# Design and Implementation of Adaptive Vibration Filter for MEMS Based Low Cost IMU

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## Abstract

*Abstract*— In this work, an adaptive vibration filter was designed for Micro Electro-Mechanical System (MEMS) based low cost Inertial Measurement Unit (IMU). Designed IMU has ten degree freedom. It consists of three axis accelerometer, three axis gyroscope, three axis magnetometer and one axis barometric pressure sensor. All sensors are connected to Cortex M3 based microcontroller. Kalman Filter was used as sensor fusion algorithm. Although Kalman filter could overcome many noise sources, it could give undesirable output signal when sensors, which are combined with Kalman filter, were affected by simultaneously same noise like as vibration noise. So in order to overcome the vibration affection of IMU, an Adaptive Noise Canceller (ANC) was designed and implemented for the IMU. In addition, an experimental setup was built to compare the IMU output with and without ANC.

***Keywords—Adaptive Vibration Filter, Adaptive Noise Canceller, Kalman Filter, IMU, MEMS sesnsor***

## 1. Introduction

A physical system, which can move in free space, needs control to follow desired trajectory. Therefore, accurate orientation measurements are necessary to control these kinds of systems. Inertial Measurement Unit (IMU) is an essential device which is used for orientation measurement. An IMU can be designed with different types of sensors. Sensor based electronics, mechanics, optics are commonly used for IMU design. In last decade, Micro-Electro-Mechanical System (MEMS) types of sensors have very wide usage area because of its inexpensiveness and fast fabrication. Nowadays, in almost every smart phones, many navigation and robotic systems, MEMS sensors are used to measure the orientation. Despite of the wide usage of MEMS sensors, their measurements are corrupted from many noise sources

MEMS based IMU needs three different sensors to measure three axis orientation angle changes. Gyroscope, accelerometer and magnetometer are MEMS based sensor which are commonly used for IMU design. Accelerometer sensors are able to measure applied acceleration on its axis. In other words accelerometer can measure orientations change with using gravitational force vector. However, these sensors are capable of only measuring two axis orientations angle change because of gravitational vector intersect of only two planes. So accelerometer sensors generally are applied to roll and pitch measurements. MEMS based accelerometer is very sensitive to environmental noise. Therefore, this sensor doesn't provide reliable orientation measurements. Gyroscope is another sensor which can measure angular rate change on its axis. This sensor is capable of measuring three axis orientation angle changes. However, MEMS based gyroscope does not provide reliable orientation measurement because of bias drift problem. Thus, fusion of accelerometer and gyroscope makes it available to avoid noise and bias drift error. But this sensor group can only measure roll and pitch change. So another sensor is needed to combine with gyroscope for measuring yaw angle. Magnetometer is a general yaw sensor which works like compass and it can measure magnetic field of earth. Fusion of magnetometer and gyroscope provides more reliable yaw measurement.

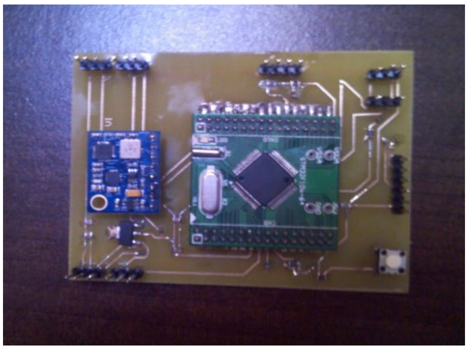
Kalman filter is a common sensor fusion algorithm. It is very widely used for IMU systems. In this work, linear Kalman filter algorithm was used for sensor fusion. Although, Kalman filter could overcome many structural and environmental noises, when sensors, in fusion algorithm, were affected simultaneously by same noise, Kalman filter could not eliminate this type noise, such as vibration. Both gyroscope and accelerometer are affected by vibration. Therefore, the IMU needs mechanical and software based vibration filter. In this work an adaptive filter was implemented on the IMU for software based vibration filter.

Adaptive filter is a mathematical tool which provides modelling of two signals in real time. Adaptive filter is based on the input and output structure of a signal. Its parameter is altered with the input-output correlation to provide desired signal output. An adaptive filter often consists of two parts. They are linear filter and adaptation algorithm. Finite Impulse Response (FIR), and Infinite Impulse Response (IIR) filters are most often linear filter parts of the adaptive filters. Least Mean Square (LMS), Mean Square Error (MSE) are most often used for adaptation algorithm of the adaptive filters [1]. There are many application of adaptive filter such as system identification, inverse modelling, linear prediction, feedforward control and Adaptive Noise Canceller (ANC). In this work, an ANC algorithm was implemented using LMS and FIR.

## 2. Sensors and Hardware of IMU

The designed IMU has four MEMS based sensor. MPU6050 is used for Gyroscope and Accelerometer. HMC5883L, another sensor, is an electronic compass. And last sensor in the IMU is BMP085, a barometric pressure sensor. Gyroscope and accelerometer sensors are in the same package in MPU6050.

Both sensors, inside the MPU6050, have 16 bit Analog Digital Converter (ADC). The MPU6050 can give digital output directly. Gyroscope is used for three axis angular velocity measurement and accelerometer is used for gravitational force vector measurement in two planes. HMC5883L is a three axis magnetometer sensor. This sensor can measure the strength and direction of the local magnetic field. The magnetometer sensor can define the yaw angle with respect to North Pole of the Earth. BMP085 is a one axis barometric pressure sensor, which is capable of measuring altitude by using air pressure and temperature change. The designed IMU system is shown in Picture 1.



Picture 1: Inertial Measurement Unit

Hardware of the IMU is based on Cortex M3 based microcontroller and sensor board. All sensors are in one board and connect to the microcontroller over Inner Integrated Circuit Communication (I2C) bus. Figure 1 shows the hardware of the IMU. The microcontroller reads all sensors and makes necessary calculation in real time. Serial interface of the microcontroller is used for debug monitoring of the system. IMU board has four PWM output port to control brushless and servo motors. One of the ADC input is used for vibration sensor.

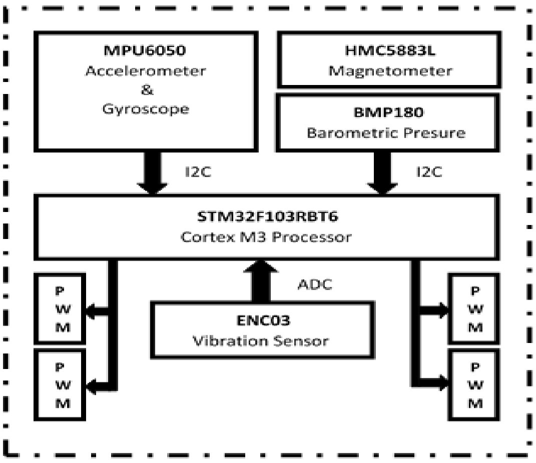



Figure 1: Hardware of The IMU

The IMU system has ten degree freedom. Therefore, system can take ten measurements. Measurement axis and symbol of the IMU are shown in fig 2. Tree axis Gyroscope sensor measurements are represented by $\boldsymbol{w_x}$, $\boldsymbol{w_y}$, $\boldsymbol{w_z}$. Three axis accelerometer measurements are represented $\boldsymbol{a_z}$, $\boldsymbol{a_y}$, $\boldsymbol{a_z}$. The measurements of the magnetometer are represented by $\boldsymbol{m_x}$, $\boldsymbol{m_y}$, $\boldsymbol{m_z}$. Finally, the barometric pressure sensor is represented by only $\boldsymbol{h_z}$ symbol.

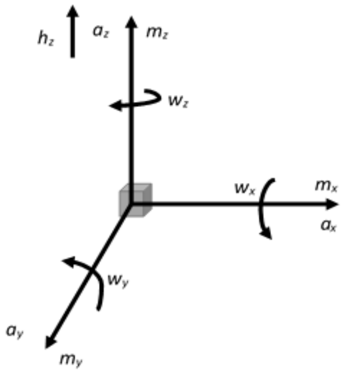



Figure 2: Measurement Axis of the IMU

MEMS based gyroscope and accelerometer sensor have similar structural error source. So, to use these sensors, error source should be defined and subtracted from measurement. Offset error, misalignment and scale factor error are main structural error source in MEMS based gyroscope and accelerometer. Gyroscope and accelerometer are expected to have no signal output when sensor is in stationary condition. But MEMS based gyroscope and accelerometer can give signal outputs in spite of being in stationary condition. These errors are called offset errors. They are added to sensor measurements as structural noise. Gyroscope and accelerometer have another error source because of misalignment of the micro mechanical mass. Scale factor error is caused by ADC unit of sensors because some data is lost during the conversion. In order to overcome these structural noises, the sensors in IMU, were calibrated. Details of the calibration can be found in reference [2].

## 3. Filter Model

Filters are one of the most important part of designing IMU. There are many noise sources for sensors. Therefore, hardware and software based filters are necessary in order to obtain high accuracy measurement from the sensors. There are two essential noises for sensors; one is structural noise and the other is environmental noise. Environmental and structural noises are varied according to sensor types. Some MEMS based movement sensors, such as accelerometers, are very sensitive to small impact and vibration. On the other hand, electronic compass sensor which measures magnetic field of the earth is not sensitive to mechanical vibration, but it is affected by electromagnetic field of electronic device and some metals. So, while accelerometer sensor needs mechanical vibration filter and software based low pass filter, electronic compass sensor needs shielding and calibration. For that reason, sensors in IMU should be analyzed well in order to define filter model.

### 3.1. Kalman Filter

Kalman filter is an optimal filter which is based on mean square error minimization. It uses a set of mathematical equation which estimate state of a system. Kalman filter has a very wide application area, particularly autonomous or assisted Navigation system. It is capable to provide more reliable sensor measurement in noisy environment. For this reason, Kalman filter is an important part of IMU system. It is used mainly for sensor fusion algorithm in IMU. Kalman filter algorithm has two main parts; one is time update and the other one is measurement update. These two parts call each other recursively. Because of the recursive structure, Kalman filter can be used for real time system

State equations of discrete time linear measurement system are shown in equation 1, 2.

$$x_k = A\hat{x}_{k-1} + Bu_k + w_{k-1} \tag{1}$$

$$z_k = Hx_k + v_k \tag{2}$$

A, B, and H index represent the state space matrix. White noise of the system is represented by $w_{k-1}$ and $v_k$. In equation 1, $x_k$ is signal value and $u_k$ is control signal and In equation 2, $z_k$ represent measurement value. For measurement system, there is no control signal so $Bu_k$ is negligible. System covariance matrix is defined in equation 3 and 4.

$$E[w_k w_k^T] = Q_k \tag{3}$$

$$E[v_k v_k^T] = R_k \tag{4}$$

System state estimation is defined in equation 5.

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-) \tag{5}$$

In equation 5, $K_k$ represents Kalman gain and is calculate as equation 6.

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1}. \tag{6}$$

Equation 7 and 8 represent prıor and posterior error covariance matrix.

$$P_k^- = A\ P_{k-1} A^T + Q \tag{7}$$

$$P_k = (I - K_k H)P_k^- \tag{8}$$

The recursive Kalman filter algorithm is shown in fig. 3. The details of the above equations can be found in Welch and Bishop [3]. Kalman filter in IMU has six inputs and three outputs. The Accelerometer sensor provides roll and pitch angle which are combined gyroscope roll and pitch angular rate change with Kalman filter. The magnetometer sensor provide yaw angle which is combined gyro yaw angular rate change with Kalman filter.

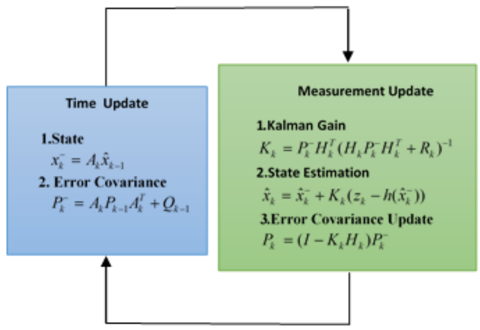



Figure 3: Kalman Filter Algorithm

Kalman filter gives roll, pitch and yaw angle of the system. Angle measurement block is shown in fig. 4.

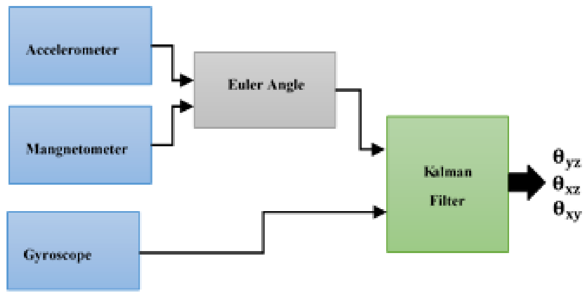



Figure 4: Kalman Block Diagram

### 3.2. Adaptive Vibration Filter

The Adaptive filter in IMU is based on Adaptive Noise Canceller (ANC). ANC is an optimal filtering that makes an estimate of the noise in the source signal and subtracts the noise from the source signal. Filtering processes in ANC could have two or more input. Main input is signal source that contains noises and signal together; others are reference input signals which are correlated with noise. It is possible to make simultaneously adaptation for different noise source with ANC. But every noise should have its own reference input and adaptation algorithm. The basic structure of the ANC for one noise input is shown in fig. 5.

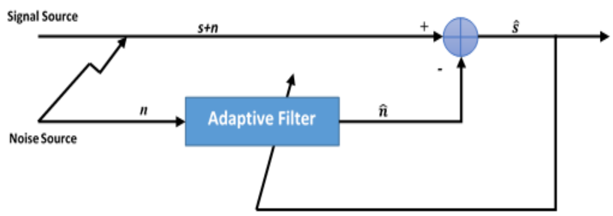



Figure 5: Basic Adaptive Noise Canceller Diagram

In figure 5, the source and the noise signal are represented by $s$ and $n$ symbols. $\hat{n}$ is estimated noise and $\hat{s}$ is filtered output of the adaptive filter. ANC is updated by using filtering parameter of adaptation criteria. As known, filter and adaptation criteria are important parts of the ANC.

The criteria are generally based on the minimization of the error. Different types of algorithm could be used for the minimization criteria. e.g. Least Mean Squares (LMS) algorithm, the Recursive Least Squares (RLS) algorithm, Normalized least Mean Squares(NLMS) etc. In IMU, LMS was implemented for adaptation criteria. Because LMS is computationally easy and could be applied on real time data simultaneously [4, 5]. In addition, for filtering, FIR was chosen. Adaptive filter structure could be seen in fig. 6. LMS update the FIR filter coefficient using step descent algorithm.

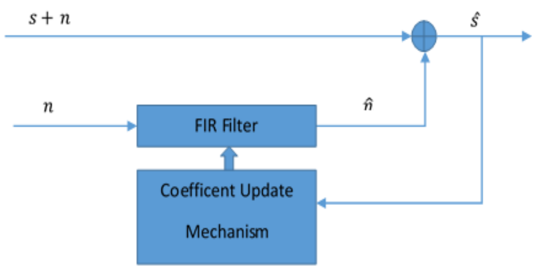



Figure 6: ANC Block In IMU

Basic FIR filtering is defined in equation 9, which is summation of input signal array multiplied with filter coefficient $b_i$.

$$n_k = \sum_{i=0}^{K-1} b_i x_{k-i} \tag{9}$$

The output of the ANC is defined in equation 10. Noise in the signal is subtracted from noise correlated filter output. Therefore The ANC output is expected to be close to the main signal.

$$\hat{s} = s + (n - \hat{n}) \tag{10}$$

Taking expectation of squaring the equation 10 is

$$E[\hat{s}^2] = E[s^2] + E[(n-\hat{n})^2]. \tag{11}$$

Minimization of equation 11 minimizes the expected value of noise, because signal power will not be affected by minimization. Above-referred state is shown in equation 12.

$$\min E[\hat{s}^2] = E[s^2] + \min E[(n-\hat{n})^2] \tag{12}$$

Therefore, the minimization criteria is

$$J = E[\hat{s}^2] \tag{13}$$

In order to obtain mean square error solution, partial derivative of equation 13 is taken with respect to filtering coefficients. So the result is shown in equation 14.

$$\frac{\partial J}{\partial b_i} = 2E[\hat{s}_k x_{k-i}] = 2E[s_k x_{k-i}] - 2\sum_{m=0}^{K-1} b_m E[x_{k-m} x_{k-i}] \tag{14}$$

Optimum solution is shown in equation 15.

$$(S_x b = x_{xs}). \tag{15}$$

Iterative gradient algorithm of the filter coefficient is

$$\forall i \in [0, K-1] b_i(k+1) = b_i(k) + \delta E(s_k x_{k-i}). \tag{16}$$

In equation 16, $\delta$ represents adaptation step. The convergence criteria depend on the adaptation step in equation 17.

$$|\delta| < \frac{2}{\lambda_{\max}} \tag{17}$$

In equation 17, $\lambda_{max}$ is maximum Eigen value of the $S_x$. However, the mean value of $E(\hat{s}_k x_{k-i})$ is unknown, so The mean value of $E(\hat{s}_k x_{k-i})$ is replaced with $\hat{s}_k x_{k-i}$ in stochastic gradient algorithm. So the convergences depend on small adaptation step in equation 18.

$$\forall i \in [0, K-1] b_i(k+1) = b_i(k) + \delta(s_k x_{k-i}) \tag{18}$$

In IMU, three axis gyro measurements are filtered using ANC. Because of using analog gyroscope sensor as vibration sensor, noise signal is correlated with main signal. But Analog gyro sensor is capable of only one axis measurement. Therefore analog gyroscope sensor is settled on pitch axis of system and tilt angle change is subtracted from analog gyroscope sensor. ANC works when system is stationary. The basic block of ANC is shown in fig. 7.

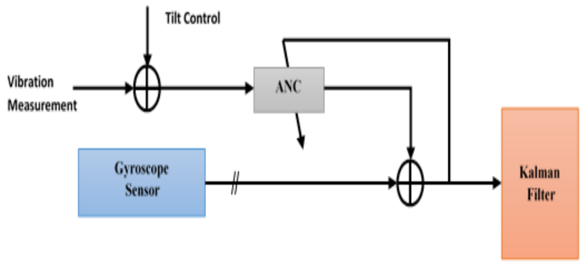



Figure 7: Adaptive Noise Canceller

## 4. Experimental Result

The designed ANC algorithm is implemented on dual tilt rotor system which has two brushless motors and two servo motors. The brushless motors are driven by Electronic Speed Controller (ESC). The servos and brushless motors are controlled by Pulse Width Modulated (PWM) signal which is generated by the IMU. Servos are used for changing tilt angle of brushless motors. Brushless motors provide force to vertical direction by using three blade propellers. The test system can be seen on Pic. 2. There are many vibration sources on the system such as mechanical structure of system, servos, and brushless motors. But Main vibration sources are brushless motors and propellers. In order to increase the vibration in the system, both propellers are chosen clock wise (CW) direction and both brushless motors are settled CW direction. The IMU is mounted on center of the main arm with mechanical vibration absorber.

Vibration sensor is mounted directly on mechanical skeleton on center of the system.

Picture 2: Experimental Setup

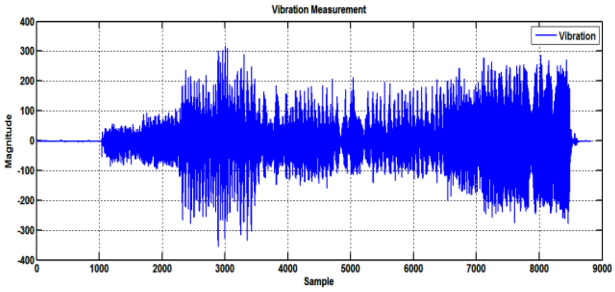



Figure 8: Vibration measurement

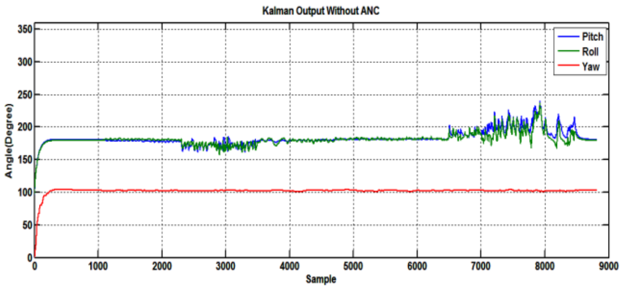



Figure 9: Kalman filter output without ANC

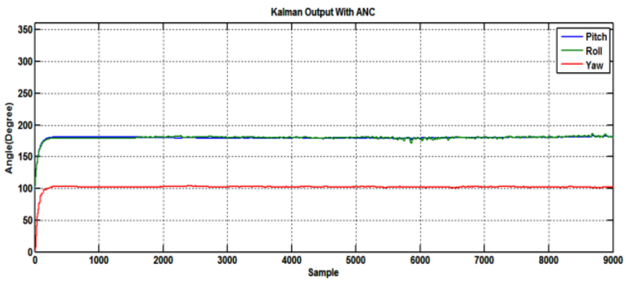



Figure 10: Kalman filter output with ANC

In the experiment, firstly, the IMU system operates and measures yaw, pitch and roll angle change, after 20 seconds, brushless motors operates with initial speed (approximately 2700rpm) then in every 10 seconds, the motor speed is increased 400 rpm automatically. When brushless motor speed rises approximately 4300 rpm, the system is stopped. During the test process, IMU sends vibration value, yaw, pitch and roll angle data to computer over serial interface of microprocessor.

Vibration measurement change is shown in fig. 8. Its characteristic varies according to the speed of the system. Low and high speed of system causes more vibration; however speed change does not linearly depend on vibration because of mechanical structure of the test system. In addition, the IMU output has different behavior. Because, Kalman filter in the IMU could overcome some vibration change but not all. When both gyroscope and accelerometer are affected from vibration noise, Kalman filter gives output signal as if there is orientation change. The IMU output signal without ANC could be seen in fig. 9. The Pitch and roll angle outputs are affected by vibration of the system. But the yaw output is not affected by vibration because magnetometer does not have mechanical mass inside. On the other hand, when the ANC suppress the vibration noise in gyroscope sensor, vibration affection tremendously decreases. The figure 10 shows the Kalman filter output signal with ANC.

## 5. Conclusions

In this work, an adaptive noise canceller was implemented for low cost IMU in order to suppress vibrations which corrupt the Kalman filter output. Adaptive noise canceller is based on MSE and FIR filtering. All algorithms run on the microcontroller. One axis analog gyroscope sensor is used as vibration sensor. Therefore vibration data contains both tilt angle change and vibration noise. To obtain the vibration, tilt angle control input signal is subtracted from vibration sensor measurements. IMU output signal is compared with ANC and without ANC algorithm. Experimental results show that ANC algorithm suppresses the vibration of test setup and Kalman filter provides more reliable and stable roll and pitch angle measurements. On the other hand, the vibration sensor has slow response time and ANC algorithm consumes approximately 6.3 ms CPU time every iteration. So, system refresh time must be limited at 50 Hz, but it is possible to improve the refresh frequency using different vibration sensor which has higher response time and faster microcontroller having higher clock frequency.

## 5. References

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