Analytical Review on the Techniques to Improve the Performance of Tilt Measurement by MPU 6050

Nayyer Nayab Malik and M. Javed Hyder

***Abstract*—This paper presents the viable techniques for implementation of inertial measurement unit (IMU) to effectively determine the orientation of mobile platform. Usually IMU is a MEMs device composed of three axis accelerometer and gyro. The raw data coming out of the sensor does not give the actual value due to induced noise and drift that requires proper filtering techniques to interpret the true output. In this research different approaches for filtering data are briefly discussed. Apart from that, the effect of utilizing multiple sensors on the quality of combined measured signals is also analyzed. The small scale experimental model has been setup, consisting of rectangular platform having capability to rotate in two dimensional axes. The sensors mounted on the platform are employed to detect the degree of tilt. The arduino mega 2560 is used to acquire data from IMU (MPU 6050) and Labview environment is selected as a software platform for the implementation. The current investigation would help in selecting the suitable methodology for achieving the high performance application of IMUs. The results show that the kalman filter precisely detects the inclination level requiring high computational cost. Increasing the number of sensors not only improves the performance of recorded data but also adds redundancy to the fail safe system.**

***Index Terms*—MPU 6050, Calibration Technique, Stability Platform, Multi Sensor Multi Fusion Strategy, LabVIEW.**

I. INTRODUCTION

THE estimation of orientation by inertial measurement units (IMUs) is becoming essential part of many applications including airborne& marine vehicles, tracking equipment, stability platforms, robots, bio-mechanical technology etc [1], [2], [3], [4], [5]. IMUs are the low cost MEMs devices usually consisting of accelerometers and gyros to determine the rotational movement of the maneuvering systems. The raw data from accelerometer is highly prone to noise due to vibrational and gravitational effects. Furthermore the gyroscope information is perturbed by the drift caused from the integration of measurement over time [6], [7]. To get the authentic details of measured response, different techniques have been developed to rectify the errors caused by the stochastic and systematic errors. In this paper, comprehensive analysis of some established filtering algorithms and calibration strategies have been carried out, giving reasonably true approximation of attitude of a body. Apart from that effect of fusion of data extracted from multiple sensors on the performance of the real-time monitoring is also briefly discussed.

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The disturbance and distortions in measuring the tilt from the IMU (MPU 6050) are usually mitigated by applying different filtering procedures. The accelerometers require low pass filter to attenuate the noise factor while high pass filter is needed to reduce the drifting effect of gyros [7]. In the past research various algorithms have been proposed to get sensible data. There are different approaches to get the degree of inclination either by utilizing the individual accelerometer/ gyro or by employing the sensor fusion techniques that combines the effect of both. The tilt level extracted only from accelerometers or gyro alone does not give appropriate pitch and roll information due to perturbations of the sensor response. The smoothing filters [6], [9] (moving average, Shavitzky-Golay) are able to filter the noise to some extent but induces delay in measured signal giving ambiguous response. To overcome these issues sensor fusion algorithms are adopted [10]. There are three basic sensor fusion algorithms including Kalman Filters, Extended Kalman Filter and Complementary Filters. The predominant approach is to utilize kalman filter that precisely estimates the orientation of a body, but it is highly complex and requires more computational resources. A popular method that is mostly applied to body level evaluation is complimentary filter. This method is not only easy to implement but also gives reasonably accurate results [17], [16]. The Enhanced Kalman Filter (EKF) is another way based on (KF) that is specifically evolved for conditioning the nonlinear system response to find out the rational readings of Euler angles. But due to several assumptions made by EKF, some of the of information is lost effecting the accuracy of the data [11]. Other advanced algorithms like particle filters and fuzzy logic procedures have been recently developed and implemented on various applications to get the valid data [13], [12].

To improve the performance of the readings obtained from IMUs, different considerations are to be made. The most important factor is the choice of the filter algorithm based on the type of application and the available computational resources. The static errors including static biases, scaling and sensor misalignment are also to be accounted for achieving reliable data. Apart from that the effect of system redundancy (by introduction of multiple MPU 6050 modules) are to be analyzed to check the quality of the measured orientation.

In this paper different filtering and calibration techniques are investigated to accurately measure the Euler angles of the tilting platform. A small scale experimental setup has been developed to examine and verify the capability of the adopted procedures. The inclination information from MPU mounted on the platform is acquired by Arduino Mega through

I^2C protocol. The algorithms are implemented in LabVIEW environment and performance data is analyzed. Calibration procedures are also discussed in the paper to get the appropriate reading. The main goal of this paper is the selection of the optimized criteria to attain appropriate and sustainable data from IMU.

II. Mitigation Techniques of MPU 6050

The emergence of MEMS technology played a vital role in the production of small scale and cost effective (with low power consumption) devices like IMU. Due to smaller size, these equipments are more prone to noise and disturbance. MPU 6050 consists of three axis accelerometers and gyros. The gyro gives the drifting output as the angular velocity is integrated overtime and any offset can persist. The accelerometer on the other hand are greatly affected by the vibration and external forces can give the wrong values[6]. To get the realistic orientation from the sensor, different methods are adopted to nullify the effect of induced errors.

A. Selection of Appropriate Filtering Algorithm

The sensor fusion filtering algorithms are employed to accurately determine the Euler angles. The roll angle is obtained by the accelerometer values from the x & z axis while the pitch is evaluated using the the y & z axis data [14], [11], [6], [15].

$$\phi_a = atan2(a_x, a_z) \tag{1}$$

$$\theta_a = atan2(a_y, a_z) \tag{2}$$

The gyro gives out the information based on the angular rates ($\dot{\phi}_g$ and $\dot{\theta}_g$) which are needed to be integrated over time to evaluate the Euler angles.

$$\phi_g = \int_{t_o}^{t} \dot{\phi}_g \tag{3}$$

$$\theta_g = \int_{t_o}^{t} \dot{\theta}_g \tag{4}$$

The choice of the filter is an important task that follows the considerations and requirements of a system. Various strategies have been presented in past research. Some of the popular techniques for 6 DOF IMU's are briefly discussed below:

1) Complementary Filter: Complementary filters are one of the popular techniques that are usually adopted due to its simplicity and ease of application[16]. Actually it make use of the high pass and low pass filters simultaneously. The low pass filters are used to reduce the jittery effect of accelerometers while the high pass filters minimize the drift of gyros. By fusing the accelerometer and integrated gyro data to get the realistic output signal. The complimentary filters iteratively update the Euler angles by the following updating formulas [6]:

$$\phi_c = \alpha(\phi_c + \phi_g \delta t) + (1 - \alpha)\phi_a \tag{5}$$

$$\theta_c = \alpha(\theta_c + \theta_g \delta t) + (1 - \alpha)\theta_a \tag{6}$$

The value of α is adjusted to properly tune the filter. To get the best possible results various optimization techniques can be applied.

2) Kalman Filter: Kalman filters are the widely used to estimate the behavior of the linear systems and Gaussian noise[18]. The mentioned scheme is a complex algorithm that is not only difficult to be implemented but also consumes more computational resources. The derivation of the kalman filter from the Bayesian analysis and the least square technique proves it to be the optimal solution for attenuating the noise and other signal distortions. It is a complex approach based on the state space vectors involving the present and previous values to approximate the signal. It precisely estimates the state value by combining values from sensors and a predicted theoretical output based on the system's dynamic model. Kalman filter model is developed by choosing the the pitch and roll angles from the accelerometers then estimating the constant gyro deviation.The predicted state for the system is calculated with the following equations [17], [6]:

$$x_k = Ax_{k-1} + Bu_k + w_{k-1} \tag{7}$$

The measurement model is represented by:

$$z_k = Hx_k + v_k \tag{8}$$

where A denotes state space matrix, B denotes the control matrix , H denotes observation matrix while u_k denotes the fixed drift from gyro. The discrete form of kalman filter equations are given by:

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_k \tag{9}$$

where subscript " $-$ " show the prior state

$$P_k^- = AP_{k-1}A^T + Q \tag{10}$$

$$K_k = P_k^- H^T (HP_K^- H^T + R)^{-1} \tag{11}$$

$$\hat{x}_k = \hat{x}^- + k_k(z_k + H\hat{x}_k^-) \tag{12}$$

$$P_k = (1 - K_k H)P_k^- \tag{13}$$

In the above equations $\hat{x}$ is the observer , H represents the transition matrix of the dynamic model and measurement model, Q shows the noise covariance matrix,R denotes updating parameters, P_k is the error covariance matrix and K_k is the kalman gain

3) Extended Kalman Filter: The Extended Kalman filter that is an extension of Kalman Filter that linearizes the system about its current state for estimating the nonlinear system. In some cases where the nonlinear system is approximated with a linear model, EKF may not perform well due to the missing data. The choice of unrealistic initial guess may lead to inappropriate response. This approach involve the computation of Jacobian matrices to derive the state-transition and observation matrices.In this approach (llike Kalman Filter) the predictor step of this filter, the current state and uncertainty of the system at the previous time step are propagated [11].

$$\hat{x}_k^- = f(\hat{x}_{k-1}, u_{k-1}) \tag{14}$$

$$P_k^- = A_k P_{k-1} A_k^T + Q \tag{15}$$

A_k is the Jacobian matrix containing the partial derivatives of the system function f(.) with respect to the current state, evaluated at the posterior state estimate of the last time step.

$$A_k = \left.\frac{\partial f(x)}{\partial x}\right|_{x=\hat{x}_{k-1}} \tag{16}$$

In the correction step, the prior state estimate is rectified with a full measurement.

$$K_k = P_k^- H_k^T (H P_K^- H_k^T + R)^{-1} \tag{17}$$

$$\hat{x}_k = \hat{x}^- + k_k(z_k + h\hat{x}_k^-) \tag{18}$$

$$P_k = (1 - K_k H_k) P_k^- \tag{19}$$

H_k is the Jacobian matrix that contains the partial derivatives of the measurement function h(.) with respect to the current state, evaluated at the prior state estimate.

$$H_k = \left.\frac{\partial h(x)}{\partial x}\right|_{x=\hat{x}_k^-} \tag{20}$$

Since the Jacobian matrices A_k and H_k are evaluated at the most recent state estimates, they must be computed on-line, leading to high computational costs.

B. Calibration of Static Errors

The IMUs due to smaller and are prone to systematic errors that are dependent on the function sensor input and the environmental conditions [19]. These errors can easily be removed by simple calibration techniques. Different types systematic errors can be observed including DC offsets, scalability factor, cross coupling and g-dependent disruptions [8], [20], [21]. The offset errors persist when the sensor output shows constant change in the reading for different tilting levels. Similarly the scalability errors occur due high or low sensitivity of the IMU that can result in unrealistic reading. Both the offset and scalability error can be calibrated by adding a certain value to the output response generated for different orientations. Cross-axis sensitivity is when the sensor picks up inertial forces which are not applied along its sensitive axis, this includes when the axes of the triad are not aligned correctly. Repeated adjustment is required to adjust the mounted sensor and the fixtures on the mobile platform. The g-errors are the fixed errors raised when a gyroscope mistakenly measures a specific fore as an angular rate that can be decreased through manual calibration of platform structure. Thermal errors are emerged due to varying environmental conditions. It can only be calibrated in lab environment at different temperatures.

C. Multi Module Muti Sensor Fusion

One unique way of reducing the noise is to utilize more than one IMUs. The modules are mounted on opposite sides of the platform on the same translational axis to get the complementary Euler values. The combined effect of the signals obtained from the sensor modules is filtered to achieve the reliable readings. It not only improves the quality of signal but also helpful in determining the sensor faults. Multiple Module Sensor Fusion can easily integrated to the system each module is accessed by I^2C protocol.

III. Experimental Setup

The experimental setup consists of a rectangular platform. The MPU 6050 module is mounted below the platform at appropriate positions.Two servo motors are attached to the platform producing the tilting affect. The motors and the sensor are connected to the data acquisition and control device (Arduino 2560) which generates and accepts the data signals. The acquired response from the sensor is then sent to the computer where it is filtered, analyzed, interpreted and displayed.

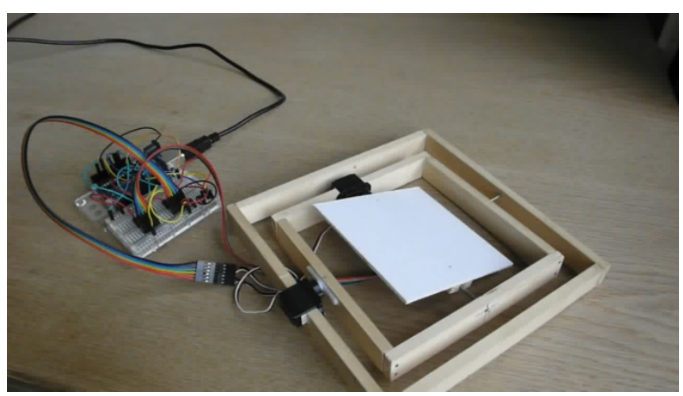

Fig. 1. Experimental Setup for Tilting Platform

The filtering algorithms have been implemented in LabVIEW environment. The data is logged to an excel file which is available for further analysis. The experiments are reconducted using multi sensor modules.

For carrying out the experiment, the platform is set to known fixed tilting level. Before determining the orientation from the

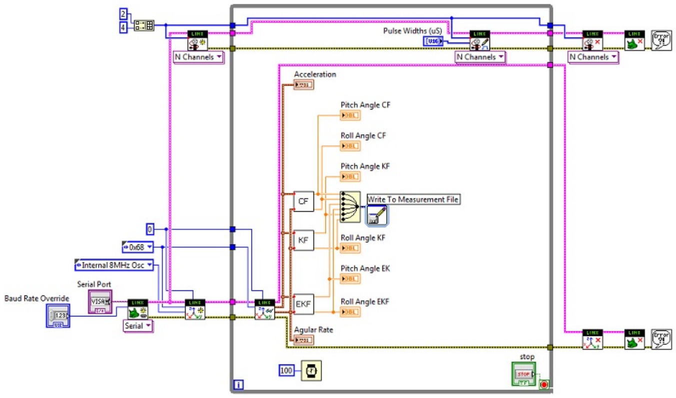

Fig. 2. Implementation of Algorithms in LabVIEW Environment

setup, calibration is carried out to reduce the static errors deviating the signal response giving inappropriate results. Initially the trial was performed with a single IMU (MPU 6050) against three different algorithm based signal conditioning techniques including kalman filter, extended kalman filter and complimentary filter. Same investigation is followed with combination of two sensor modules.

IV. Results and Analysis

The results obtained from the IMU are logged into the excel file. The data is then analyzed , compared and the performance is evaluated by Root Mean Square Error (RMSE). The trends based on the choice of filters and number of sensors mounted on the platform are discussed below:

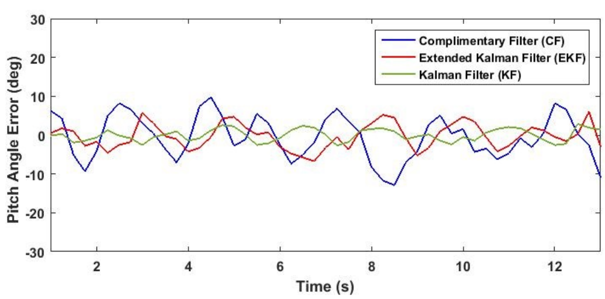

Fig. 3. Single Sensor Module Pitch Detection with Different Filtering Techniques

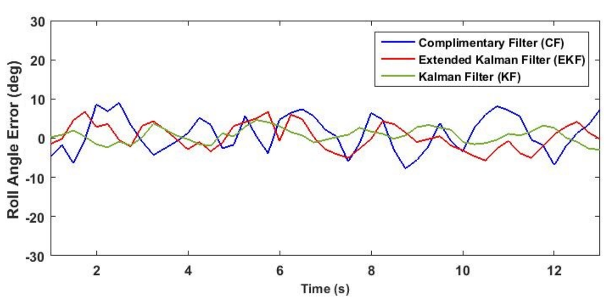

Fig. 4. Single Sensor Module Roll Detection with Different Filtering Techniques

From the fig 3-4 it is observed that for a single IMU mounted on a platform the signal generated moderate disturbance. The Comparison of different data processing techniques reveal that the Kalman Filter gives the most appropriate output in contrast to the Extended Kalman Filter and Complimentary filter. EKF is based on the KF with some assumptions regarding the nonlinearity of a system that lead to the ambiguity in interpretation of data. The complimentary filter on the other hand does not give the precise information of orientation of a body.

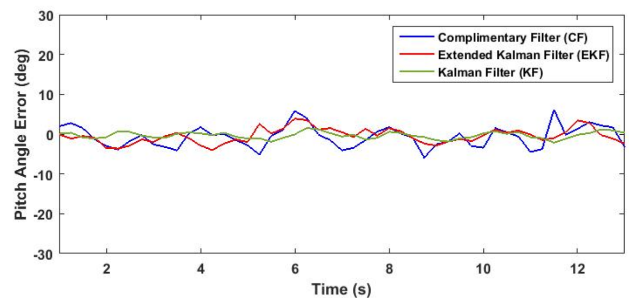

Fig. 5. Multiple Sensor Module Pitch Detection with Different Filtering Techniques

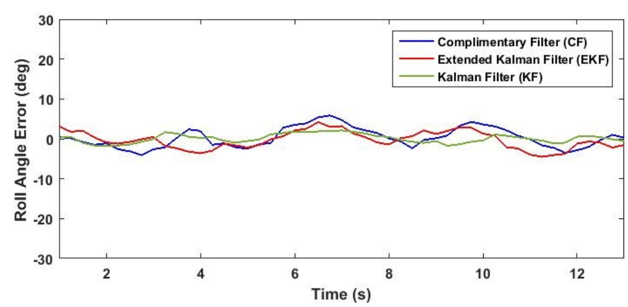

Fig. 6. Multiple Sensor Module Roll Detection with Different Filtering Techniques

It is noticed that by adding another IMU module more refined signals are obtained. Similar pattern of the filtering methods are noticed with some improvement in the detection of appropriate Euler angles . The overall performance of the variable parameters are shown in Table 1.1:

Table1.1: Performance of Multi Sensor Multi Fusion Strategy

Euler Parameters	No. of IMU's	RMSE Values		
		Kalman Filter (KF)	Extended Kalman Filter (EKF)	Complimentary Filter (CF)
Pitch	1	3.84	4.21	4.89
Roll	1	2.43	3.15	3.68
Pitch	2	1.9	2.67	3.04
Roll	2	1.46	1.71	2.04

V. Conclusion

This paper investigates the mitigation techniques to improve the performance of MPU 6050 modules for precise estimation of orientation of maneuverable platform. IMU's are developed from the MEM's technology owing high perturbations bassed on stochastic and and systematic errors. The experimental model platform has been setup to examine the effect of the adopted calibration technique. Repeated experiments are conducted involving the filtering algorithm's and multi modules fusion strategy. Results show that the Kalman Filter(KF) reveal superior performance than both Extended Kalman(EKF) and Complimentary Filters (CF). The complex structure of kalman Filter (KF) and EKF needs advance controllers with more computational resources. The implementation of these procedures on simple 8bit micro-controllers reduces their efficiency. In case of finely tuned complimentary filters, reasonable response can be obtained. Furthermore the use of multi-sensor modules enhance the quality of the acquired signals by noise cancellation. It is therefore concluded that by employing KF with integration of multi modules leads to precise measurement of Euler angles at expense of high computational resources provided that the systematic errors are primarily removed.

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