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Research Article

Performance Evaluation of IMU Filtering Techniques in Yaw-Pitch-Roll Calculations

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Abstract – This study provides a comparative analysis of the performance of three popular filtering techniques Madgwick, Mahony, and Complementary filters used for processing data obtained from Inertial Measurement Unit (IMU) sensors. The effectiveness of these filters in estimating Euler angles, also known as yaw, pitch, and roll, was evaluated in terms of memory usage, processing time, and accuracy. Separate programs were developed for each filtering technique and tested under various scenarios. The experimental results reveal the strengths and weaknesses of each filter. It was observed that the Madgwick filter generally provided higher accuracy but required more computational power. The Mahony filter performed better in fast dynamic movements, while the Complementary filter was found to be suitable for applications with lower computational requirements. This study offers guidance in selecting the most appropriate filtering technique for IMU-based orientation estimation applications and provides new perspectives for future research.

Keywords – IMU, Sensor Fusion, Madgwick Filter, Mahony Filter, Complementary Filter, Embedded System.

I. INTRODUCTION

Inertial Measurement Units (IMUs) are critical components for orientation and motion tracking in various applications such as robotics, aerospace, navigation systems, and mobile devices. Accurately estimating yaw, pitch, and roll angles is vital for the performance of these systems [1]. However, IMU sensors are prone to errors due to noise, drift, and external accelerations, necessitating the use of sensor fusion algorithms [2].

Among the various filtering and sensor fusion techniques used in processing IMU data, the Madgwick filter, the Mahony filter, and the Complementary filter stand out for their real-time performance. The Madgwick filter is favored for its low computational cost while providing high accuracy [3]. By fusing both accelerometer and gyroscope data, this filter ensures more stable and reliable orientation estimation [4]. Particularly in dynamic conditions, the Madgwick filter mitigates the effects of external accelerations, providing reliable angle estimates [5].

The Mahony filter, on the other hand, employs proportional and integral feedback mechanisms to provide fast and accurate angle estimates [6]. This filter performs particularly well in low-dynamic or static applications [7]. Studies show that Mahony outperforms Madgwick slightly in scenarios involving static or low-dynamic conditions where external forces or accelerations are minimized [8].

Complementary filters are widely used in systems with limited processing power due to their simple structure and low computational requirements [9]. However, they may exhibit lower accuracy compared to other methods, particularly in yaw angle estimation [10]. The literature has examined the performance of these filters in various applications. Parikh et al. (2021) compared different sensor fusion algorithms for IMU-based attitude estimation and noted that the Madgwick filter best mitigated the effects of external accelerations [11]. Ludwig and Burnham (2018) compared the Madgwick and Mahony filters with the Extended Kalman Filter (EKF) on quadcopter flight data, showing that the Mahony filter provided the best orientation estimation when optimized parameters were used [3].

Jouybari et al. (2019) compared different methods for determining the orientation of a lightweight buoy and found that the Mahony algorithm was more accurate than other algorithms in estimating roll and yaw angles [1]. Additionally, there are proposed methods to enhance the performance of the Complementary filter [12].

In this study, the performance of the Madgwick, Mahony, and Complementary filters in calculating yaw, pitch, and roll angles using IMU sensors has been comprehensively compared in terms of memory usage, processing time, and accuracy. The comparison, conducted through separate programs written for each method, aims to contribute to the selection of the most appropriate filter for different applications. The remainder of this paper is organized as follows: Section 2 explains the methodology and experimental setup. Section 3 presents and discusses the results obtained. Finally, Section 4 summarizes the study's conclusions and offers suggestions for future research.

II. MATERIALS AND METHOD

In this study, three different sensor fusion algorithms Madgwick filter, Mahony filter, and Complementary filter were used for processing data obtained from IMU sensors. No trial-and-error efforts were conducted for parameter tuning during the implementation of the filters. Instead, the default parameter values (e.g., PI parameters) were utilized. This section first provides brief information about the methods. Following that, the test setup is described

A. *Madgwick Filter*

The Madgwick filter, proposed by Sebastian Madgwick in 2010, is an orientation estimation algorithm that provides a good balance between computational efficiency and accuracy [1]. This filter performs quaternion-based orientation estimation using gradient descent optimization. The pseudocode for the filter is presented in Table 1.

Table 1: Pseudocode of Madgwick filter

```
function madgwickUpdate(gyro, accel, mag, dt, beta):
    // Calculate quaternion derivative from gyroscope data
    q_dot_omega = 0.5 * quaternionMultiply(estimatedQuaternion, [0, gyro.x, gyro.y, 
gyro.z])

    // Calculate gradient descent step
    f = calculateObjectiveFunction(estimatedQuaternion, accel, mag)
    J = calculateJacobian(estimatedQuaternion)
    gradient = matrixMultiply(transposeMatrix(J), f)

    // Calculate the derivative of the quaternion
    q_dot_est = q_dot_omega - beta * normalizeVector(gradient)

    // Update quaternion
    estimatedQuaternion = estimatedQuaternion + q_dot_est * dt

    // Normalize quaternion
    estimatedQuaternion = normalizeQuaternion(estimatedQuaternion)
return estimatedQuaternion
```

B. *Mahony Filter*

The Mahony filter, developed by Robert Mahony and colleagues, is an orientation estimation algorithm that performs particularly well in high-dynamic movements [14]. This filter corrects angular velocity measurements using a complementary feedback structure. The pseudocode for the Mahony filter is presented in Table 2.

Table 2:Pseudocode of Mahony filter

```
function mahonyUpdate(gyro, accel, mag, dt, kp, ki):
    // Calculate the orientation error
    e = calculateOrientationError(estimatedRotation, accel, mag)

    // Update gyroscope bias estimate
    estimatedBias = estimatedBias + ki * e * dt

    // Calculate corrected angular velocity
    correctedGyro = gyro - estimatedBias + kp * e

    // Update the orientation matrix
    deltaR = matrixExponential(crossProductMatrix(correctedGyro * dt))
    estimatedRotation = matrixMultiply(estimatedRotation, deltaR)

    // Orthonormalize the orientation matrix
    estimatedRotation = orthonormalizeMatrix(estimatedRotation)

return estimatedRotation
```

C. *Complementary Filter*

The Complementary filter is a simple and effective method used to combine data from different sensors [15]. This filter merges high-frequency gyroscope data with low-frequency accelerometer data (and magnetometer data, if available).

Table 3: Pseudocode of Complementary filter

```
function complementaryUpdate(gyro, accel, dt, alpha):
    // Calculate angle change from gyroscope data
    gyroAngle = previousAngle + gyro * dt

    // Calculate angle from accelerometer data
    accelAngle = calculateAngleFromAccel(accel)

    // Apply complementary filter
    estimatedAngle = alpha * gyroAngle + (1 - alpha) * accelAngle

    previousAngle = estimatedAngle

return estimatedAngle
```

D. *Test System*

The setup shown in Figure 1 was prepared to test the filters under equal conditions.

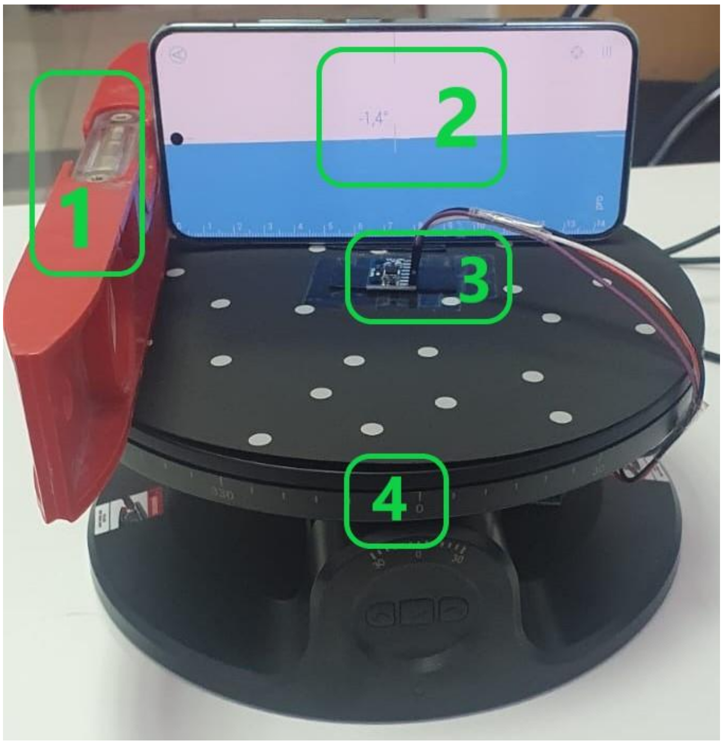

Figure 1: Test setup for IMU sensor

The descriptions of the numbered items in the test setup are as follows:

1) **Spirit Level (bubble level):** The inclination can be measured with an accuracy of 0.1 degrees using a mobile application. The application was calibrated using a spirit level placed on a flat surface.

Subsequently, the real-time position of the turntable was observed, and any offset errors were corrected.

2) **Mobile Application for Measuring Tilt Angle**: This was used to compare the accuracy of the data obtained from the IMU sensor. The smartphone, with the application installed, was positioned to have the same height and tilt as the sensor.
3) **IMU Sensor**: This is a module containing an MPU6050 accelerometer and gyroscope sensor. The gyroscope measurement range can be set between 250 and 2000 degrees/s, and the accelerometer range can be adjusted between 2 and 16 g. In this study, the gyroscope was set to 250 degrees/s and the accelerometer to 2g.
4) **Turntable**: A turntable with high repeatability and positional accuracy was used to ensure that data from the sensors were collected under consistent conditions each time. Since the turntable performs tilt operations on a single axis at +/- 30 degrees, the sensor was rotated 90 degrees to measure the pitch and roll angles. For yaw angle measurement, the turntable's 360-degree constant speed rotation feature was utilized. The code for all methods was compiled separately and uploaded to the microcontroller, and all tests followed the same procedures.

III. RESULTS AND DISCUSSION

Three different filtering methods were selected for the fusion of accelerometer and gyroscope data. The primary rationale behind this selection was the requirement for low computational power, making these methods suitable for implementation in embedded systems.

Embedded system software was developed to convert the 3-axis accelerometer and 3-axis gyroscope data obtained from the sensor into Euler angles (yaw, pitch, roll) and process these data through various filters. To test the accuracy of the obtained angles, a tilt motion was applied to a Revopoint turntable at 5-degree intervals. Angle values were recorded while the table was stationary at each position. The tilt at each angle was measured as a reference value using a mobile application installed on a smartphone placed on the turntable. The angle values obtained for each filter are presented in Tables 4 and 5. All sensor values in these tables are the average of 10 data points collected every 100 ms. Data collection was conducted as the turntable moved in 5-degree increments, and only the data recorded after the table reached a stable position were analyzed.

Table 4: The results of the Pitch angle tests

Filter Type	Reference angle value	Angle value measured via the IMU sensor	Absolute Error	Mean Absolute Error
Madwich	5,7	5.6	0,1	0,283
	10,7	10,6	0,1	
	15,6	15,4	0,2	
	20,6	20,2	0,4	
	25,6	25,2	0,4	
	30,5	30,0	0,5	
Mahony	5,8	5,7	0,1	0,300
	10,7	10,6	0,1	
	15,7	15,5	0,2	
	20,7	20,4	0,3	
	25,7	25,2	0,5	
	30,7	30,1	0,6	
Complementary	5,8	5,8	0,0	0,083
	9,9	9,9	0,0	
	15,7	15,8	0,1	
	20,6	20,7	0,1	
	25,6	25,8	0,2	
	30,6	30,7	0,1	

Table 5: The results of the Roll angle tests

Filter Type	Reference angle value	Angle value measured via the IMU sensor	Absolute Error	Mean Absolute Error
Madwich	5,9	5,8	0,1	0,250
	10,8	10,7	0,1	
	15,0	14,8	0,2	
	20,7	20,5	0,2	
	25,8	25,4	0,4	
	30,7	30,2	0,5	
Mahony	5,7	5,7	0,0	0,283
	10,6	10,7	0,1	
	15,5	15,4	0,1	
	20,7	20,3	0,4	
	25,6	25,2	0,4	
	30,6	29,9	0,7	
Complementary	5,7	5,6	0,1	0,300
	10,6	10,5	0,1	
	15,6	15,4	0,2	
	20,5	20,2	0,3	
	25,6	25,1	0,5	
	30,5	29,9	0,6	

Table 6 presents the memory usage of each filter method, the amount of RAM used for variables, and the time required for the filtering process. The time measurements were obtained using the microcontroller's timer function, while the memory data were gathered through the compiler.

Table 6: System source usages of the filters

Filter Type	Execution Time (ms)	Used Program Memory (byte)	Used Ram Memory (byte)
Madwich	2,0404	13614	693
Mahony	1,4388	13034	709
Complementary	0,6500	10400	748

To test the results of the filter methods under dynamic conditions, a 30-degree tilt motion was applied to the turntable via a mobile application developed for the Revopoint Turn Table. Data were recorded at 100 ms intervals during the movement, and data collection was terminated once the turntable reached its final position. The roll angles obtained from the filters are shown in Figure 2. Upon examining the graph, variations in the time taken to reach -30 degrees can be observed. These discrepancies are related to the time required for the mobile application to execute the tilt command. Ignoring this difference, the Complementary filter was observed to reach the target angle first, followed by the Mahony and Madgwick filters approaching the target measurements sequentially.

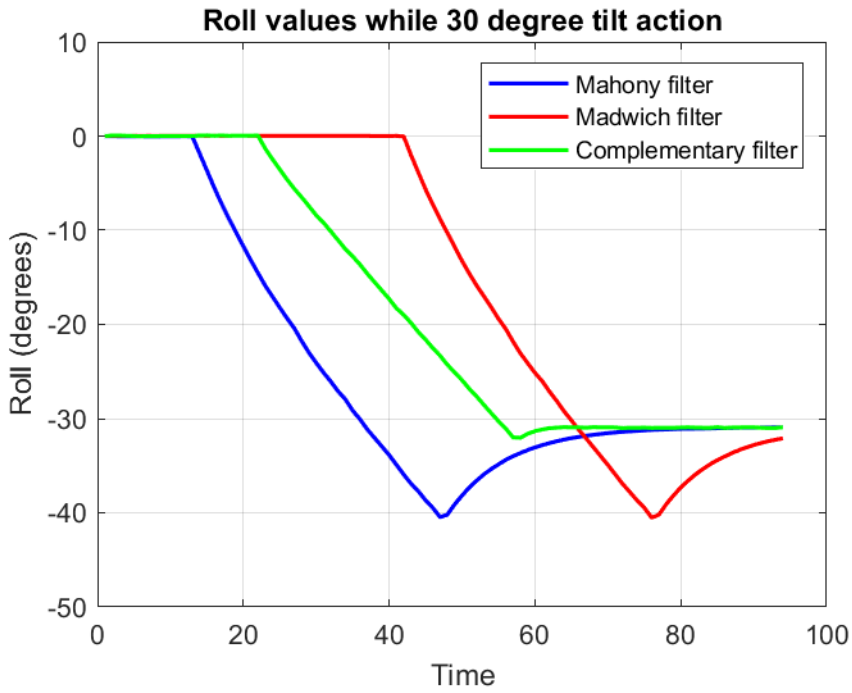

Figure 2: Roll values for dynamic test of filters

A similar test was conducted to compare the performance of the filters in determining the yaw angle. In the software, the initial yaw angle was set to 180 degrees for the Madgwick and Mahony filters, and 0 degrees for the Complementary filter. After running each filter program, the turntable was rotated at a constant speed to measure the yaw angle. The behavior of the filters is illustrated in Figure 3.

The Complementary filter, which performs well in estimating pitch and roll angles, produced results with a progressively increasing error in the yaw angle. This filter combines the data from two sensors at a fixed ratio. Specifically, it assumes that the gyroscope data is accurate over the long term and calculates the orientation angle using gyroscope readings. The accelerometer data is used to correct short-term sudden errors. However, this method does not dynamically adapt to errors in the accelerometer and gyroscope data, but instead combines them at a constant ratio. As a result, deviations in the yaw angle occur more rapidly due to the accumulation of gyroscope errors, and the accelerometer fails to provide adequate correction. Additionally, yaw angle estimation in this method is based on a simple numerical integration principle (yaw += gyro_z * dt), which also integrates errors over time.

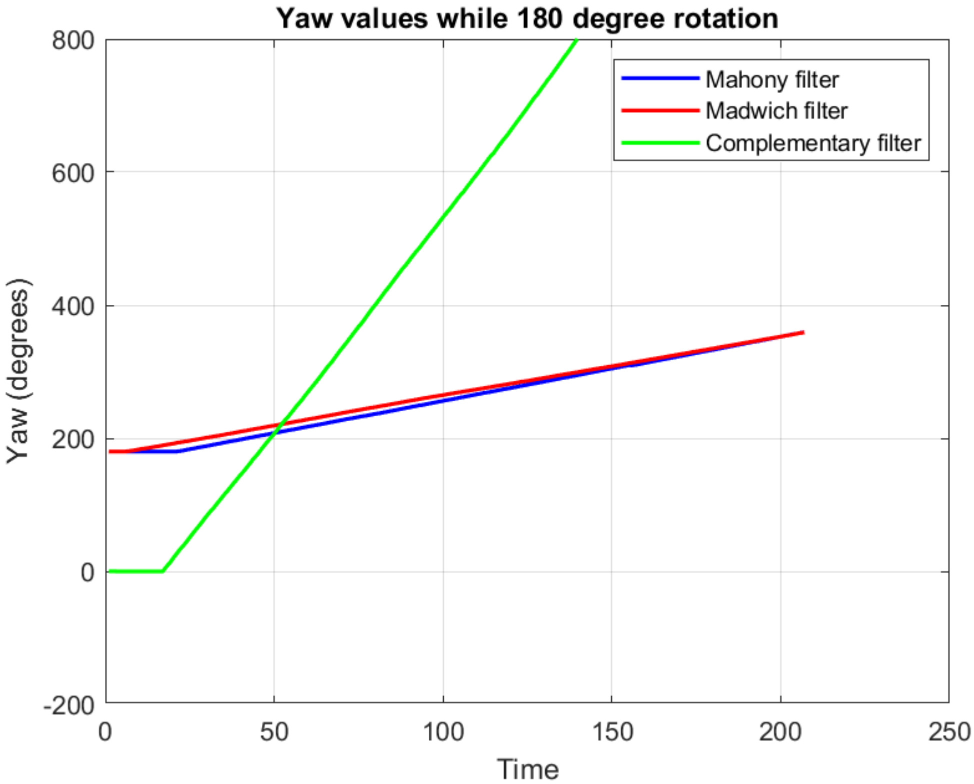

Figure 3: Yaw values for dynamic test of filters

IV. CONCLUSION

This study assessed the performance of Madgwick, Mahony, and Complementary filters for IMU-based yaw, pitch, and roll angle calculations, evaluating their accuracy, memory usage, and execution time. The results indicated that the Madgwick filter, although offering high accuracy with a mean absolute error (MAE) of 0,283 degrees in pitch and 0,250 degrees in roll, also had the highest computational cost, with a processing time of 2,0404 ms and memory usage of 13.614 bytes. The Mahony filter performed well in dynamic conditions, particularly with rapid motion, showing an MAE of 0,300 degrees for pitch and 0,283 degrees for roll, while requiring 1,4388 ms to execute and using 13.034 bytes of memory. In contrast, the Complementary filter, while the highest accurate with an MAE of 0,083 degrees in pitch and 0,300 degrees in roll, had the lowest computational requirements, executing in just 0,65 ms and using 10.400 bytes of program memory.

The numerical results suggest that while the Madgwick filter is preferable for applications prioritizing accuracy, its higher computational demand limits its use in resource-constrained systems. The Mahony filter offers a good balance between performance and efficiency, making it ideal for applications involving dynamic movements. The Complementary filter, with its low computational cost, is well-suited for embedded systems where processing power is limited, though at the expense of accuracy, particularly in yaw estimation.

In conclusion, the choice of filter should be guided by the application's specific requirements for accuracy, computational efficiency, and memory usage. Future work may involve optimizing these algorithms for even better performance, particularly in real-time systems where a trade-off between accuracy and computational resources is critical.

REFERENCES

[1] Jouybari, A., Amiri, H., Ardalan, A., & zahraee, N. (2019). Methods comparison for attitude determination of a lightweight buoy by raw data of IMU. Measurement. https://doi.org/10.1016/J.MEASUREMENT.2018.11.061.

[2] Song, S., Pei, Y., & Hsiao-Wecksler, E. (2022). Estimating Relative Angles Using Two Inertial Measurement Units Without Magnetometers. IEEE Sensors Journal, 22, 19688-19699. https://doi.org/10.1109/JSEN.2022.3203346.

[3] Ludwig, S., & Burnham, K. (2018). Comparison of Euler Estimate using Extended Kalman Filter, Madgwick and Mahony on Quadcopter Flight Data. 2018 International Conference on Unmanned Aircraft Systems (ICUAS), 1236-1241. https://doi.org/10.1109/ICUAS.2018.8453465.

[4] Madgwick, S. (2010). An efficient orientation filter for inertial and inertial/magnetic sensor arrays. *Report x-io and University of Bristol (UK)*, *25*, 113-118.

[5] Parikh, D., Vohra, S., & Kaveshgar, M. (2021). Comparison of Attitude Estimation Algorithms With IMU Under External Acceleration. 2021 IEEE International Symposium on Smart Electronic Systems (iSES) (Formerly iNiS), 123-126. https://doi.org/10.1109/iSES52644.2021.00037.

[6] Jouybari, A., Ardalan, A., & Rezvani, M. (2017). EXPERIMENTAL COMPARISON BETWEEN MAHONEY AND COMPLEMENTARY SENSOR FUSION ALGORITHM FOR ATTITUDE DETERMINATION BY RAW SENSOR DATA OF XSENS IMU ON BUOY. ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 497-502. https://doi.org/10.5194/ISPRS-ARCHIVES-XLII-4-W4-497-2017.

[7] Liu, M., Cai, Y., Zhang, L., & Wang, Y. (2021). Attitude Estimation Algorithm of Portable Mobile Robot Based on Complementary Filter. Micromachines, 12. https://doi.org/10.3390/mi12111373.

[8] Jouybari, A., Ardalan, A., & Rezvani, M. (2017). EXPERIMENTAL COMPARISON BETWEEN MAHONEY AND COMPLEMENTARY SENSOR FUSION ALGORITHM FOR ATTITUDE DETERMINATION BY RAW SENSOR DATA OF XSENS IMU ON BUOY. ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 497-502. https://doi.org/10.5194/ISPRS-ARCHIVES-XLII-4-W4-497-2017.

[9] Romadhany, F., Triwiyatno, A., & Setiyono, B. (2013). DESAIN SENSOR MARG (MAGNETIC, ANGULAR RATE, AND GRAVITY) DENGAN METODE NON-LINEAR COMPLEMENTARY FILTER SEBAGAI NAVIGASI GERAK QUADROTOR TEKNIK ELEKTRO UNIVERSITAS DIPONEGORO. , 2, 534-541. https://doi.org/10.14710/TRANSIENT.2.3.534-541.

[10] Quoc, D., Sun, J., Le, V., & Luo, L. (2015). Complementary Filter Performance Enhancement through Filter Gain. International Journal of Signal Processing, Image Processing and Pattern Recognition, 8, 97-110. https://doi.org/10.14257/IJSIP.2015.8.7.10.

[11] Parikh, D., Vohra, S., & Kaveshgar, M. (2021). Comparison of Attitude Estimation Algorithms With IMU Under External Acceleration. 2021 IEEE International Symposium on Smart Electronic Systems (iSES) (Formerly iNiS), 123-126. https://doi.org/10.1109/iSES52644.2021.00037.

[12] Wen, X., Liu, C., Huang, Z., Su, S., Guo, X., Zuo, Z., & Qu, H. (2019). A First-Order Differential Data Processing Method for Accuracy Improvement of Complementary Filtering in Micro-UAV Attitude Estimation. Sensors (Basel, Switzerland), 19. https://doi.org/10.3390/s19061340.

[13] Madgwick, S. O., Harrison, A. J., & Vaidyanathan, R. (2011, June). Estimation of IMU and MARG orientation using a gradient descent algorithm. In 2011 IEEE international conference on rehabilitation robotics (pp. 1-7).

[14] Mahony, R., Hamel, T., & Pflimlin, J. M. (2008). Nonlinear complementary filters on the special orthogonal group. IEEE Transactions on automatic control, 53(5), 1203-1218.

[15] Redhyka, G., Setiawan, D., & Soetraprawata, D. (2015). Embedded sensor fusion and moving-average filter for Inertial Measurement Unit (IMU) on the microcontroller-based stabilized platform. 2015 International Conference on Automation, Cognitive Science, Optics, Micro Electro-Mechanical System, and Information Technology (ICACOMIT), 72-77. https://doi.org/10.1109/ICACOMIT.2015.7440178.