IRDH International Journal of Technology, Agriculture & Natural Sciences
https://irdhjournals.com/ijtans
Vol 2, No 2 (2025) : July. E-ISSN : 3032-2286

Application of Kalman Filter on Gyroscope to Reduce Noise and Improve Responsiveness in Shooting Simulator System

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INDEXING

Keywords:
Keyword 1 ; Gyroscope
Keyword 2 ; Responnsiveness
Keyword 3 ; Firing simulator
Keyword 4 ; Kalman Filter

ABSTRACT

Shooting simulators are essential tools in military exercises, enabling soldiers to develop their shooting skills in a controlled and safe environment. However, the effectiveness of these simulators is often hindered by noise in gyroscope sensor data, which is used to track weapon motion. This noise can lead to inaccuracies in determining the position and orientation of the weapon, thereby reducing the precision of aiming and the realism of the simulation. In turn, this affects the responsiveness and overall performance of the training system, potentially diminishing the quality of soldiers' practice sessions. To address this issue, the implementation of a Kalman filter proves to be highly effective. By processing noisy gyroscope data, the Kalman filter minimizes inaccuracies, enhances motion tracking, and ensures smoother and more realistic weapon handling during simulation. This improvement not only boosts the accuracy of the simulator but also ensures a more reliable and responsive training experience for soldiers.

Article History
Received 18 November 2024; Revised 06 December 2024; Accepted 30 December 2024 ; Publish 01 July 2025

INTRODUCTION

Shooting simulators have become a vital component of modern military training, enabling soldiers to enhance their shooting skills in a safe, controlled, and cost-effective environment (Fadillah *et al.*, 2022); (Huo *et al.*, 2022). These simulators allow for scalable and intensive training while reducing operational costs and minimizing the risk of injury (Adi *et al.*, 2022). Central to the operation of shooting simulators are various sensors designed to replicate the experience of real-world shooting. One such sensor is the gyroscope, which tracks the orientation and rotation of weapons in real time to simulate weapon handling accurately (Alfian *et al.*, 2021).

However, the gyroscope sensor's effectiveness is often compromised by noise in the generated data. This noise arises from several factors, including electromagnetic interference, hardware imperfections, and environmental vibrations (Tritunggal *et al.*, 2023). Studies show that noise in gyroscope data can result in deviations of up to 15% in positional accuracy and delays of up to 100 milliseconds in responsiveness, rendering the simulation less precise and realistic. Consequently, this reduces the effectiveness of the training, as it fails to replicate real-world conditions accurately (Utomo *et al*., 2020).

Addressing the noise problem is critical to improving the performance and reliability of shooting simulators. While various noise-reduction methods exist, such as moving average filters or Gaussian smoothing, these approaches often fall short in dynamic systems where real-time responsiveness is crucial. The Kalman Filter has emerged as a superior alternative due to its recursive nature and ability to provide optimal state estimation by integrating prior predictions with noisy measurements *(*Setiawan *et al*., 2021).

The Kalman Filter operates by iteratively updating estimates based on the current state and measurements, minimizing prediction errors through weighted averages. Specifically, in gyroscope data processing, it uses a mathematical model to predict the weapon's position and orientation, adjusts this prediction using real-time sensor data, and outputs a corrected estimate. For example, in drone navigation systems, the Kalman Filter has been shown to reduce orientation errors by 20%-30% compared to traditional methods, demonstrating its effectiveness in similar applications (Kang *et al*., 2019).

This study aims to evaluate the effectiveness of the Kalman Filter in reducing noise in gyroscope data and enhancing the responsiveness and realism of shooting simulators. Experiments will be conducted to compare the simulator's performance before and after applying the Kalman Filter, focusing on metrics such as positional accuracy, responsiveness, and system stability. Additionally, this research will explore optimal parameter configurations, practical implementation challenges, and potential solutions. By integrating theoretical insights and practical guidelines, this study seeks to contribute to the development of more advanced and reliable shooting simulators for military training (Ansori, 2020; Asnada and Sulistyono, 2020).

LITERATURE REVIEW

The dynamic performance of a Kalman filter (KF) was analyzed. This filter is used to combine multiple measurements from a gyroscope array to reduce noise and improve the accuracy of individual sensors (Xue *et al*, 2012). A principle for accuracy improvement by the KF was briefly presented to obtain an optimal estimate of the input rate signal. Simulations were conducted to analyze the influence of crucial factors on the KF's dynamic performance. These factors included input signal frequency, signal sampling, and KF filtering rate. Finally, a system comprised of a six-gyroscope array was designed and implemented to test the dynamic performance. Experimental results indicated that the 1σ error for the combined rate signal was reduced to about 0.2°/s in the constant rate test. This represents a reduction by a factor of more than eight compared to a single gyroscope (Xue *et al*, 2014).

Accelerometer and gyroscope modules, used for measuring the orientation of a quadcopter, often generate noisy signals. These noisy signals directly affect control strategies. High-speed quadcopter motors contribute to elevated noise levels, making real-time control challenging. In this work, the Kalman filter was applied to noisy measurements obtained from accelerometer and gyroscope modules. Measurements were conducted under two conditions: motors stopped and activated at high speed. The Kalman filtering was applied separately for each measurement, yielding noticeable improvements in noise levels for both cases. Additionally, joint implementation from accelerometer and gyroscope modules was conducted to optimize predicted signal levels. Results demonstrated that the proposed Kalman filtering method is effective for real-time measurement of quadcopter orientation, even when using low-cost measurement modules (Karahoda *et al.*, 2015).

Traditional noise reduction and compensation methods based on conventional models are often not applicable. This paper proposes a noise reduction method for MEMS gyroscopes in a static base state using multi-layer combined deep learning. The combined model integrates a Convolutional Denoising Auto-Encoder (Conv-DAE) and a Multi-layer Temporal Convolutional Neural Network with Attention Mechanism (MultiTCN-Attention). This approach leverages the robust data processing capabilities of deep learning to extract noise features from past gyroscope data. The method also utilizes the Particle Swarm Optimization algorithm (PSO) for optimizing Kalman filter parameters, significantly enhancing noise reduction accuracy. Experimental results indicate that, compared to the original data, the proposed combined model reduces noise standard deviation by 77.81% and 76.44% on the x and y axes, respectively. Furthermore, when compared to the existing Autoregressive Moving Average with Kalman filter (ARMA-KF) model, the noise standard deviation is reduced by 44.00% and 46.66% on the x and y axes, respectively. This approach decreases noise impact by nearly three times (Huo *et al.*, 2022).

Relevance To Simulation Research

The noise reduction techniques for accelerometer and gyroscope modules can improve the quality of data used in drone control algorithms. Applying a Kalman filter in real-time measurement systems can ensure smoother and more accurate adjustments to drone positioning, leading to higher-quality photographic outputs (Nwadiugwu *et al* , 2021 ; Maidanov *et al*, 2023).

The combined deep learning model proposed by Huo *et al.*, (2022). could further enhance the system by learning complex noise patterns and predicting optimal adjustments. For instance, incorporating a Conv-DAE and MultiTCN-Attention mechanism could reduce noise in sensor data during long-exposure photography. This would allow the drone to maintain stable orientation even in challenging environments, improving image clarity and precision.

Deep Learning and Kalman Filter in Research Context

Deep learning and Kalman filters play complementary roles in enhancing system performance. The Kalman filter excels in real-time noise reduction and optimal signal estimation, making it ideal for dynamic and continuously changing environments (Yang and Mao, 2023). On the other hand, deep learning techniques, such as Conv-DAE and MultiTCN-Attention, offer robust capabilities to model and learn from historical data (Yu and Shao, 2024). This enables the system to handle more complex noise patterns and predict better control strategies.

RESEARCH METHOD

1. This research uses mixed methods, which combines two methods: qualitative and quantitative research. Qualitative research uses literature to support the research and collects reference data. Quantitative research collects data using research formulas and primary data during field research.
2. Research Instruments
   This study uses variables as research instruments. These variables are as follows :

a. Free Variables.
The independent variable used to collect research data is the dependent variable that is affected by the specified number of independent variables. The independent variables in this design include:
1) Tilt angle on the shooting simulator manually.
2) The kalman filter method is used to reduce noise.
3) The responsiveness is measured and analyzed after the use of kalman filter on the gyroscope.

b. Dependent Variable
The variable obtained after the independent variable is subjected to testing with certain parameters. The dependent variables in this design include:
1) The level of interference or unwanted signals in the data from the gyroscope.
2) Accuracy and precision after noise is reduced.

c. Block Diagram

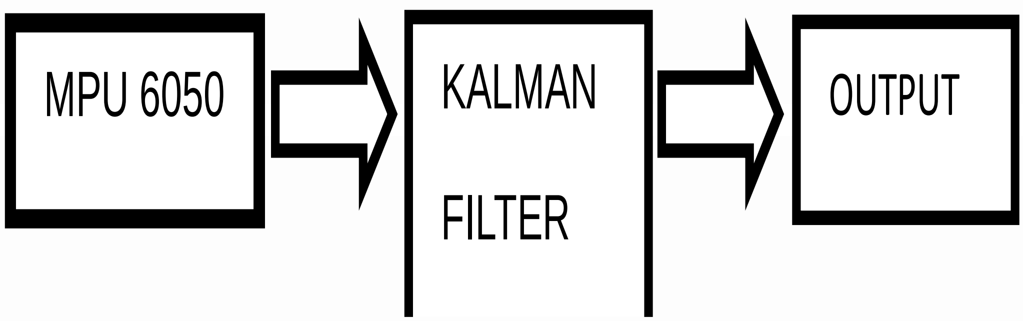

Figure 1. Block Diagram
(Source : Author, 2024)

The above figure shows the block diagram of the Kalman filter process, where the MPU 6050 sensor input will be filtered using a Kalman filter due to the very large noise inside the sensor and the very small noise is removed from the sensor after filtering.

RESULT AND DISCUSSION

This test using the MPU-6050 Sensor with Kalman Filter as a Silencer collects data from each piece of equipment used. Some sensors must have different characteristics and measurement results according to the media and conditions. The suitability between functions and ways of working is expected to achieve the expected results.

1. Test results of Roll (X) and Pitch (Y) angular tilt before filtering.

Table 1. MPU6050 testing on Roll (X) angle before filtering at 90 Degree angle.

MPU 6050 Testing at Roll Angle (X) Before Filtering at 90 Degree Angle				
Data	Degree Arc	Unfiltered Angle	Difference	Error (%)
1	90	90,30	0,30	0,333
2		90,30	0,30	0,333
3		90,29	0,29	0,322
4		90,29	0,29	0,322
5		90,28	0,28	0,311
Average			0,29	0,324

Based on the results from Table 1, testing the MPU6050 at a Roll (X) angle of 90 degrees on 5 test data shows an average error of 0.324%. The percentage of test error is obtained by dividing the difference in sensor readings by the protractor angle multiplied by 100%.

The average error formula is as follows:

$$\text{Average } (\sum) = \frac{test\ 1 + test\ 2 + test\ 3 + test\ 4 + test\ 5}{5}$$

The formula for finding the error value is as follows:

Error (%)

$$= \frac{Reference\ value - Test\ value}{Reference\ Value}$$

The following is the calculation of the average value and error value of the MPU6050 sensor on the Roll (X) axis:

$$\sum = \frac{90.30^{\circ} + 90.30^{\circ} + 90.29^{\circ} + 90.29^{\circ} + 90.28^{\circ}}{5}$$

$$\text{Error} = \frac{Reference\ value - Test\ value}{Reference\ Value} \text{ x } 100\%$$

$$\text{Error} = \frac{90 - 90.30}{90} \text{ x } 100\%$$

$$\text{Error} = 0.333\%$$

And the average error obtained from sensor testing is:

$$\text{Avarage} = \frac{\sum Error}{number\ of\ errors}$$

$$\text{Avarage"} = \frac{1.621}{5}$$

$$\text{Avarage} = 0.324\%$$

Table 2. MPU6050 testing at Pitch (Y) angle before filtering at 90 Degree angle.

MPU 6050 Testing at Pitch Angle (Y) Before Filtering at 90 Degree Angle				
Data	Degree Arc	Unfiltered Angle	Difference	Error (%)
1	90	90,13	0,13	0,144
2		90,13	0,13	0,144
3		90,14	0,14	0,156
4		90,14	0,14	0,156
5		90,13	0,13	0,144
Average			0,13	0,149

Based on the results from Table 2, testing the MPU6050 at a Pitch (Y) angle of 90 degrees on 5 test data shows an average error of 0.149%. The percentage of test error is obtained by dividing the difference in sensor readings by the protractor angle multiplied by 100%. The average error formula is as follows:

$$\Sigma = \frac{90.13^{\circ} + 90.13^{\circ} + 90.14^{\circ} + 90.14^{\circ} + 90.13^{\circ}}{5}$$

$$\text{Error} = \frac{Reference\ value - Test\ value}{Reference\ Value} \text{ x } 100\%$$

$$\text{Error} = \frac{90.13 - 90}{90} \text{ x } 100\%$$

$\text{Error} = 0.144\%$

And the average error obtained from sensor testing is:

$$\text{Average} = \frac{\sum Error}{number\ of\ errors}$$
$$\text{Average} = \frac{0.744}{5}$$

$$Average = 0.149\%$$

2. Test results of Roll (X) and Pitch (Y) angular tilt after filtering.

Table 3. MPU6050 testing at Roll angle (X) after filtered at 90 Degree angle.

MPU 6050 Testing at Pitch Angle (Y) Before Filtering at 90 Degree Angle				
Data	Degree Arc	Unfiltered Angle	Difference	Error (%)
1	90	90,00	0	0
2		90,01	0,01	0,011
3		90,01	0,01	0,011
4		90,02	0,02	0,022
5		90,02	0,02	0,022
Average			0,01	0,013

Based on the results from Table 3, testing the MPU6050 at a Roll angle (X) of 90 degrees on 5 test data shows an average error of 0.013%. The percentage of test error is obtained by dividing the difference in sensor readings by the protractor angle multiplied by 100%.

The average error formula is as follows :

$$\Sigma = \frac{90.00^{\circ} + 90.01^{\circ} + 90.01 + 90.02^{\circ} + 90.02^{\circ}}{5}$$

$$= 90.00^{\circ}$$

$$\text{Error} = \frac{Reference\ value - Test\ value}{Reference\ Value} \text{ x } 100\%$$

$$\text{Error} = \frac{90 - 90.00}{90} \text{ x } 100\%$$

$\text{Error} = 0\%$

And the average error obtained from sensor testing is:

$$\text{Average} = \frac{\sum Error}{number\ of\ errors}$$

$$\text{Average} = \frac{0.066}{5}$$

$$Average = 0.013\%$$

Table 4. MPU6050 testing on Pitch (Y) angle after filtered at 90 Degree angle

MPU 6050 Testing at Pitch Angle (Y) Before Filtering at 90 Degree Angle				
Data	Degree Arc	Unfiltered Angle	Difference	Error (%)
1	90	90,01	0,01	0,011
2		90,02	0,02	0,022
3		90,00	0	0
4		90,02	0,02	0,022
5		90,03	0,03	0,033
Average			0,02	0,018

Based on the results from Table 4, testing the MPU6050 at a Pitch(Y) angle of 90 degrees on 5 test data shows an average error of 0.018%. The percentage of test error is obtained by dividing the difference in sensor readings by the protractor angle multiplied by 100%.

The average error formula is as follows:

$$\Sigma = \frac{90.01^{\circ} + 90.02^{\circ} + 90.00 + 90.02^{\circ} + 90.03^{\circ}}{5}$$

$$= 90.01^{\circ}$$

$$\text{Error} = \frac{Reference\ value - Test\ value}{Reference\ Value} \text{ x } 100\%$$

$$\text{Error} = \frac{90 - 90.01}{90} \text{ x } 100\%$$

$\text{Error} = 0.011\%$

And the average error obtained from sensor testing is:

$$\text{Average} = \frac{\sum Error}{number\ of\ errors}$$

$$\text{Average} = \frac{0.088}{5}$$

$$Average = 0.018\%$$

3. MPU6050 Sensor Test Graph
   Based on the results of the MPU6050 sensor test serial monitor before filtering in Table 1 to Table 2 and after filtering in Table 3 to Table 4 can be seen in the following graphical image:

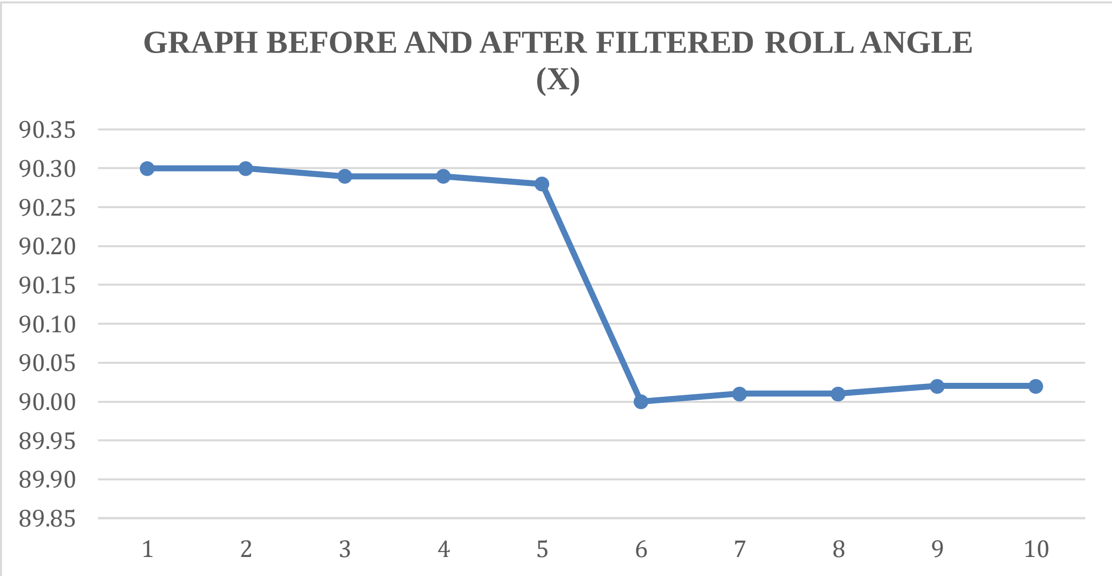

Figure 2. Graph Before and After Filtered Roll Angle (X)

Figure 2 is a graph of the MPU6050 sensor test before filtering and after filtering the Roll (X) axis at an angle of 30 degrees. On the Roll angle sensor graph before filtering, this sensor has an error of 90.30 degrees and has the smallest error of 90.00. In the sensor reading graph before filtering, there is a large error value and after filtering, the error value is significantly reduced because the noise contained in the sensor has used a Kalman Filter.

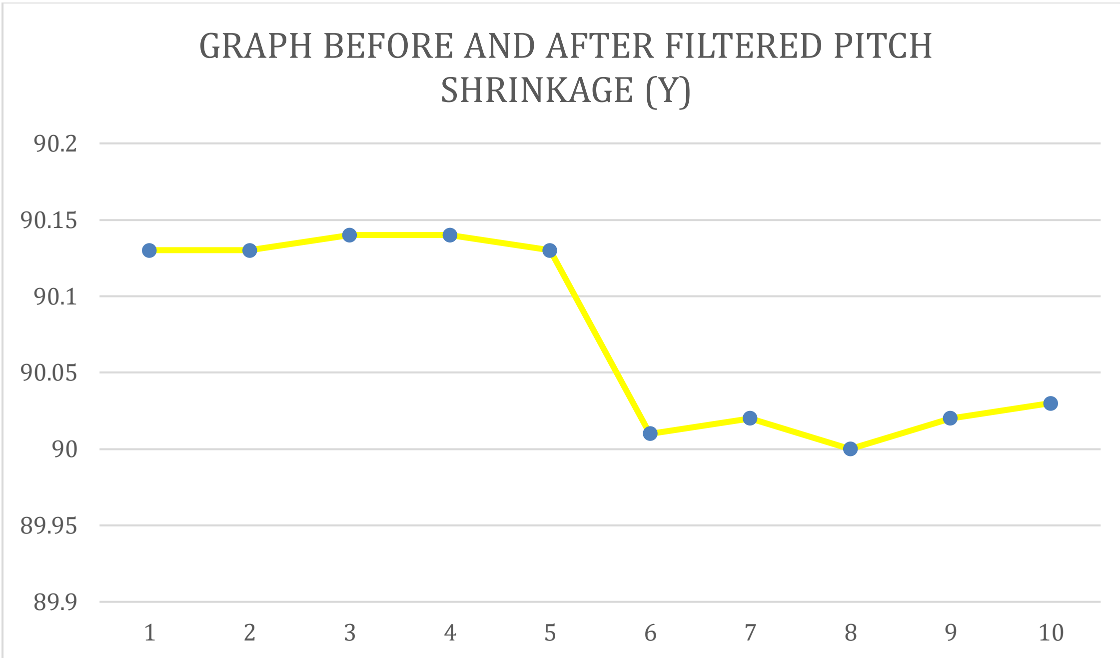

Figure 3. Graph Before and After Filtered Pitch Shrinkage (Y)

Figure 3 is a graph of the MPU6050 sensor testing before filtering and after filtering on the Pitch (Y) axis at an angle of 30 degrees. On the Pitch angle sensor graph before filtering, this sensor has an error of 90.14 degrees and has the smallest error of 90.00. In the sensor reading graph before filtering, there is a large error value and after filtering, the error value is significantly reduced because the noise contained in the sensor has used a Kalman Filter. We may inform that :

a. The Kalman Filter effectively reduces the noise in the MPU6050 sensor data, thus improving the accuracy in detecting tilt angles in the Roll (X) and Pitch (Y) axes in the shooting simulator. This noise reduction allows for more accurate simulations, which is critical for precision in training in military applications.
b. The average error rate decreased significantly after the application of the Kalman filter, from 0.324% and 0.149% before filtering to 0.013% and 0.018% after filtering for Roll (X) and Pitch (Y). This shows the effect of the filter in improving the reliability of data from gyroscope measurements.
c. This research confirmed that the use of Kalman filter on gyroscope data in a shooting simulator provides a more stable and responsive simulation experience, allowing soldiers to train with a system that is more accurate and responsive to real-world conditions by minimizing interference from sensor noise.

CONCLUSION

Based on the results of the analysis of the kalman filter method on the gyroscope to reduce noise to improve responsiveness in the shooting simulator using the MPU6050 Sensor as a Noise Reducer, conclusions can be drawn:

1. This tool can work well, this tool will work if it detects a 30 degree tilt.

2. By using Kalman filter can reduce the noise contained in the MPU6050 sensor output, at the Roll (X) angle before filtering has an error of 0.333% while after filtering has an error of 0% and at the Pitch (Y) angle before filtering has an error of 0.144% while after filtering has an error of 0.011%.

ACKNOWLEDGMENT

The suggestions that can be done in further research so that it can be developed for the better include:

1. Research the effect of the Kalman Filter on latency in the shooting simulator, because a slow response can reduce the effectiveness of the filter. This can lead to filter adjustments to minimize lag.
2. After good results in the simulator, conduct trials on real devices or environments with more complex conditions to see if the Kalman Filter remains effective in more dynamic situations.
3. Extend the research by incorporating data from other sensors, such as accelerometers or magnetometers, to obtain more accurate data and reduce dependence on a single gyroscope.

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