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Analysis of the Kalman Filter with the MPU6050 Accelerometer and Gyroscope

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Abstract - *Reliable sensor measurements are essential for autonomous navigation, control systems and various other applications. We studied a model of a gesture controlled wheelchair. A key finding is that the processing unit must be able to filter out noise so that the efficacy of the wearable device is improved. In this paper, we demonstrate the application of the Kalman filter to combine measurements in the presence of noise or drift, to calculate the orientation from the inertial measurement unit, MPU6050. We report the behaviour of the gyroscope and accelerometer by measuring their output values individually first, and then passing them through the Kalman Filter. Alternatives such as the recursive average and moving average filters are also discussed. The characteristics of the filter for different parameters such as the standard deviation are plotted. Finally, the Kalman gain convergence for a steady state is verified.*

Keywords - *Control systems, IIR filters, Kalman filters, Adaptive signal processing, Adaptive filters, Signal processing algorithms, Gesture recognition.*

I. INTRODUCTION

1.1 The MPU6050 gyroscope and accelerometer

Micro Electro Mechanical Systems or MEMS fall under the micro mechatronic class of systems which contain both mechanical and electronic parts. They are used as sensing units in barometers, pressure sensors, inertial measurement devices and accelerometers. The MPU6050 chip [1] is a capacitive MEMS. It uses a moving plate or sensing element, which changes the capacitance. This change is measured and converted to appropriate electrical signals. The MPU6050 Inertial Measurement Unit is a MEMS containing a 3-axis accelerometer and gyroscope. The sensor contains two sensors, an accelerometer and a gyroscope, which can be independently used to measure angles.

1.2 Use of Kalman Filter for noisy signals

The gyroscope values are prone to drift (Fig. 2.) and the accelerometer values tend to be noisy (Fig. 3.). We investigate if we can somehow combine them to provide a better state estimate using the Kalman filter. It is a linear optimal status estimation method [2]. It is used to update the prediction of an evolving state (Fig. 1). We now discuss the gyroscope and accelerometer measurements.

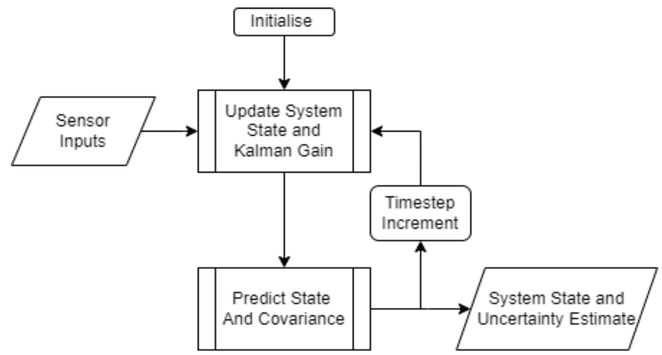

Fig. 1. Kalman Filter Flow Chart.

II. RELATED WORK

In our study, we have applied a simple linear Kalman filter for eliminating noise sensor measurements in a human machine interface developed by us. Some of the recent research on optimal sensing and optimal signal conditioning focused on performance tests in a car with low cost accelerometers. Signal-to-noise ratio improvements of more than 30 dB were shown with the Kalman filter [3]. There has been recent work in improving the state estimation based on hybrid models of the Kalman filter and neural networks. This development integrates the Kalman filter and neural network instead of adopting them in succession. Here, the state-space model is trained by the neural network for the filter, and the parameters for the neural network in turn, are updated by the Kalman filter [4].

III. PROPOSED METHODOLOGY

2.1 Gyroscope

The orientation of the sensor is described through three angular values: pitch, roll and yaw. The gyroscope measures all three values. For the sake of illustration, we focus on the pitch at the k^{th} measurement, $\theta(k)$, which is given by:

$$\theta_k = \int_0^{k\,\Delta\tau} \varphi\, dt \qquad (1)$$

$$\theta_k = \theta_{k-1} + \varphi\,\Delta\tau \qquad (2)$$

where, φ is the angular frequency (rad/s) and $\Delta\tau$ is the time step (s). Equation 2 is the simple form we use for numerical integration. Here, θ_{k-1} represents the previous measurement. From these equations, it is evident that errors in the data are accumulated over time, leading to a drift in the measured value (Fig. 2).

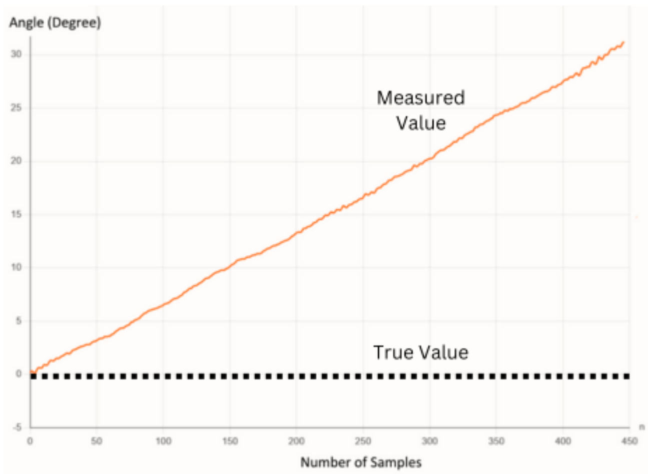

Fig. 2. Gyroscope drift from the true value

2.2 Accelerometer

The MPU6050's accelerometer measures linear acceleration in three dimensions. It may be noted that we can independently calculate the pitch using the accelerometer measurements. However the following plot shows that the data is noisy. With the sensor at rest, noise is in the range of ±0.5° (Fig. 3).

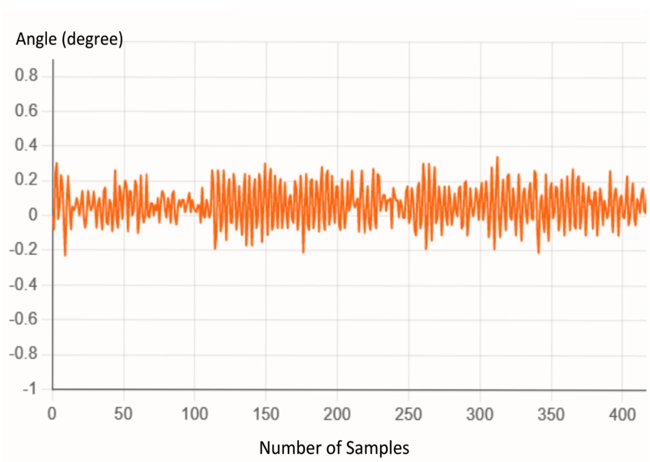

Fig. 3. Noise in measured angle at complete rest.

Thus, we see that neither sensor, by itself, provides clean or precise data. In the case of the gyroscope, the error accumulates with time, whereas the accelerometer data is noisy. A quick and accurate estimation of state in the presence of multiple inaccurate sensor data is important in real time applications like autonomous vehicles. We now explore the application of a few filters to improve the accuracy of the predicted state. Here, a Kalman filter is used and all 6 data points given by the sensor are passed into it. (one from each sensor per axis, 3-axis)

2.3 Recursive Average and Moving Average Filters

The recursive average filter maintains an average of all the data received up to the current time step. About a steady value, this filter works well with noise in a fixed range (Fig 4.). However the output drags on older data which may be obsolete and irrelevant to the present data

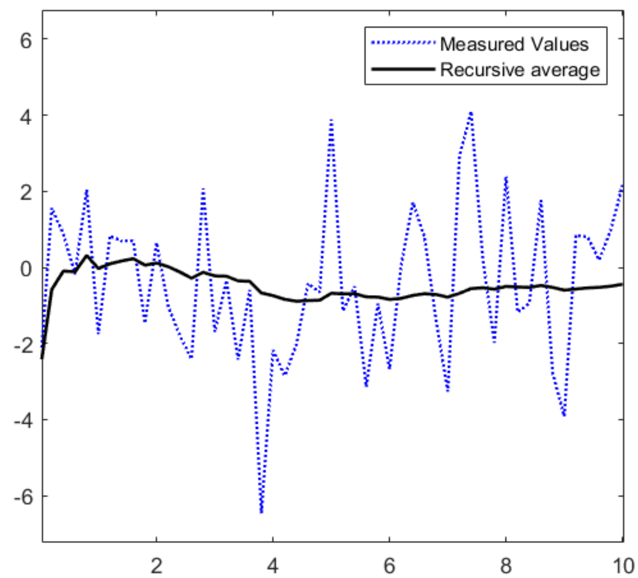

Fig. 4. Recursive Average filter on a noisy but steady value

Thus we try the moving average filter where we calculate the average of the previous n data points at a particular time step k. Fig 5(a) and 5(b) show the measured values and their corresponding averages for two values of n. We find that n acts as a tradeoff between the accuracy and noise reduction of the output curve.

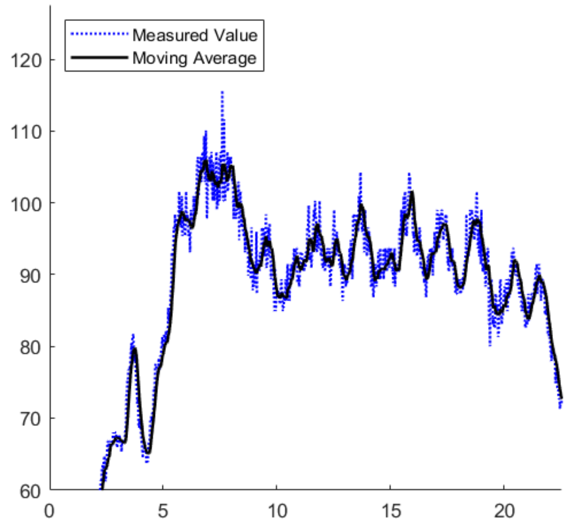

Fig. 5(a). Moving Average filter where n = 10

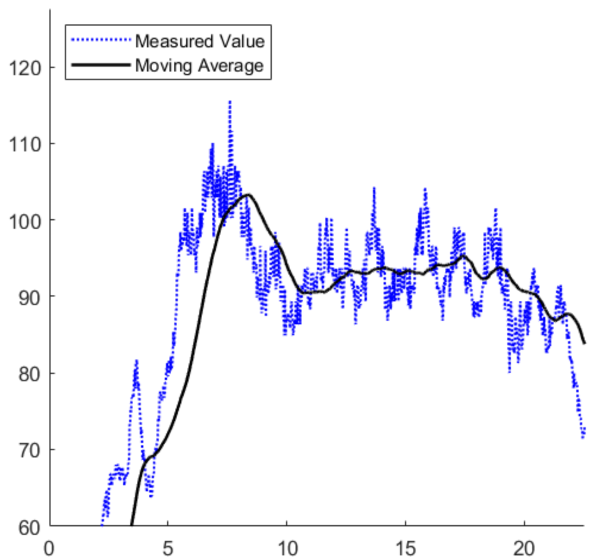

Fig. 5.(b) Moving Average filter where n = 100.

Essentially, it acts as a low pass filter, and is not suitable for filtering accelerometer data. Now we implement the Kalman filter. It can be seen as a particular approach to combining approximations of an unknown value to produce a better approximation [5].

2.4 Mathematical Equations for the Kalman Filter

The pitch of the system is considered to be the 'state'. Here, both the gyroscope and accelerometer give us models for the state but as noisy data. The first equation governs the process model which predicts the current state of the system.

$$X_{(k)} = F \cdot X_{(k-1)} + B \cdot u_{(k)} \tag{4}$$

where, $X_{(k)}$ describes the state of the system at timestep k, F is the state transition matrix (F=1 for this one dimensional filter), $X_{(k-1)}$ is the previous state vector at k-1, B is the control-input matrix and $u_{(k)}$ is the rotation rate from the gyroscope in degrees per second. Thus the equation in our case reduces to:

$$\theta_{(\text{predicted at k})} = \theta_{(k-1)} + \varphi \cdot \Delta\tau \tag{5}$$

The second equation is the measurement model which gives the predicted error covariance [6].

$$z_{(k)} = H \cdot x_{(k)} + v_{(k)} \tag{6}$$

where, $z_{(k)}$ is the measurement at timestep k, H is the measurement matrix and $v_{(k)}$ is the measurement noise.

$$\Psi_{(k)} = \Psi_{(k-1)} + (\Delta\tau \cdot \sigma)^2 \tag{7}$$

Where, 'σ' is the standard deviation of the gyroscope angle, and Ψ is the uncertainty in measured angle. Here, the Kalman gain is given by G.

$$G = \Psi / [\Psi + S] \tag{8}$$

Where S is the variance of the gyroscope angle and $S = \sigma^2$. For the next iteration, we update the state model and the error covariance (uncertainty) for the new timestep respectively [5].

$$\theta_{(k+1)} = \theta_{(k)} + G \cdot (\theta_{(\text{accelerometer})} - \theta_{(\text{predicted})}) \tag{9}$$

$$\Psi_{(k+1)} = (1 - G) \cdot \Psi_{(k)} \tag{10}$$

IV. EXPERIMENTAL RESULTS

3.1 Responsiveness versus Standard Deviation of the Gyroscope

The correlation between the gain and the standard deviation values for the gyroscope angle has been plotted. Three values for the angular standard deviation are used (Figure 6 (a) - 1°, Figure 6 (b)- 50°, Figure 6 (c) - 100°). In all cases, the sensor is rotated by an angle of 90 degrees within five seconds. When the standard deviation is increased, the output data is more responsive to the change in angle and reaches its rest value (-90°) in a lesser number of samples. The variance is directly proportional to the square of the standard deviation. Also, the variance is directly proportional to the uncertainty in angle predicted. Hence, we observe a higher responsiveness to change in data with a higher standard deviation. It is verified that the filter relies more on measurement values rather than previous predictions when gain ≈ 1. (note that the measurement noise is less filtered). With a low standard deviation, the output data is very reluctant to change and the slopes are smoother (Fig. 4).

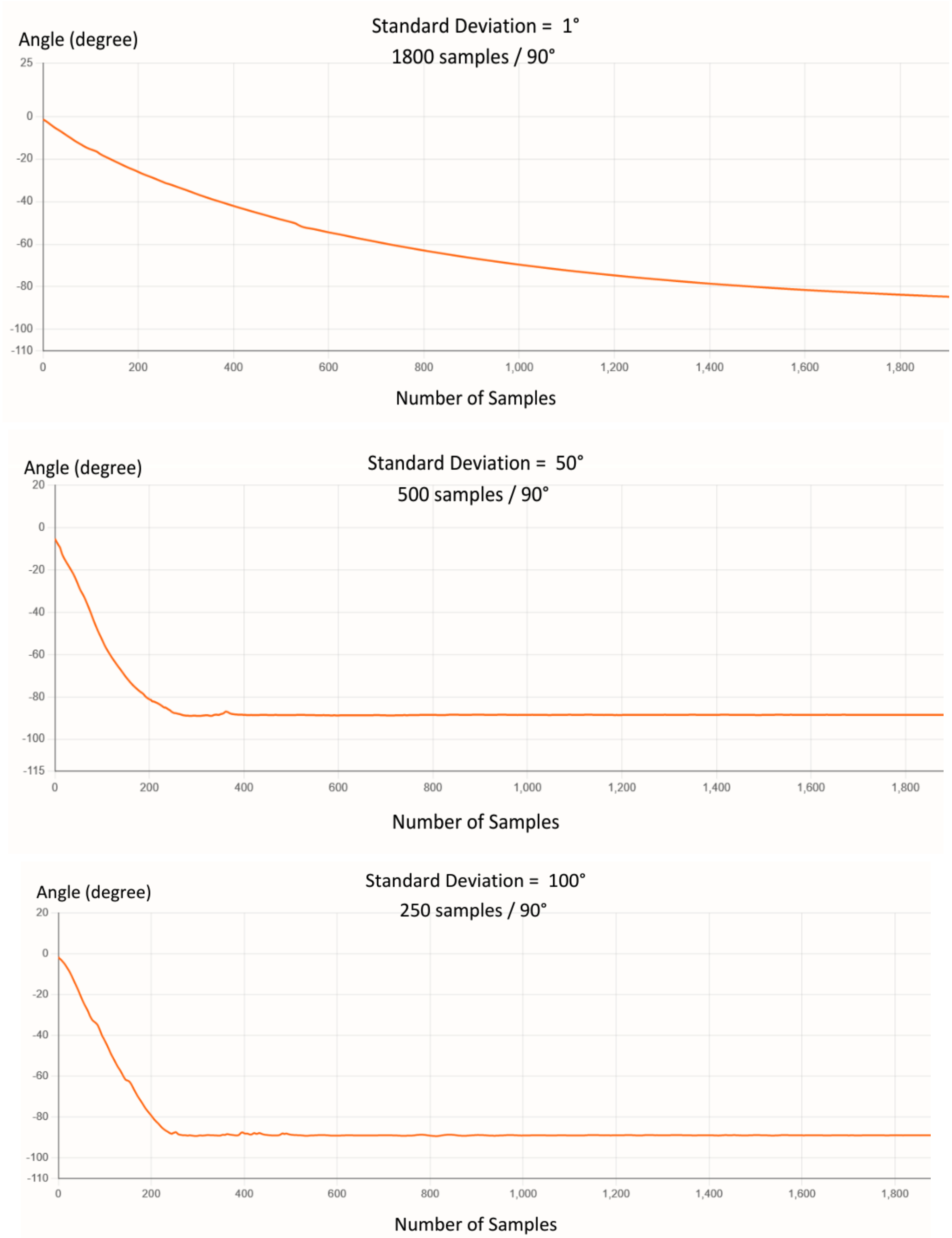

Fig. 6. Ninety degree sensor rotation with a standard deviation equal to (a) 1° (b) 50° (c) 100°

3.2 Kalman gain convergence

Initially, the filter calculates the pitch using measurement data i.e. the accelerometer values, and the gain starts off closer to 1. Then, over progressive samples, the gain is seen to asymptote to a steady value close to 0. The filter calculates the angles mainly using the gyroscope values in this state and relies on past data. This verifies the Kalman gain convergence for a steady state system where the estimated states converge to the actual system states in successive samples (Fig. 7). Figure 8 shows the measured values exhibiting stability after implementation of the filter.

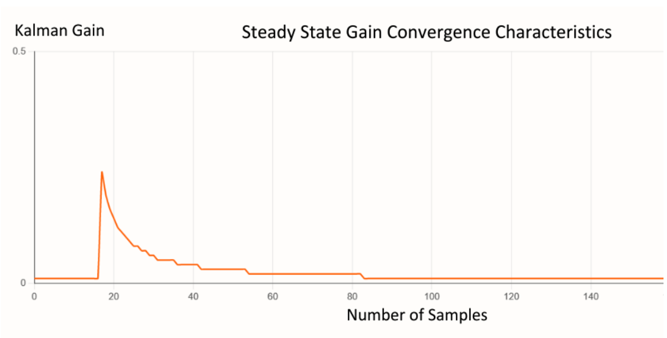

Fig. 7. Kalman gain convergence curve

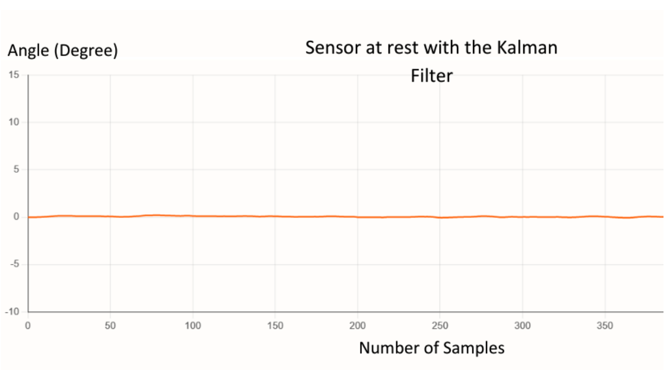

Fig. 8. Measured pitch with the Kalman filter while the sensor is at rest

V. GESTURE CONTROLLED WHEELCHAIR

Powered wheelchairs contain interfaces which may be hard to use for users lacking fine motor skills in their hands. This problem is fixed with a gesture controlled interface and the Kalman noise filter. The user pilots the wheelchair by wearing a glove retrofitted with the MPU6050 sensor. Sensor data is sent to the arduino which checks if the data lies in a specified range. Since the data has been passed through the filter, the ranges for the movements are fine tuned and narrowed. Using conditional statements, the arduino outputs the wheelchair movements to take place. A set of heavy duty servo motors are powered with the L298N motor driver, in sync to achieve forward and turning motions of the wheelchair (Fig. 9. And Fig. 10.).

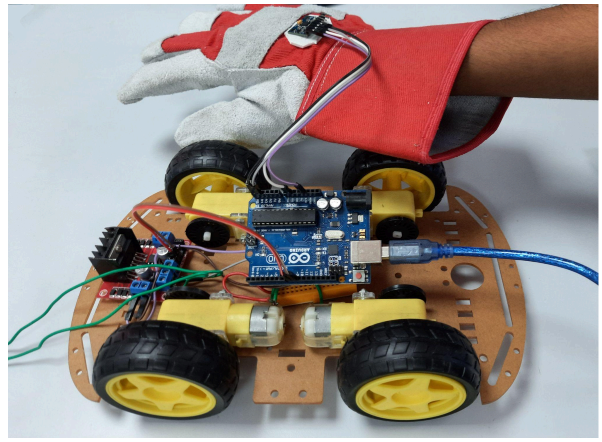

Fig. 9. Wheelchair prototype.

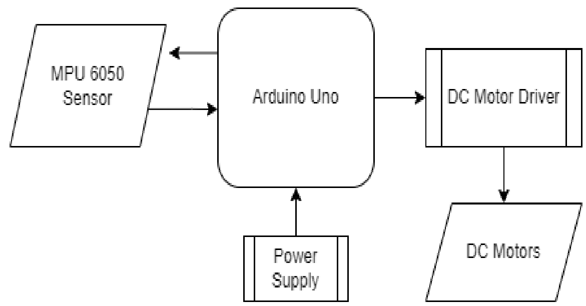

Fig. 10. Flowchart for the gesture controlled wheelchair.

VI. CONCLUSION

The applications of the gyroscope and accelerometer sensors are diverse. This paper focuses on a linear implementation of the filter with inexpensive sensors and a human gesture control. However, the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) can be studied in further detail for nonlinear systems [5]. Hybrid models of the Kalman filter with neural networks is another research avenue which may be explored further. In our project, a human to machine interface is developed to aid the control of a motorised wheelchair from a glove, which houses an inbuilt sensor.

- Individual gyroscope data is found to drift from true value at rest and individual accelerometer data is found to be noisy.
- The data from both sensors successfully predict a closer estimate to true value after they are passed into a one dimensional Kalman filter.
- The variation of the Kalman gain with respect to the standard deviation of the gyroscope angle is plotted and verified.
- Steady state Kalman gain convergence is observed for the sensors.

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