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Comparative Analysis of Filtering Techniques for AGV Indoor Localization with Ultra-Wideband Technology

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ABSTRACT

This paper investigates the filtering techniques to enhance the accuracy of indoor localization for Autonomous Guided Vehicles (AGVs) using Ultra-Wideband (UWB) technology. A comprehensive comparative analysis of various filtering approaches, including the Kalman Filter (KF), Moving Average Filter (MA), Savitzky-Golay Filter (SG), Weighted Average Filter (WAF), and their combinations, are conducted. The primary focus of this paper is the integration of a Moving Average-Kalman Filter (MAKF) with an extended window size of 201. Experimental findings reveal significant performance differences among these filtering techniques. The most effective approach is the MAKF technique, achieving an accuracy of 85.13% and the lowest path deviation of 0.17 meters. Conversely, the MA exhibits the lowest accuracy at 68.83%. Notably, the WAF attains an accuracy of 72.46% but exhibits a significantly higher path deviation of 2.65 meters compared to 1.45 meters of the MA filtering technique. The proposed MAKF acknowledged for its ability to effectively reduce noise with real-time responsiveness, represents a significant advancement in AGV indoor localization techniques.

Keywords: AGV, indoor localization, Kalman filter, moving average, Savitzky-golay, UWB

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INTRODUCTION

Indoor localization poses intricate challenges for Autonomous Guided Vehicles (AGVs) operating within industrial environments. Precise AGV positioning is imperative for

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optimizing operational efficiency and ensuring safe navigation (Liu et al., 2022). Unlike outdoor scenarios where the Global Positioning System (GPS) is readily available, indoor environments lack consistent satellite-based positioning and are often cluttered with obstacles and sources of interference.

Integrating Ultra-Wideband (UWB) technology with advanced filtering techniques has emerged as a promising solution to address these challenges. UWB technology, known for its ability to provide accurate distance measurements (Flueratoru et al., 2020) and resistance to signal reflections, is a key enabler for indoor localization. However, in an indoor environment, interference can introduce noise and inaccuracies into the raw UWB data (Borhan et al., 2023), necessitating filtering techniques to enhance accuracy.

This research aims to comprehensively evaluate and compare various filtering methods, including the established Kalman Filter (KF), the straightforward Moving Average Filter (MA), the polynomial-based Savitzky-Golay Filter (SG), and the Weighted Average Filter (WAF). This paper also explores the integration of these filters and their impact on AGV indoor localization.

The primary objective of this research is to provide insights into the effectiveness of filtering techniques in reducing noise and improving AGV positioning accuracy within an indoor environment. This study is supported by conducting experiments involving AGV platforms equipped with UWB hardware in an indoor scenario.

Furthermore, this research introduces the Moving Average-Kalman Filter (MAKF) with a large window size of 201 as an innovative approach for balancing noise reduction and real-time responsiveness, crucial for AGV operations in dynamic environments. The decision to employ a window size of 201 reflects a deliberate choice to capitalize on the advantages of an odd window size. This choice ensures that important dynamic patterns in the data are well-preserved and contribute to the overall robustness of the filtering processes. Moreover, a larger window size helps reduce the impact of fluctuations or noise in the input data.

Filtering Techniques for Indoor Localization

Numerous filtering methods have been explored to enhance the accuracy of AGV indoor localization. KF has been a prominent choice due to its ability to assimilate noisy measurements and provide state estimates with optimal accuracy. Yi et al. (2021) have demonstrated the efficacy of KF in AGV positioning. MA, known for its relatively high accuracy and low computational overhead, has also been investigated (Dangkham, 2018). MA filters offer real-time responsiveness, making them suitable for AGV applications in dynamic environments. However, MA alone may exhibit inaccuracies in speed measurement due to factors such as multipath effects and environmental interferences (Fakhoury & Ismail, 2023).

SG has been applied to smoothen UWB data (Laanen et al., 2023). SG filters use polynomial regression to eliminate high-frequency noise components while preserving underlying trends. This characteristic makes them appealing for certain AGV scenarios. WAF has been introduced for its ability to improve the accuracy of indoor localization with lower computation complexity (Cheng et al., 2011). WAF filters allow practitioners to adapt filter behavior to specific AGV localization requirements by assigning varying weights to data points.

Ultra-Wideband Technology for Indoor Localization

Li et al. (2019) have explored the integration of UWB hardware into AGV systems to retrieve the position of the AGV. UWB localization system generally involves anchors, which are stationary UWB transceiver modules placed in known positions throughout the environment and a tag, which is a transceiver module installed on the AGV (Bae et al., 2022). Moreover, the UWB technology possesses the capability to execute two-way-ranging (TWR) (Wei et al., 2018), a process that involves the precise measurement of time-of-flight (TOF) from the tag to the anchor, subsequently multiplied by the speed of light.

Table 1 shows the comparison of filtering techniques through the existing literature. Notably, a lack of attention is dedicated to utilizing the MA filter for AGV indoor localization, as highlighted in Table 1, specifically in real-time applications—a critical consideration for AGVs operating dynamically in indoor environments. This research gap raises fundamental questions about the untapped potential of the MA filter in improving AGV indoor positioning accuracy, noise reduction, and real-time responsiveness, as currently, there are minimal applications of the MA filter. The motivation for this study is to comprehensively address this conspicuous research gap by conducting a thorough assessment of the suitability of the MA filter and exploring its potential integration with the KF to fill this significant gap in academic research.

METHODS

The MAKF combines the KF and MA filter characteristics with a distinctive window size of 201 data points. It focuses on effectively reducing noise while preserving dynamic patterns. The algorithmic details of MAKF were also discussed, providing insights into its filtering methods.

Moving Average-Kalman Filter (MAKF)

This paper proposed the MAKF technique, which integrates the KF and MA filter characteristics, as shown in Figure 1. Sadowski and Spachos (2019) found that Kalman has better accuracy, while MA has better precision. Therefore, the MAKF in this research differs from the conventional method by integrating the recursive, optimal estimation

Table 1
Comparison of filtering techniques

References	KF	MA	SG	Other filtering techniques	AGV	UWB	Simulation	Real-time application	Reason for choosing the technique
Li et al., 2019	✓	-	-	Weighted Fusion Technique	✓	✓	-	-	To reduce the impact of positioning in line-of-sight (LOS) and non-line-of-sight (NLOS) states.
Wisanmongkol et al., 2019	-	-	-	WAF	-	-	-	✓	To mitigate multipath fading in indoor wireless positioning.
Bergmann et al., 2020	-	-	✓	-	-	-	✓	-	Its ability to smooth data points without distorting the signal tendency.
Gyulai et al., 2020	-	-	✓	-	-	-	✓	-	It effectively removes random noise from the collected spatial data obtained from the IPS.
Singh et al., 2020	-	-	✓	-	-	-	-	-	Its lightweight and accurate performance.
Rykała et al., 2020	-	✓*	-	-	-	✓	-	✓	• It helps to smooth out the data and reduce noise or fluctuations in the signal. • It helps to improve the accuracy of the location results obtained from the UWB technology.
Le Minh & Xuan, 2021	✓	-	-	-		✓	-	-	Its effectiveness in addressing the challenges of NLOS environments and improving positioning accuracy.
Lee et al., 2021	✓	-	-	-		✓	-	✓	Its ability to combine and optimize the UWB positioning and U-PDR techniques enhances the accuracy of indoor localization.
Yi et al., 2021	-	-	-	Adaptive Kalman filter		✓	-	✓	To provide better location accuracy in indoor environments with systematic noise and inadequate measuring information.
Zhou et al., 2021	-	-	-	Standard Kalman filter based on expectation maximization (SKF-EM)		✓	-	✓	To improve the positioning accuracy in NLOS environments.

Table 1 *(continue)*

References	KF	MA	SG	Other filtering techniques	AGV	UWB	Simulation	Real-time application	Reason for choosing the technique
Qiang et al., 2021	-	-	-	Fuzzy Kalman filter		✓	-	✓	To handle the large fluctuation caused by NLOS factors in complex indoor environments.
Li et al., 2022	✓	-	-	-	✓	✓	-	✓	To correct ranging errors caused by UWB multipath interference.
Guo et al., 2022	-	-	-	KF + Dilution of Precision (DOP)	-	✓	-	✓	To enhance UWB positioning accuracy in narrow spaces.
Sofianidis et al., 2022	-	✓*	-	Low pass filter	-	✓	-	✓	To improve the accuracy of the UWB-based localization system.
Alonge et al., 2022	-	-	-	Kalman-Bucy filter (KBF)	-	✓	-	✓	To deal with the velocity estimation problem in UWB localization.
Mehrabian & Ravanmehr, 2023	-	-	-	Weight-Based Optimization (WBO)	-	-	-	✓	To optimize raw RSSI values and enhance the accuracy of the IPS.

Note. * Refers to reference wherein the MA filter has been applied

Input: $input_{MAKF}$ – Noisy measurement data matrix
Output: $output_{MAKF}$ – Smoothed estimate data matrix
Initialize variables:
$N \leftarrow$ Window size for moving average
Apply Kalman Filter to $input_{MAKF}$ to obtain $kalman\_output$
for $i \leftarrow 1$ to number of rows in $kalman\_output$ **do**
    Calculate avg (moving average):
    $avg \leftarrow$ Moving average of $kalman\_output\ (1 : i, :)$ over window size N
    $signal \leftarrow kalman\_output(i,:)$
    $avg \leftarrow$ avg+signal
    Append avg to $output_{MAKF}$
end for

Figure 1. Moving Average-Kalman filter algorithm

capabilities of the KF with the simple, non-recursive smoothing features of the MA filter to mitigate the limitations of each method and provide a more effective solution for specific applications such as AGV indoor localization.

The MAKF algorithm begins with noisy measurement data, $input_{MAKF}$. The algorithm's output, labeled $output_{MAKF}$, represents a smoothed version of the measurement data, providing a more accurate representation of the AGV's position.

The first step in the MAKF algorithm is initializing the parameters, where the window size for the moving average, denoted as N, is defined. This window size determines the extent of smoothing applied to the noisy data. A larger N value results in more extensive smoothing, while a smaller value retains more of the dynamics of the original data.

Subsequently, KF is applied to the $input_{MAKF}$ data to obtain $kalman\_output$. The KF component of the MAKF processes the raw measurements and utilizes a prediction correction algorithm to estimate the state of the AGV, compensating for noise and uncertainties.

For each data point in $kalman\_output$, the algorithm calculates a moving average, or avg, using a rolling window of size N. This moving average operation acts as a smoothing mechanism, reducing the influence of noisy fluctuations and enhancing the overall precision of the data. In this step, the algorithm ensures that the filtered signal retains its real-time responsiveness while mitigating noise and inaccuracies.

Finally, the average value, representing the smoothed estimate, is combined with the KF-processed signal to create an optimized estimate of the AGV's position. This updated estimate is then appended to the $output_{MAKF}$ data matrix, ensuring that the final output reflects the improved accuracy achieved through the MAKF technique.

EXPERIMENTAL SETUP

The experiments were conducted in a controlled indoor environment to simulate complex industrial settings, such as manufacturing plants and warehouses. The environment consists of a 6.47 meter × 8 meter area with various obstacles, representing a challenging scenario for AGV navigation. The experimental environment can be seen in Figure 2.

UWB technology was utilized to gather localization data. The UWB technology employed in this research is the DWM1001-Development Board (Figure 3), which consists of anchor nodes strategically placed throughout the environment and an AGV equipped with a UWB tag. The specifications of the DWM1001 are outlined in Table 2. In this experiment, the UWB updates every 0.1 sec.

The AGV utilized in this study is a compact indoor mobile robot designed for robotics research and education. It is equipped with sensors for navigation and safety, including encoders, and a laser scanner for obstacle detection and avoidance. The AGV is shown in Figure 4.

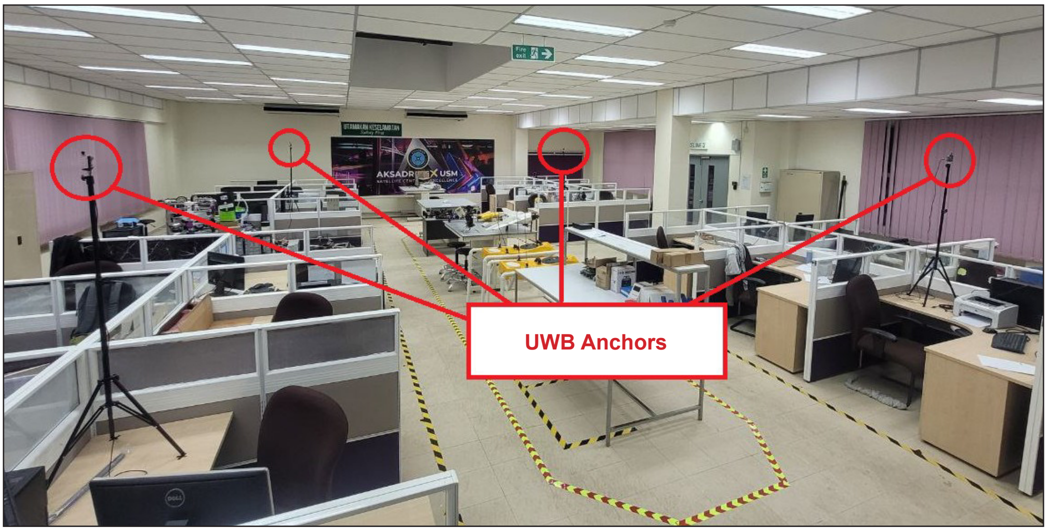

Figure 2. The experimental environment set up in a cluttered space

Table 2
DWM1001-Development board specifications

Specifications	
Accuracy range	Within 10 cm
Line-of-sight range	60 m
Data rate	6.8 Mbps
Supply voltage	3.6 V–5.5 V
Size	54 mm × 43 mm
UWB Channel 5	6.5 GHz

Figure 3. DWM1001-Development Board

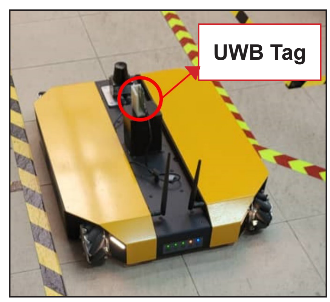

Figure 4. AGV equipped with UWB tag

The data collection procedure involved the AGV navigating the predefined route within the experimental environment. The predefined route, which is also the reference trajectory, is a straight path starting at (2,0) meter and ending at (2,8) meter, where the coordinate origin (0,0) meter is based on Anchor 2.

As the AGV moved, UWB signals were exchanged between the AGV equipped with the UWB tag and the anchor nodes. These signals were used to calculate the AGV's position and trajectory. Raw UWB data obtained during the experiments were subjected to preprocessing, which included data filtering and noise reduction to enhance the accuracy and reliability of the collected data.

Following the collection and preprocessing of the raw UWB data, the AGV operates in accordance with the reference trajectory derived from the UWB data subjected to filtration by five distinct filtering techniques: KF, MA filter, SG filter, WAF, and MAKF. For more information on these filtering techniques' working mechanisms and algorithms, please refer to the Appendix. The movement of the AGV is executed in real time rather than in a simulated environment. This real-time execution enables a comprehensive comparative assessment of the performance of the filtering techniques. Figure 5 displays the overall experimental setup.

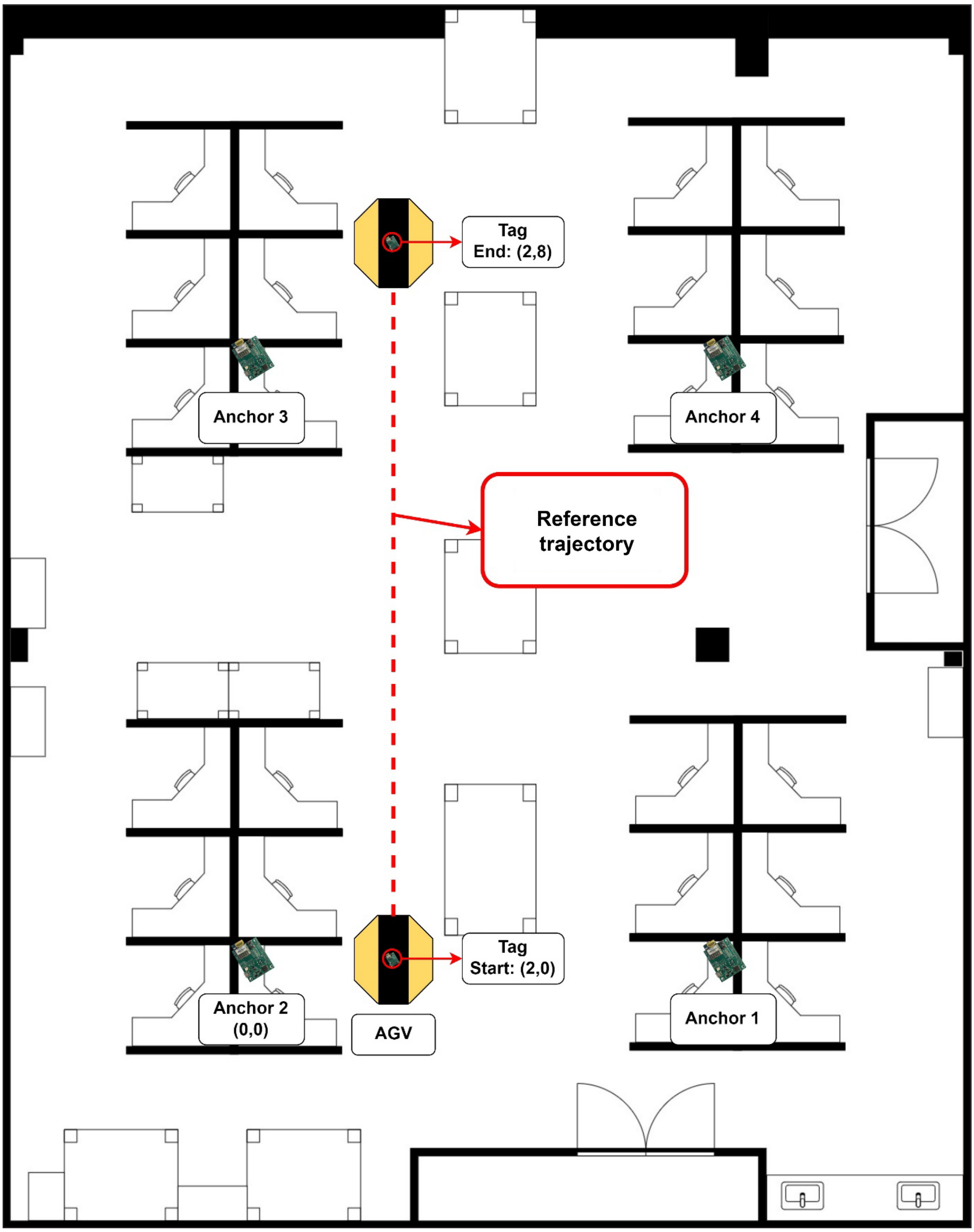

Figure 5. Overall experimental setup in an indoor environment

RESULTS AND DISCUSSION

The study provides a comprehensive analysis of the trajectories of the AGV employing various filtering techniques. These techniques offer varying trade-offs between trajectory smoothness and alignment with a reference path, as visually illustrated in Figure 6. The AGV employing the KF technique showcases generally accurate positioning, although it exhibits noticeable fluctuations, resulting in a lack of smoothness. In contrast, the AGV utilizing the MA filtering technique exhibits a smoother trajectory but deviates from the reference trajectory. It is important to note that, despite the visual deviation, smoothness is a desirable attribute for AGV operations in some contexts.

Among the analyzed techniques, the AGV trajectory employing the SG filtering technique stands out. Figure 6(c) shows that this method delivers a trajectory that aligns

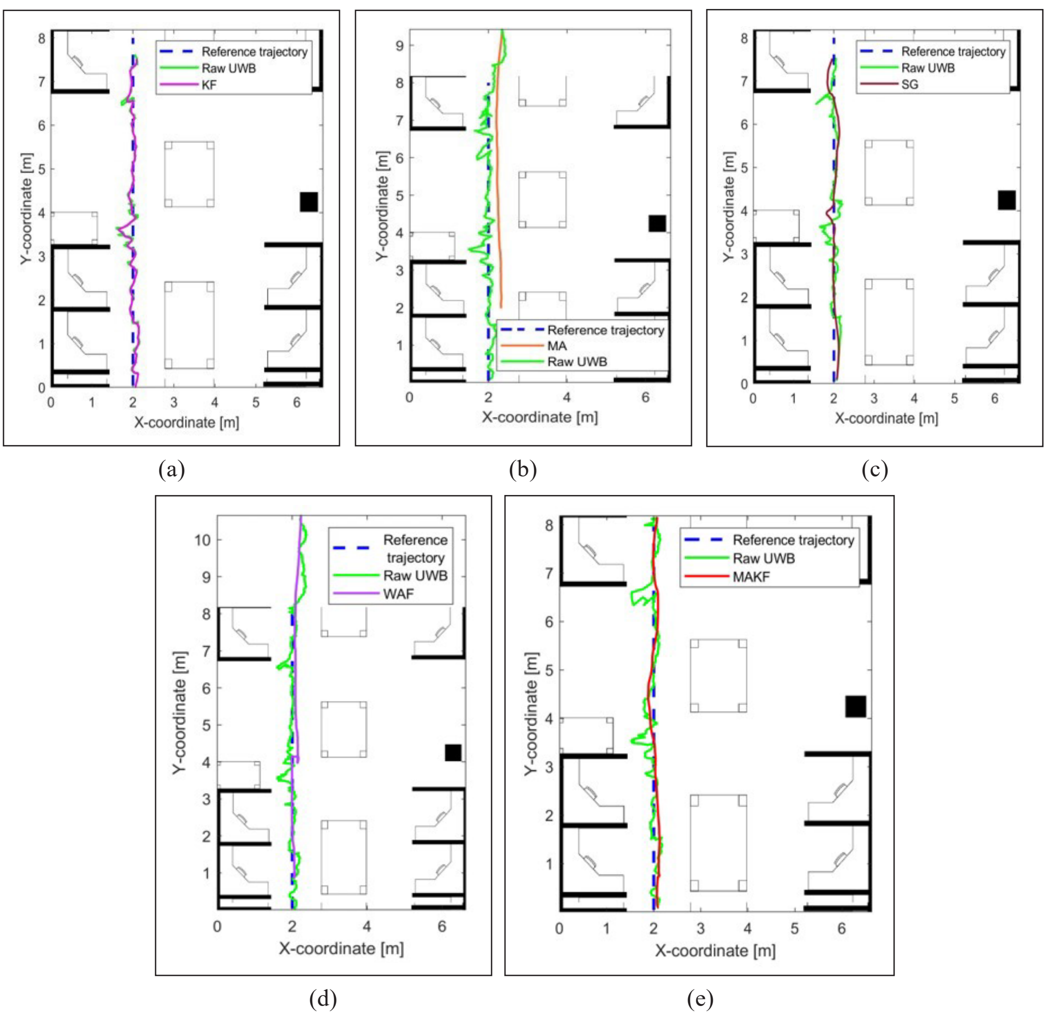

Figure 6. Real-time AGV trajectory using different filtering techniques: (a) KF, (b) MA, (c) SG, (d) WAF, and (e) MAKF

closely with the reference path, offering the best balance between trajectory accuracy and smooth movement. It is important to highlight that the visual results reflect the actual movement of the AGV and are crucial in selecting the most suitable filtering technique.

Moreover, Figure 6(d) displays the AGV's trajectory using the WAF technique. While it provides exceptionally smooth movement, the deviation from the reference trajectory is more pronounced than with the SG filter. This trade-off between smoothness and trajectory accuracy emphasizes the importance of selecting the filtering technique that aligns with specific AGV requirements.

In this comparative analysis, the proposed MAKF technique, as displayed in Figure 6(e), emerges as the most promising solution. The movement of the AGV is notably smoother compared to the conventional KF method, while it still closely follows the reference trajectory, distinguishing it from the MA filtering technique alone.

The analysis extends to key metrics such as path deviation, MSE, RMSE, and accuracy. These metrics provide a quantitative basis for evaluating the performance of the filtering techniques. Figure 7 displays the path deviation results for different filtering techniques, while Table 3 shows the accuracy, MSE and RMSE of the filtering techniques. As displayed in Figure 7, the KF method presents a low path deviation at 0.49 meters, emphasizing its accuracy in positioning. In contrast, the MA filter exhibits a higher path deviation of 1.45 meters, implying less precision in its positioning estimates.

The SG filter and WAF technique demonstrate path deviations of 0.48 meters and 2.65 meters, respectively, signifying their capability to provide accurate positioning with varying degrees of smoothness. However, the most remarkable result in the proposed MAKF with a path deviation of 0.17 meters indicates significant improvements in AGV indoor localization

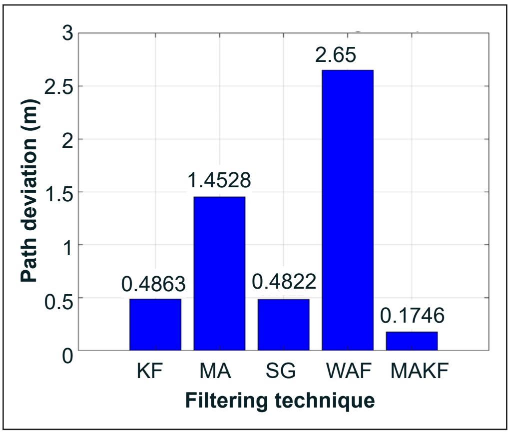

Figure 7. Path deviation results for different filtering techniques

Table 3
MSE, RMSE and accuracy results for different filtering techniques

Filtering Techniques	MSE (m)	RMSE (m)	Accuracy (%)
KF	2.0438	1.4296	82.0375
MA	6.1544	2.4808	68.8305
SG	2.244	1.4980	81.1786
WAF	4.8049	2.1920	72.4593
MAKF	1.4004	1.1834	85.1319

precision. The effectiveness of the MAKF technique in improving accuracy is supported by its RMSE of 1.18 meters and an MSE of 1.4, the lowest among the techniques evaluated.

The results obtained reveal a close relationship between accuracy, MSE and RMSE. KF demonstrates an accuracy of 82.04% with an MSE of 2.04 meters and RMSE of 1.43 meters, highlighting its effectiveness in AGV positioning. Conversely, the MA filter presents a lower accuracy of 68.83% with a higher RMSE of 2.48 meters and MSE of 6.15 meters, indicating less reliable positioning.

The SG filter strikes a balance with an accuracy of 81.18% and an RMSE of 1.5 meters, signifying the trade-off between accuracy and precision. Its MSE of 2.24 meters suggests a moderate level of accuracy in the AGV positioning compared with other filtering techniques. WAF delivers an accuracy of 72.46% but comes with a higher value of MSE and RMSE, which are 4.8 and 2.19 meters, respectively, again highlighting the intricate relationship between accuracy and precision.

The proposed MAKF excels in both accuracy and precision. With a high accuracy of 85.13% and the lowest RMSE value among the evaluated techniques at 1.18 meters, the MAKF establishes itself as a promising choice for applications demanding high accuracy and minimal positioning errors. Additionally, the MAKF recorded the lowest value of MSE, which was 1.4 meters. The low value of MSE indicates that the estimation of the filter is closer to the true positions, which further supports the efficacy of the MAKF. The comparison reveals the advantages of merging the KF and MA filters, effectively addressing their limitations.

The choice of filtering technique significantly influences AGV operations, particularly in complex indoor environments where safety and efficiency are paramount. These implications extend to various industrial sectors, where AGVs are critical in automation and logistics.

CONCLUSION

The findings presented in this study revealed significant variations in performance among the assessed filtering techniques. The highlight of this research was the introduction and assessment of MAKF, which outperformed all other techniques with an accuracy of 85.13%, an MSE and an RMSE of 1.4 and 1.18 meters, respectively. Additionally, the filter recorded the lowest value for path deviation, which was 0.17 meters. MAKF effectively improved the AGV indoor localization, combining the advantages of accuracy, minimal positioning errors, and real-time responsiveness. In contrast, the MA filter exhibited the lowest accuracy at 68.83%, and the WAF, reaching an accuracy of 72.46%, displayed a significantly higher path deviation of 2.65 meters.

These results carry significant implications for AGV indoor localization. The demonstrated effectiveness of MAKF, especially with extended window size, presents a promising solution to tackle challenges related to noise and dynamic environments in AGV operations. This study provides practical guidance for researchers and practitioners in automation and logistics, aiding filter selection and parameter optimization. Such guidance ultimately enhances the efficiency and safety of AGV applications in diverse industrial and logistical scenarios.

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