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Real Time Noise Filtering for Low Cost IMU Sensors

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Abstract: A low cost Inertial Measurement Unit (IMU) sensor typically includes a gyroscope and an accelerometer with six degrees of freedom. Due to its low manufacturing cost, it is used in many small projects. However, the raw data from these sensors are not completely reliable as the accelerometer generates a lot of noise from physical vibrations and the gyroscope tends to produce a drift over time. Special filters such as complementary filter and Kalman filter are commonly used to reduce the noise in real-time. For simple applications complementary filter is fine but more complex and precise projects such as self-balancing robots and quadcopters requires the use of the Kalman filter. The Kalman filter algorithm is quite complex and has a lot of floating point matrix multiplications which can be very heavy for a small microprocessor such as arduino. In applications like quadcopter the Proportional Integral Derivative (PID) loop has to run at minimum 80 Hz. This research aims to develop a light weight modified version of Kalman filter which can be easily included as an external library. This allows fast looping time for the microprocessor. The primary purpose of this library is for applications which require low latency such as quadcopter and self-balancing robots but the library may prove to be useful in other similar projects too.

Key words: Complementary filter, Kalman filter, quadcopter, accelerometer, gyroscope inertial measurement unit, noise filtering, arduino, embedded sensors

INTRODUCTION

An Inertial Measurement Unit (IMU) generally contains an accelerometer, gyroscope, barometer and magnetometer. The output of this sensor is fed into the control algorithm to calculate positions, velocity, altitude, heading orientation depending on the applications. IMU sensors can be found in almost all forms of computer guided vehicles such as aircraft, ships, missiles, rockets and many other guidance system. In such applications, the IMU is of supreme quality, giving stable readings with extremely high precisions and bandwidth (Maklouf *et al*., 2013). IMU sensors have also found its way into civilian day to day applications such as robots, cars, Unmanned Arial Vehicle (UAV), automated ground vehicles and other automated systems (Auger *et al*., 2013).

Problem statement: At present, it is very expensive to implement high precision IMU sensors in small projects. Production costs cannot be reduced without compromising the quality, accuracy and bandwidth of the devices. The readings from these less-expensive IMU sensors (such as MPU 6050) contains a lot of noise and is not very precise, thus the raw data is not suitable for most application. This noise is further amplified by the external vibrations and magnetic fields generated by the components on the device itself. However, supporting noise filtering algorithms can be used to filter and fuse the noisy data to get accurate data.

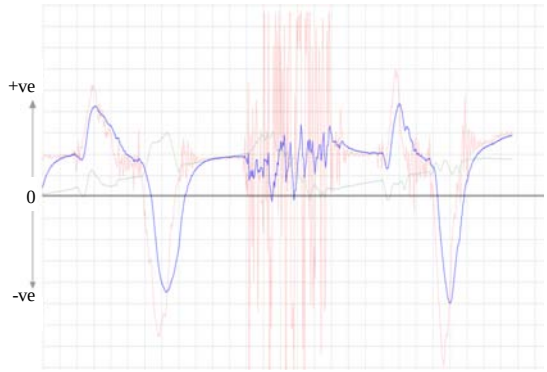

Fig. 1: Red) Accelerometer reading; green) Gyroscope reading and blue) Motor RPM

Figure 1 shows the raw data collected from a MPU 6050 sensor. The accelerometer readings (red) contains a lot of noise which is amplified by the motor vibrations but is stable over time and doesn't deviate as much from the true zero value. However, the gyroscope data (green) is very stable in short time intervals but the error accumulates over time and slowly deviates from the true value.

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MATERIALS AND METHODS

Complementary filter: The complementary filter is the simplest type of filter and very easy to implement. It gives the "best of both worlds" and by fusing the data from the gyroscope and accelerometer to a more stable filtered data. The accelerometer data keeps the output data from drifting from the true value whereas the gyroscope value removes the unwanted noise from the output. It uses a digital low pass filter on the accelerometer and a digital high pass filter on the gyroscope. The basic formulae for this type of filter is:

$$A_k = P \times (A_{k-1} + G_X \times dt) + Q \times (A_X) \quad (1)$$

Where:

$P+Q$ = 1
A_k = Current angle
A_{k-1} = Last known angle
G_x = Gyroscope measurement
A_x = Accelerometer measurement
dt = Delta time
P = Gyroscope sensitivity
Q = Accelerometer sensitivity

The basic complementary filter values can be changed to suit the need for the application (Fig. 2).

Figure 3 shows how the gyro sensitivity and accelerometer sensitivity parameters affects the output increasing the P (gyro sensitivity) value will give you a more jitter free graph. However, the drift will increase over time. Increasing the Q (acc sensitivity) will give you a more jittery graph but is reliable for long term.

Kalman filter: Kalman filter is a linear, discrete time, finite dimensional time-varying system that calculates the state estimate minimizing the mean square error. It computes by consecutive cycles of prediction and filtering. This filter is very powerful as it supports estimations of the past, present and even future states and can also compute when the precise nature of the modeled system is unknown.

Kalman filter was developed over 50 years ago by Rudolf E. Kalman. This filter was even used in Apollo Navigation Computer in Neil Armstrong's historic journey to the moon in 1969. Its minimum computational requirements, recursive properties and quick optimal estimator allows it to be used in a wide range of applications. Kalman filter is widely used for global positioning receivers, phase locked loops in radio equipment and in reading various sensor data (Faragher and Ramsey, 2012).

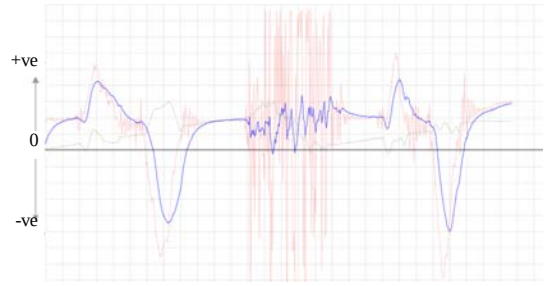

Fig 2: Complementary filter for P = 0.9; Q = 0.1; red) Accelerometer reading; green) Gyroscope reading and blue) Complementary filter output

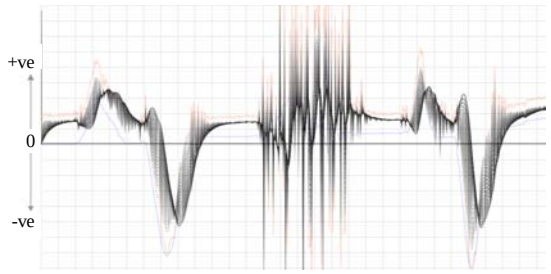

Fig. 3: Complementary filter for varying parameters P = 0.95 (black) to 0.00 (grey)

Kalman filter algorithm: The algorithm consists of three main stages calculate the kalman gain, calculate the current gain and calculate the new error in estimate (Zhang *et al*., 2014). These three phases run repeatedly over and over again filtering the raw data and estimating the output (Fig. 4).

Stage 1: Kalman Gain (KG) is calculated from the original or previous error. This previous error is re-used in the next iteration of the loop. The error in the measured data is in the range of uncertainty in the raw input data. The Kalman gain puts a relative importance between the estimated error and error in raw data. This gain is fed into the next phase for the calculation of current estimate (Fig. 5).

KG is a ratio between error in estimate and sum of error in estimate and measured value. Its value lies between 0 and 1 which tells us which parameter is more important:

$$KG = \frac{E_{EST}}{E_{EST} + E_{MEA}} \quad (2)$$

$$0 \leq KG \leq 1$$

Where:

KG = Kalman Gain
E_{EST} = Error in estimate
E_{MEA} = Error in measurement

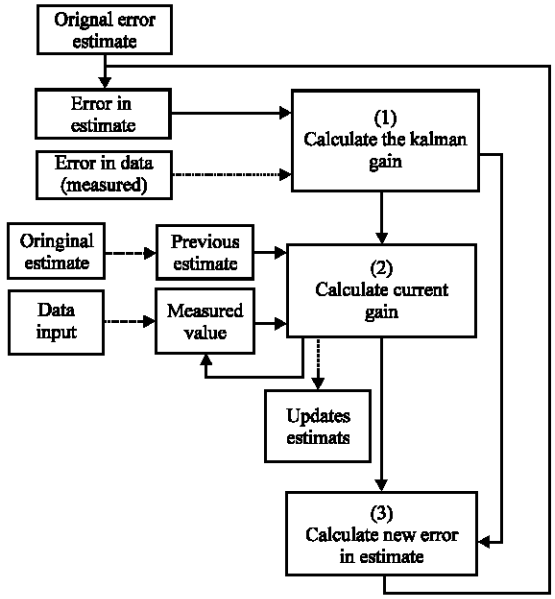

Fig. 4: Basic workflow of the Kalman filter algorithm

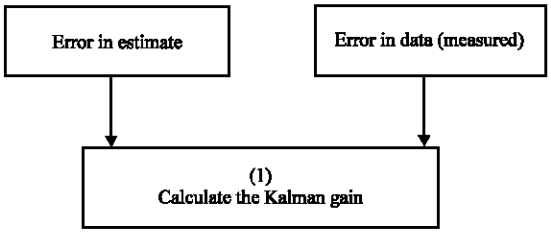

Fig. 5: Stage 1 of Kalman filter algorithm

Stage 2: In this stage, it takes into account the Kalman gain, the previous or original estimate and the raw data to calculate the current estimate. The estimate after every loop is reused in the next loop. In Kalman filter, the original (initial) estimate can be any value and the filter very quickly zeros in on the true value. By determining the KG value, we can decide which value is more important than the other. In this stage, the actual estimated value is calculated which is the main output of the algorithm:

$$EST_t = EST_{t-1} + KG[MEA - EST_{t-1}] \quad (3)$$

Where:
EST_t = Current/new estimate
EST_{t-1} = Previous estimate
MEA = Measurement

The difference between the previous estimate and current measured value is multiplied with Kalman gain which indicates the importance of the error. It is then add it to the previous estimate to come up to the current estimate (Fig. 6).

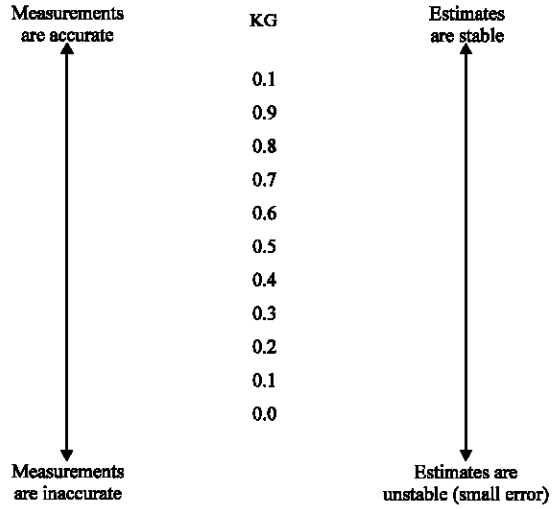

Fig. 6: Measurements and estimates according to Kalman gain

If Kalman Gain (KG) is close to 1, it means that the Error in Measurement (E_{MEA}) is very small (Stage 1) and the measurements are quite accurate. Therefore, the ($MEA-EST_{t-1}$) is very important and take a large portion of that. But if Kalman gain is small (close to 0) it means the Error in Measurement (E_{MEA}) is very large, then less emphasis is put on that therefore a small portion of the difference is taken. Typically, over time the Kalman gain will become smaller and smaller which indicates the estimates are getting closer to the true value and the result is not affected much by the noise in the measured value.

Stage 3: This stage takes into account of the Kalman gain and the current error estimate to calculate the estimate for the next loop:

$$E_{ESTt} = \frac{(E_{MEA})(E_{ESTt-1})}{(E_{MEA}) + (E_{ESTt-1})} \quad (4)$$

Or:

$$E_{ESTt} = [1-KG](E_{ESTt-1})$$

In general, the second equation is used for matrices where [1-KG] is the inverse of Kalman Gain. So if KG is high, the error in measurement is smal and it can quickly close in on the real value. If the KG is very low, then error in measurement is very large and therefore, we don't reduce the error in estimate very quickly and it zeros in to the real value very slowly.

Kalman filter in matrix form: Kalman filter is more frequently used in the form of matrix with

multidimensional inputs. The flowchart below gives a brief idea of how the matrices are calculated in the filter. A simple moving object in space with acceleration/deceleration is used as an example (Fig. 7).

The state matrix X is essentially the initial state and process covariance matrix (Ribeiro, 2004) and is typically the property value of the object. In this example, the state object will contain the position, velocity (2 dimensional) and acceleration (3 dimensional). The process covariance matrix simply represents the error in the process. This variable keeps track of the error through the filter loop:

$$X_k = AX_{k-1}+Bu_k+W_k$$

$$X = \begin{bmatrix} y \\ \dot{y} \end{bmatrix} B \begin{bmatrix} 1/2dT^2 \\ dT \end{bmatrix} = u = [g]$$

$$AX = \begin{bmatrix} 1 & dT \\ 0 & 1 \end{bmatrix} \begin{bmatrix} y \\ \dot{y} \end{bmatrix} = \begin{bmatrix} y+dT\dot{y} \\ 0+\dot{y} \end{bmatrix} \quad (5)$$

$$Bu = \begin{bmatrix} 1/2dT^2 \\ dT \end{bmatrix} [g] = \begin{bmatrix} g\,1/2\,dT^2 \\ gdT \end{bmatrix}$$

$$Xk = \begin{bmatrix} Y_{k-1}+dTY_{k-1}+1/2dT^2g \\ 0+Y_{k-1}+dTg \end{bmatrix}$$

The next part calculates the theoretical value based on calculation on the previous state. The u vector represents the control variable which includes the factors that are controlling the movement of the object such as the readings. Matrix a and b are simple matrices that are used to convert the old state to the new state. These matrices may need to be calculated separately at the beginning depending on the nature of filtering. The process covariance matrix is also updated periodically using A inverse and noise (Q).

Once, the predicted matrix is calculated, the actual reading is taken and merged with the prediction. The X_{km} is the actual reading; Matrix C is used to convert it into the right format and Z_k takes care of the measurement noise. Once, we have Y_K, we use the Kalman gain (K) to decide how much of the predicted value and actual measured value should be used in the final value.

Once the loop is complete, it updates the new process covariance matrix and also shows the updated state as an output.

Kalman filter Mathematical equations: The Mathematical equations to estimate the current state of the system at time k are as follows.

Prediction: First the current state is predicted based on the previous states and the new gyro measurement. The Matrix B is called the control unit since an extra input is included to estimate the current state at time k:

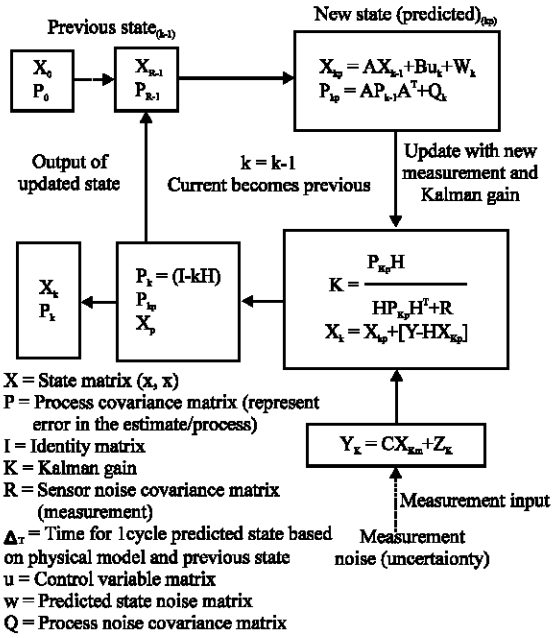

Fig. 7: Equation at each stage of the Kalman filter in matrix form

$$X_{k|k-1} = Fx_{k-1|k-1}+B\theta_k \quad (6)$$

Next the priori error covariance matrix is estimated based on the previous error covariance matrix:

$$P_{k|k-1} = FP_{k-1|k-1}+F^T+Q_k \quad (7)$$

This matrix is used to understand the importance of the values in the estimated state. The smaller the value, more importance is given to the current estimated state. The error covariance matrix will increase since we last updated this estimate. Therefore, the above equation can be explained as multiplying the error covariance matrix by the state model F and the transpose of Matrix F^T and add the current process noise Q_k at time k. The error covariance matrix is a 2×2 matrix as shown:

$$P = \begin{bmatrix} P00 & P01 \\ P10 & P11 \end{bmatrix} \quad (8)$$

Update: First the difference between the current measurement z_k and the priori state $x_{k|k-1}$ is computed. This is called innovation. H is the observation model that is used to map the priori state which is the measurement from the accelerometer and this y_k is not a matrix:

$$Y_k = Z_k-H\,x_{k|k-1} \quad (9)$$

Next the innovation covariance is calculated based on the priori covariance matrix and the measurement covariance matrix R. This value predicts the reliability of the measurement:

$$S_k = HP_{k|k-1}H^T+R \tag{10}$$

The bigger the value of measurement noise is the larger S_k will be. Therefore, less importance is given to the incoming measurement. S_k is not a matrix.

Next the Kalman gain is calculated. It indicates how much we trust the innovation measurements over error covariance:

$$K_k = P_{k|k-1}H^TS_k^{-1} \tag{11}$$

Kalman gain K_k is a 2×2 matrix as shown:

$$K=\begin{bmatrix}K_0\\K_1\end{bmatrix} \tag{12}$$

Now the posteriori estimate of the current state is updated by adding the priori state $x_{k|k-1}$ with the Kalman gain times the innovation y_k:

$$X_{k|k} = X_{k|k}+K_kY_k \tag{13}$$

Lastly, the posteriori error covariance matrix is updated:

$$P_{k|k} = \left(I-K_kH\right)P_{k|k-1} \tag{14}$$

Modeling

Kalman filter with single variable input: When the underlying model of application and sensor is simple, a single variable Kalman filter is sometimes enough to get rid of noise from the readings. This can be used where there is only accelerometer reading available or to smooth out the accelerometer reading and then merge it with the gyroscope readings. Since, only one reading is considered equations becomes very simple as shown:

$$\begin{aligned}P_k &= P_{k-1}+Q\\ KG &= \frac{P_k}{\left(P_k+R\right)}\\ X_k &= X_{k-1}+KG\times\left(M_k-X_{k-1}\right)\\ P_k &= \left(1-KG\right)\times P_k\end{aligned} \tag{15}$$

Where:

P = Estimated error
Q = Process noise
KG = Kalman Gain
R = Sensor noise
X = Value/output
M = Measurement/input
P = Estimated error

The filter needs to be initialized with the process noise Q and sensor noise R. The initial estimated error P and initial value of X need not be initialized. However, P should be high enough so that it can narrow down to its correct value. But adjusting the P and R is very important to get proper output.

Kalman filter with double variable input: For a more complex application, Kalman filter can be used in its real form of fusing the data of accelerometer and gyroscope. Some of these steps shows how equation can be simplified and implemented as:

$$\begin{aligned}X_{k|k-1} &= FX_{k-1|k-1}+B\theta_k\\ \begin{bmatrix}\theta\\ \theta_b\end{bmatrix}_{k|k-1} &= \begin{bmatrix}1 & -\Delta t\\ 0 & 1\end{bmatrix}\begin{bmatrix}\theta\\ \theta_b\end{bmatrix}_{k|k-1}+\begin{bmatrix}\Delta t\\ 0\end{bmatrix}\theta_k\\ &= \begin{bmatrix}\theta-\theta_b\Delta t\\ \theta_b\end{bmatrix}_{k-1|k-1}+\begin{bmatrix}\Delta t\\ 0\end{bmatrix}\theta_k\\ &= \begin{bmatrix}\theta-\theta_b\Delta t+\theta\Delta t\\ \theta_b\end{bmatrix}\\ &= \begin{bmatrix}\theta-\Delta t\left(\theta-\theta_b\right)\\ \theta_b\end{bmatrix}\end{aligned} \tag{16}$$

In Eq. 16, $\theta k|k-1$ which is the priori state is equal to the estimate of the previous state plus rate times Δt. And we assume the estimated bias equal to the previous one. This can be implemented as:

$$\begin{aligned}\text{Rate} &= \text{new\_rate-bias}\\ \text{Angle} &= \text{angle+rate}\times dt\end{aligned}$$

Now, we calculate the error covariance matrix P. Although, it contains complex matrix multiplication and transpose but can be simplified as shown:

$$\begin{aligned}P_{k|k-1} &= FP_{k-1|k-1}F^T+Q_k\\ \begin{bmatrix}P_{00} & P_{01}\\ P_{10} & P_{11}\end{bmatrix}_{k|k-1} &= \begin{bmatrix}1 & -\Delta t\\ 0 & 1\end{bmatrix}\begin{bmatrix}P_{00} & P_{01}\\ P_{10} & P_{11}\end{bmatrix}_{k|k-1}\begin{bmatrix}1 & 0\\ -\Delta t & 1\end{bmatrix}+\begin{bmatrix}Q\theta & 0\\ 0 & Q\theta_b\end{bmatrix}\Delta t\\ &= \begin{bmatrix}P_{00}-\Delta tP_{10} & P_{01}-\Delta tP_{11}\\ P_{10} & P_{11}\end{bmatrix}_{k|k-1}\begin{bmatrix}1 & 0\\ -\Delta t & 1\end{bmatrix}+\begin{bmatrix}Q\theta & 0\\ 0 & Q\theta_b\end{bmatrix}\Delta t\\ &= \begin{bmatrix}P_{00}-\Delta tP_{10}-\Delta t\left(P_{01}-\Delta tP_{11}\right) & P_{01}-\Delta tP_{11}\\ P_{10}-\Delta tP_{11} & P_{11}\end{bmatrix}_{k|k-1}+\begin{bmatrix}Q\theta & 0\\ 0 & Q\theta_b\end{bmatrix}\Delta t\\ &= \begin{bmatrix}P_{00}-\Delta tP_{10}-\Delta t\left(P_{01}-\Delta tP_{11}\right) & P_{01}-\Delta tP_{11}\\ P_{10}-\Delta tP_{11} & P_{11}+Q\theta_b\Delta t\end{bmatrix}\\ &= \begin{bmatrix}P_{00}-\Delta t\left(\Delta tP_{11}-P_{01}-P_{10}+Q\theta\right) & P_{01}-\Delta tP_{11}\\ P_{10}-\Delta tP_{11} & P_{11}+Q\theta_b\Delta t\end{bmatrix}\end{aligned} \tag{17}$$

In C, this can writte as:

$$\begin{aligned}P[0][0] &= P[0][0]+dt\times(dt\times P[1][1]-\\ &\quad P[0][1]-P[1][0]+Q\_angle\\ P[0][1] &= P[0][1]-dt\times P[1][1]\\ P[1][0] &= P[1][0]-dt\times P[1][1]\\ P[1][1] &= P[1][1]+Q\_gyro\_bias\times dt\end{aligned} \tag{18}$$

Next, we calculate the innovation:

$$\begin{aligned}y_k &= Z_k-Hx_{k|k-1}\\ &= Z_k-\begin{bmatrix}1 & 0\end{bmatrix}\begin{bmatrix}\theta\\ \theta_b\end{bmatrix}_{k|k-1}\\ &= Z_k-\theta_{k|k-1}\end{aligned} \tag{19}$$

In C, we can write this as:

$$Y = new\_angle\_angle \tag{20}$$

Next, we calculate the innovation covariance:

$$\begin{aligned}S_k &= HP_{k|k-1}H^T+R\\ &= \begin{bmatrix}1 & 0\end{bmatrix}\begin{bmatrix}P_{00} & P_{01}\\ P_{10} & P_{11}\end{bmatrix}_{k|k-1}\begin{bmatrix}1\\ 0\end{bmatrix}+R\\ &= P_{00k|k-1}+R\\ &= P_{00k|k-1}+var(measurement)\end{aligned} \tag{21}$$

This equation can be written as:

$$S = P[0][0]+R\_measure \tag{22}$$

Next, we calculate the Kalman gain:

$$\begin{aligned}k_k &= P_{k|k-1}H^TS_k^{-1}\\ \begin{bmatrix}K_0\\ K_1\end{bmatrix} &= \begin{bmatrix}P_{00} & P_{01}\\ P_{10} & P_{11}\end{bmatrix}_{k|k-1}\begin{bmatrix}1\\ 0\end{bmatrix}S_k^{-1}\\ &= \begin{bmatrix}P_{00}\\ P_{10}\end{bmatrix}_{k|k-1}S_k^{-1}\\ &= \frac{\begin{bmatrix}P_{00}\\ P_{10}\end{bmatrix}_{k|k-1}}{S_k}\end{aligned} \tag{23}$$

In Eq. 23 the last step, we have directly divided by S_k. However, we can do this since, we have changed the value of S to a single variable that is not a matrix. In the original form, it is a matrix and we had to take the inverse of it and multiply with the other matrix. In C code, we can write this as:

$$\begin{aligned}K[0] &= P[0][1]/S\\ K[1] &= P[1][0]/S\end{aligned} \tag{24}$$

Now, we update the posteriori state using the Kalman gain and previous posteriori state:

$$\begin{aligned}X_{k|k-1} &= X_{k|k-1}+k_kY_k\\ \begin{bmatrix}\theta\\ \theta_b\end{bmatrix}_{k|k-1} &= \begin{bmatrix}\theta\\ \theta_b\end{bmatrix}_{k|k-1}+\begin{bmatrix}k_0\\ k_1\end{bmatrix}_k y_k\\ &= \begin{bmatrix}\theta\\ \theta_b\end{bmatrix}_{k|k-1}+\begin{bmatrix}k_0 & y\\ k_1 & y\end{bmatrix}_k\end{aligned} \tag{25}$$

In C:

$$\begin{aligned}angle &= angle+K[0]\times y\\ bias &= bias+K[1]\times y\end{aligned}$$

To update the posteriori matrix:

$$\begin{aligned}P_{k|k} &= (1-k_kH)P_{k|k-1}\\ \begin{bmatrix}P_{00} & P_{01}\\ P_{10} & P_{11}\end{bmatrix} &= \left(\begin{bmatrix}1 & 0\\ 0 & 1\end{bmatrix}-\begin{bmatrix}k_0\\ k_1\end{bmatrix}_k\begin{bmatrix}1 & 0\end{bmatrix}\right)\begin{bmatrix}P_{00} & P_{01}\\ P_{10} & P_{11}\end{bmatrix}_{k|k-1}\\ &= \left(\begin{bmatrix}1 & 0\\ 0 & 1\end{bmatrix}-\begin{bmatrix}k_0 & 0\\ k_1 & 0\end{bmatrix}_k\right)\begin{bmatrix}P_{00} & P_{01}\\ P_{10} & P_{11}\end{bmatrix}_{k|k-1}\\ &= \begin{bmatrix}P_{00} & P_{01}\\ P_{10} & P_{11}\end{bmatrix}_{k|k-1}-\begin{bmatrix}k_0P_{00} & k_0P_{01}\\ k_1P_{00} & k_1P_{01}\end{bmatrix}_k\end{aligned} \tag{26}$$

In C, we can reduce it to:

$$\begin{aligned}P\_temp &= P\\ P[0][0] &= P[0][0]-k[0]\times P\_temp[0][0]\\ P[0][1] &= P[0][1]-k[0]\times P\_temp[0][1]\\ P[1][0] &= P[1][0]-k[1]\times P\_temp[0][0]\\ P[1][1] &= P[1][1]-k[1]\times P\_temp[0][1]\end{aligned} \tag{27}$$

RESULTS AND DISCUSSION

The exact same raw data is used as input for all the graphs. For simplicity, only one axis is been used. In Fig. 8, the blue line shows the output value. Although, it lags behind the real value but most of the noise is removed. It can be used in applications where a slight delay is acceptable.

In Fig. 9, it shows decreasing the sensor noise value R, will give a more non-delayed output. The R_measure, Q_angle and Q_bias values can be further tweaked to change the behaviour (Fig. 10-14).

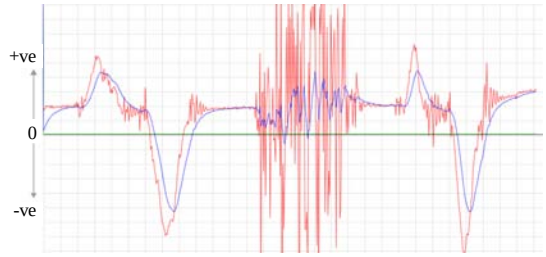

Fig. 8: Single variable Kalman filter on accelerometer value with P = 1.05; Q = 0.125; R = 10; red) Raw data and blue) Output

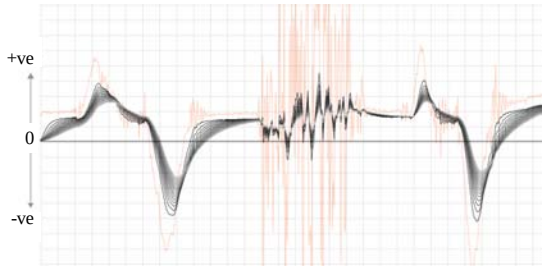

Fig. 9: Single variable Kalman filter on accelerometer value with variable R = 2 (black) to 40 (grey)

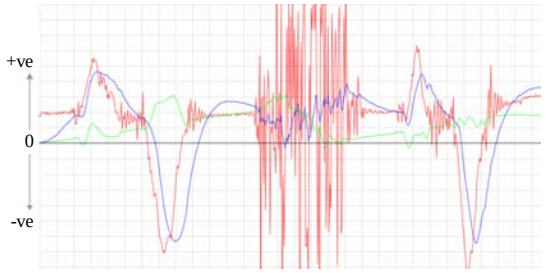

Fig. 10: Kalman filter output for multiple variable

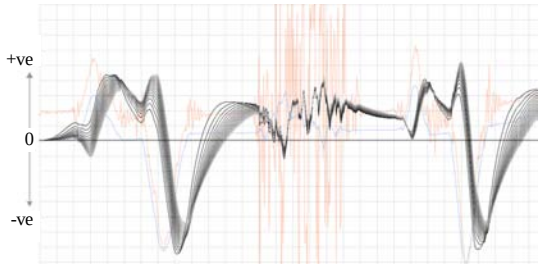

Fig. 11: Kalman filter with variable R_measure = 0.03 (black) to 0.43 (grey)

Library: The above algorithms are implemented and uploaded as an open-source project in GitHub. This library can be included in projects. The individual parameters can also be adjusted to suit the requirements.

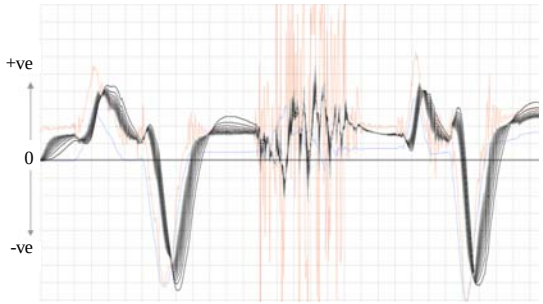

Fig. 12: Kalman filter with variable Q_angle = 0.001 (black) to 0.041 (grey)

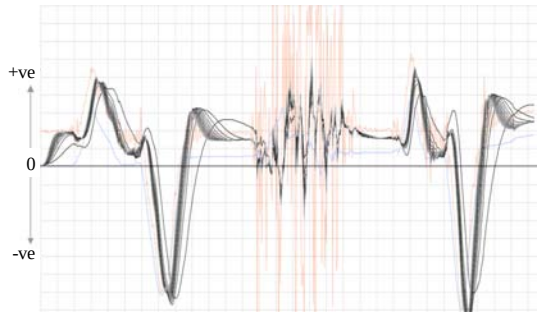

Fig. 13: Kalman filter with variable Q_bias = 0.003 (black) to 0.403 (grey)

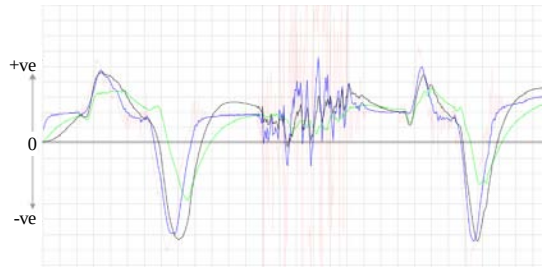

Fig. 14: Red) Accelerometer reading; green) Complementary filter and blue) Single variable Kalman filter and black) Double variable Kalman filter

Algorithm; GitHub Link:

https://github.com/diganta162004/KalmanFilterLite.git

Usage:

```
Kalman kalman = new Kalman()
float Q_angle = 0.001f
  Q_bias = 0.003f
  R_measure = 0.03f
kalman.setAngle(0.0)
kalman.set_params(Q_angle, Q_bias, R_measure)
while (data is available){
  // collect accelerometer (ax)
  // gyroscope (gx) and
  // delta time (dt)
  double angle = kalman.getAngle (ax, gx, dt)
```

CONCLUSION

In this study, we have seen three algorithms that can be used to remove noise from the raw data of a low cost IMU sensor. All of these algorithms are very lightweight and can be used in low processing devices such as Arduino without compromising the speed for other process. These are tested using an Arduino Uno board with a MPU6050 IMU sensor along with a simple PID algorithm for quadcopter runs well over 80 Hz (minimum for a stable quadcopter). Each of these algorithms gives a slightly different graph, based on delay, jitter and sensitivity.

The graph depicts all the filter outputs together. Each of these lines have a different behavior. As discussed in equations, the constant values can be further manipulated to get different outputs. However, deciding which algorithm will work best depends on the nature of the application.

LIMITATIONS

The algorithms managed to smooth out most of the noise, a from the motors running at high RPM. In the test scenario small amount of motor vibration steel creeps in to the output data. These are high frequency vibration noise no motor damping or frame vibration damping material is used which enabled us to get the raw result. However, in real life projects, one would generally balance the motors and use damping materials on the structure which helps to reduce these motor vibrations.

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REFERENCES

Auger, F., M. Hilairet, J.M. G uerrero, E. Monmasson and K.T. Orlowska *et al*., 2013. Industrial applications of the Kalman filter: A review. IEEE. Trans. Ind. Electron., 60: 5458-5471.

Faragher, R., 2012. Understanding the basis of the Kalman filter via. a simple and intuitive derivation (lecture notes). IEEE. Signal Process. Mag., 29: 128-132.

Maklouf, O., A. Ghila, A. Abdulla and A. Yousef, 2013. Low cost IMU-GPS integration using Kalman filtering for land vehicle navigation application. Intl. J. Electr. Rob. Electron. Commun. Eng., 7: 1-7.

Ribeiro, M.I., 2004. Kalman and extended Kalman filters: Concept, derivation and properties. MSc Thesis isR-Instituto de Sistemas e Robotica, Lisbon, Portugal.

Zhang, J., G. Welch, G. Bishop and Z. Huang, 2014. A two-stage Kalman filter approach for robust and real-time power system state estimation. IEEE. Trans. Sustainable Energy, 5: 629-636.