much better than complementary filter output because the Complementary output is much drift as gyroscope output.

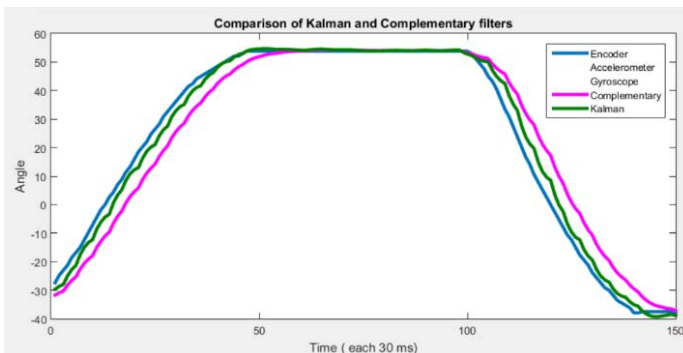


Fig. 19 Experimental setup for comparison process

For long term observation, RMSE (Root mean square error) method is used for the above experiments in this research work. This method can be express by using following equation and the results are shown in Table 1.

$$RMSE = \sqrt{\frac{\sum_{i=0}^N (\text{encoder}(i) - \text{IMU}(i))^2}{N}} \quad (6)$$

TABLE I
RMSE RESPONSE OF COMPLEMENTARY AND KALMAN FILTERS

Exp	Kalman			RMSE			
	Q angle	Q bias	R meas	Acc	Gyro	Com	Kal
1	0.0010	0.0030	0.0300	4.6268	3.9885	3.5689	12.7522
2	0.0010	0.0030	0.0010	4.4061	9.6989	8.2978	10.1673
3	0.0010	0.0030	0.0001	2.5255	5.5820	4.7698	3.2707
4	0.0010	0.1000	0.0001	3.1475	7.8699	6.6629	2.9872

Experiment I points out the bad estimation of Kalman filter which is worse than accelerometer, gyroscope and complementary filter. The value of RMSE error is 12.7522 and it is not acceptable range. But in experiment II, RMSE of Kalman

filter reduced to the value of 10.1673 as decrease R_{measure} covariance. Experiment III gives lower RMSE error while R_{measure} covariance is reduced to the value of 0.0001. Among them, experiment IV give lowest RMSE value of 2.9897 which is even half of Complementary filter value. It successfully points out a balance between estimation accuracy in a few milli-second.

VI. DISCUSSIONS AND CONCLUSION

In this research work, a comparative study between two filters were performed using IMU sensor fusion and quadrature encoder techniques, intended to be applied to the estimation of inclination angles of a human interactive robotic arm by experimentally. A compromise choice for filter coefficient with respect to theoretical studies and experimental observation. The experimental results pointed out that Kalman filter can be matched with the accuracy of inclination angle estimation using appropriate filter coefficient based on experimental turning. Moreover it can be clearly seen that the common filter coefficient are not good for estimation. It needs experimental test for low cost sensor and controller. Finally the Kalman based IMU fusion using Q_{angle} as 0.001, Q_{bias} as 0.1 and R_{measure} as 0.0001 shows a better and compact technique than popular Complementary filter which is less calculation than Kalman. As an advantage, the comparison method used in this research work shows the way of coefficient finding for other types of filters and helps the accuracy checking. The further extension for next step would be expanding the study of inclination angle estimation using other MEMS (Micro-electro-mechanical System) sensors and more appropriate sensor fusion methods.

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