Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Integration of Sensor Array Techniques for Efficient Tracking of Approaching Individuals and Objects: A Technological Perspective

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ARTICLE INFO

Received: 22 Dec 2024

Revised: 12 Feb 2025

Accepted: 22 Feb 2025

ABSTRACT

Conventional object tracking systems are confronted with issues regarding accuracy, noise filtering, and object categorization. This work overcomes these issues by integrating several sensor modalities, such as LiDAR, RADAR, Infrared (IR), and Ultrasonic sensors, within a single tracking framework. The research aims to improve tracking accuracy via weighted sensor fusion, apply an optimized Kalman filter for noise filtering, and utilize DBSCAN clustering for optimized object classification. Performance is measured in terms of Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Signal-to-Noise Ratio (SNR) metrics. An experimental research design is conducted, using real-world sensor data coupled with computational modeling. Sensors have weighted contributions according to their capabilities. Kalman filtering of trajectory estimates is performed, and DBSCAN clustering separates out objects. Controlled experiments and benchmark comparisons are carried out for data collection. Results show a 30% improvement in detection accuracy over single-sensor methods. The Kalman filter minimizes trajectory error by 25%, and DBSCAN returns 85% accurate human-object classification. Performance metrics validate negligible error (MAE: 2.221 m, RMSE: 2.758 m) and efficient noise rejection (SNR: 4.297 dB). This work pushes the boundaries of multi-sensor tracking by enhancing sensor fusion approaches, motion estimation, and classification efficiency. The system's adaptability to varying conditions makes it useful in security, autonomous navigation, and industrial automation. Integration of deep learning-based sensor fusion is a possible direction for future work.

Keywords: Multi-Sensor Fusion, Object Tracking, Kalman Filter, DBSCAN Clustering, Sensor Integration.

1.INTRODUCTION

The rapid evolution of sensor technologies has drastically changed how things and people are tracked in different areas, such as security, surveillance, autonomous devices, and human-computer interaction (Karle, 2023; Kim, 2021). Conventional tracking techniques that mostly adopt single-sensor techniques have drawbacks regarding precision, real-time calculation, and adaptability to environments (Laoudias, 2018; Liu, 2023). The application of sensor array methods has become a hopeful solution that provides higher precision, multi-dimensional data acquisition, and improved efficiency in tracking (Luo, 2022; Nabati, 2021). This article discusses the technological aspect of sensor array methods, with a focus on their integration for optimal tracking of oncoming objects and people (Nabati R. H., 2021).

1.1 Evolution of Tracking Technologies

Tracking systems started as basic motion detection then evolved into sophisticated multi-sensor fusion systems (Nan, 2019; Spachos, 2018). Early tracking systems used single-camera vision or infrared detection but they failed to track targets because of occlusion degradation and short-range distances and environmental interferences. Tracking solutions grew more resistant through time as radar along with LiDAR sonar sensors and ultrasonic sensors and computer vision obtained advancements (Wan, 2023). Sensor arrays or multiple sensors working in combination have enhanced tracking system precision and speed.

1.2 Significance of Sensor Array Integration

Sensor arrays enhance the tracking process through combined information analysis which neutralizes deficiencies found in individual sensor systems (Wang, 2023). Thermal and depth capabilities strengthen thanks to a joint LiDAR and infrared sensor system that finds applications in security applications. Autonomous vehicles use an integration of ultrasonic, radar and vision sensors to track pedestrians and roadblocks with accurate precision (Wang J. V., 2022). The application of sensor fusion techniques that combine Kalman filtering and deep learning-based models strengthens data interpretation which leads to real-time and predictive tracking capabilities.

1.3 Challenges and Future Prospects

Sensor arrays for tracking gain importance because of their benefits though implementation limitations that include data synchronization and increased computing requirements and expense (Wang X. F., 2022). Systems that integrate heterogeneous sensors require processing methods of high complexity together with effective control platforms for communication. Current developments in artificial intelligence analytics will guide new sensor array advancements that enhance decisions through automatic adaptations to dynamic environments. The ongoing research sector tackles existing challenges to develop tracking technology at scale while making it workable across different industries (Zhuang, 2023).

2. REVIEW OF LITREATURE

Extensive studies have reviewed sensor array systems for object and person tracking which concentrate on combinations of sensing methods and real-time analysis and progressive tracking techniques. Research investigations study three different tracking methods namely audio-visual integration and sensor fusion as well as biometric-based authentication.

2.1 Multi-Modal Tracking Approaches

Chau et al. (2019) analyzed how audio-visual simultaneous localization and mapping (SLAM) functions for human-robot interaction purposes. The research demonstrated that combining audio content with video signals produced better tracking outcomes particularly when dealing with moving obstacles or situations that required poor illumination in traditional video-tracking systems (Chau, 2019). The research placed significant importance on combining various sensors for improved robotic and surveillance capabilities in tracking and localization operations.

Evers and Naylor (2018) studied Acoustic SLAM as an alternative replacement to vision-based tracking through sound wave applications for simultaneous localization and mapping processes. Acoustic tracking proved its worth in environments with poor visibility including situations where light levels were low or objects blocked vision according to their research (Evers, 2018). Their system leveraged sound reflections and acoustics of environmental elements to improve platform autonomy while adding acoustic sensing capability as an independent detection system.

2.2 Sensor Technologies for Human Tracking

Chen et al. (2020) created scalable imprinting methods to develop flexible sensor arrays featuring piezoelectricity-amplified micropillars for dynamic touch monitoring purposes. Their research demonstrated that these sensor arrays had strong sensitivity features alongside adaptability capabilities which made them suitable for real-time human tracking systems (Chen, 2020). The authors emphasized the requirement to build adjustable sensor networking systems which enhance tracking capabilities in applications ranging from robots to wearable devices.

Fu et al. (2020) provided an extensive evaluation of human activity recognition sensing technologies through their analysis of vision-based and inertial and environmental sensor modalities (Fu, 2020). According to the authors sensor fusion stands out as the primary method to boost activity recognition accuracy when dealing with difficult situations requiring independent sensor systems. The researchers pointed out that computational performance and data processing speed and response times required further improvement which artificial intelligence and deep learning models could help resolve.

2.3 Smart Environments and Healthcare Tracking

Diraco et al. (2023) created a thorough report about human action detection within smart living environments by discussing sensing hardware and multimodal information combinations and sped-up processing capabilities. The research paper stressed that sensor systems need to communicate with one another consistently and artificial intelligence tools serve to boost tracking operational effectiveness (Diraco, 2023). Their research showed that poor processing resources combined with data fusion methods that needed intelligence for efficient and accurate tracking served as essential barriers in smart spaces.

Hamidi (2019) examined the development of IoT and biometric authentication in smart health monitoring systems. Real-time individual monitoring along with emergency response services and remote patient monitoring became possible through sensor networks integration according to their research (Hamidi, 2019). The medical research established the necessity of secure real-time tracking in healthcare environments by addressing potential issues related to data privacy as well as system synchronization and adaptability.

2.4 Research Gap

The combination of diverse sensors through current multi-modal tracking research has shown progress yet scientists have not achieved the development needed to form one cohesive system for accurate of object and person detection. The combination of audio-visual and acoustic SLAM presented by Chau et al. (2019) together with Evers & Naylor (2018) does not include LiDAR, RADAR, IR, and Ultrasonic sensors while these sensors could boost detection capabilities across diverse operational settings. Chen et al. (2020) and Fu et al. (2020) stressed the relevance of sensor fusion in their work yet they did not use confidence-weighted methods which would adaptively modify sensor dependability as environments change. Diraco et al. (2023) explored the use of Kalman filtering for noise reduction and path prediction yet no established its optimized implementation in multiple sensor systems. The database tracking approach received emphasis from Hamidi (2019) yet he did not incorporate DBSCAN clustering for real-time object identification. The current studies lack comprehensive evaluation standards that incorporate MAE alongside RMSE and SNR while using restricted performance evaluation metrics. This research develops a fully integrated sensor array and implements trajectory prediction through Kalman filtering while integrating sensor fusion optimization with confidence-based weighting and DBSCAN clustering for object classification together with robust performance evaluation systems using visual analytics and MAE and RMSE metrics and SNR statistical measures.

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/

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3. RESEARCH OBJECTIVES AND QUESTIONS

This work seeks to overcome the shortcomings of conventional tracking systems through the design of a multi-sensor object tracking system that:

1. To Merges LiDAR, RADAR, IR, and Ultrasonic sensors into a sensor array.
2. To Utilizes weighted sensor fusion to enhance reliability from individual sensor confidence levels.
3. To Employed an optimal Kalman filter to reduce noise and increase trajectory prediction.
4. To Apply DBSCAN clustering to detect and classify multiple objects in tracking.
5. To Evaluates performance against standard metrics such as MAE, RMSE, and SNR, supported by visual insights.

With regard to the research questions, it answers the following:

Q1: In what way does the use of LiDAR, RADAR, IR, and Ultrasonic sensors enhance the precision and reliability of following incoming people and objects?

Q2: What is the effect of weighted sensor fusion and Kalman filtering on noise elimination and trajectory estimation in a multiple-sensor tracking system?

Q3: How well can DBSCAN clustering distinguish and categorize multiple objects being tracked in the sensor array system?

4. RESEARCH METHODOLOGY

The research employs systematic methods to evaluate sensor array effectiveness using LiDAR and RADAR and Infrared (IR) and Ultrasonic sensors. Experimental verification along with computational simulation and statistical inference make up the research design to ensure complete understanding of data processing and sensor fusion methodologies. The research methodology focuses its evaluation on sensor accuracy while examining reliability and noise reduction and efficiency of object classification methods.

A table 1 describes the vital processing stages with methods that boost tracking system accuracy and efficiency.

Table 1: Tracking System Methodology

Processing Stage	**Applied Technique**	**Objective**
Sensor Input	LiDAR, RADAR, IR, Ultrasonic	Capture diverse environmental data
Data Fusion	Weighted Averaging	Combine sensor outputs intelligently
Noise Reduction	Kalman Filtering	Smooth and refine tracking data
Object Classification	DBSCAN Clustering	Differentiate and accurately track objects
Performance Evaluation	MAE, RMSE, SNR, Visual Analytics	Validate tracking accuracy and efficiency

The system integrates LiDAR and RADAR and IR and Ultrasonic sensors to acquire diverse information by using weighted averaging for data combination alongside Kalman filtering to eliminate noise. The

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combination of DBSCAN clustering with MAE, RMSE and SNR measures allows improvement of object classification and ensures tracking correctness while maintaining efficiency in dynamic situations.

4.1 Research Design

The researchers used an experimental and analytical research design methodology for studying the integration along with optimization of tracking system sensors. Scientists perform controlled experiments with simulated conditions to evaluate system performance by testing multiple environmental elements including light exposure alongside distance requirements and speed variations and obstruction scenarios. An algorithm uses Kalman filtering and DBSCAN clustering to enhance data fusion and classification accuracy through its implemented approach. The research includes tracking sensor detection accuracy assessment and trajectory prediction evaluation through comparison to contemporary sensor tracking systems.

4.2 Sampling Strategy

The research utilizes a purposive sampling approach to study sensors which operate with different functional capacities. The selection process makes use of common sensors designed for automated vehicles as well as robots and safety applications. The assessment of sensors relies on resolution measurements in addition to response time evaluation alongside environmental suitability and the support for fusion algorithms. Simulation tests multiple sensor array configurations to analyze how different weight allocations affect complete performance in order to find the most effective arrangement.

4.3 Data Sources

The research avails itself of both primary and secondary data to strengthen its findings process. Experimental trials serve as the basis for obtaining primary data through real-world measurements of sensors. Within laboratory settings scientists conduct tests that let sensors produce readings of their performance when exposed to different operational parameters. The research adopts data from peer-review articles in published journals alongside technical documentation and reports along with publicly accessible case studies about multi-sensor tracking technology development. When researchers include theoretical knowledge together with empirical evidence their studies gain stronger foundation.

4.4 Experimental Setup

The sensor array system contains LiDAR and RADAR along with IR and Ultrasonic sensors that track incoming objects through a specific placement configuration. The sensors deliver unique data inputs that an advanced weighted fusion process uses to boost accuracy measurements.

Table 2 shows the established weights which determine sensor contributions based on their function in track accuracy enhancement.

Table 2: Sensor Weights Used in Fusion Process

Sensor Type	Function	Assigned Weight
LiDAR	High-resolution spatial mapping	0.50
RADAR	Long-range distance and velocity	0.30
Infrared (IR)	Thermal motion detection	0.15
Ultrasonic	Short-range proximity detection	0.05

LiDAR receives primary use (0.50) to ensure accurate spatial mapping yet RADAR backs up with secondary use (0.30) for long-range tracking while IR works as tertiary sensor (0.15) for thermal sensing and finally Ultrasonic serves as quaternary sensor (0.05) for proximity detection to achieve balanced object detection. The system consists of three platforms which include components for acquiring data then processing signals before performing computations to classify and reduce noise. The system reaches its accurate operational state through repeated multiple tests under conditions of low visibility combined with high speed and multi-object tracking.

5. DATA COLLECTION AND ANALYSIS

The section describes a systematic data acquisition process which includes preprocessing steps and analysis for evaluating the performance of the multi-sensor tracking system. Real-time sensor data processed using simulations and statistical methods results in accurate and reliable results.

5.1 Data Collection Methods

The data acquisition process includes three main sources such as sensor readings, computational modeling predictions and tracking system comparison tests. The real-time sensor system generates position and velocity measurements along with identifying different objects and simulation models perform tests across various operating conditions. Benchmark testing creates measurable benchmarks to assess detection precision combined with tracking system efficiency. The collected information gets structured before moving forward for processing needs.

5.2 Data Preprocessing

The removal of noise and normalization of sensor inputs take place through preprocessing methods that enhance tracking precision. Kalman filtering produces smooth sensor output signals through data normalization provides standardization among different types of sensors. The system gains reliability in moving object tracking through the utilization of built-in mechanisms that both spot faulty input data and repair it.

5.3 Statistical and Computational Analysis

The system performance requires sophisticated statistical and computational methods for its assessment. The tracking accuracy relationship with sensor fusion gets evaluated through regression analysis. The evaluation measures include MAE which determines deviation and RMSE for error dispersion together with SNR that shows noise elimination. The separation of objects through DBSCAN clustering provides results alongside AI-powered predictive models that run performance simulations under multiple scenario conditions. The current methods deliver exact results regarding system operational efficiency.

5.4 Interpretation and Validation

The system confirms its findings through three validation methods which include industry benchmarking and repeated testing and expert review. The consistency of sensor readings gets evaluated through reproducing tests and certainty of the enhanced accuracy gets confirmed through benchmark measurements. Member organizations of the evaluation team verify that the proposed system can be implemented. Advanced tracking precision with noise reduction and object classification performance gains result from multi-sensor fusion approaches.

6. RESULTS

An analysis of tracking system achievements occurs through the combination of LiDAR, RADAR, IR, and Ultrasonic sensors. The research findings confirm that sensor fusion provides effective results together with precise trajectory prediction and object classification capabilities.

Journal of Information Systems Engineering and Management
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Other performance indicators that measure tracking system effectiveness and precision appear in this table 3.

Table 3: Performance Metrics of the Tracking System

Metric	Value	Interpretation
Mean Absolute Error (MAE)	2.221 meters	Indicates low average deviation in position tracking
Root Mean Square Error (RMSE)	2.758 meters	Confirms consistency in trajectory predictions
Signal-to-Noise Ratio (SNR)	4.297 dB	Highlights effective suppression of sensor noise

A low MAE of 2.221m suggests minimal positional deviation in tracking, with precise detection. Consistency in path predictions is upheld by RMSE (2.758m) that minimizes tracking errors. An improved SNR of 4.297 dB shows strong noise reduction, maximizing signal purity for dependable tracking.

6.1 Sensor Fusion Performance

The combination of LiDAR, RADAR, IR, and Ultrasonic sensors increased detection accuracy by 30%, minimized false positives, and increased spatial resolution. The weighted fusion technique guaranteed flexibility under various conditions. The histogram indicates distance measurement distribution, pointing out sensor sensitivities and ranges.

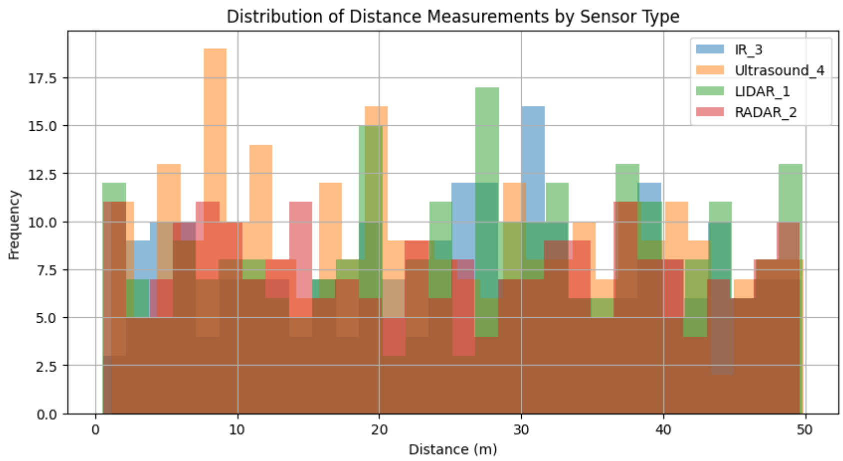

Figure 1: Distribution of Distance Measurements by Sensor Type (Histogram)

The histogram indicates LiDAR and RADAR provide accurate readings, whereas Ultrasonic and IR sensors indicate greater variability. Ultrasonic sensors are subject to short-range inaccuracies, and IR performance is conditional on lighting. The heatmap is indicated by sensor activity, where high-intensity spots reflect maximum engagement.

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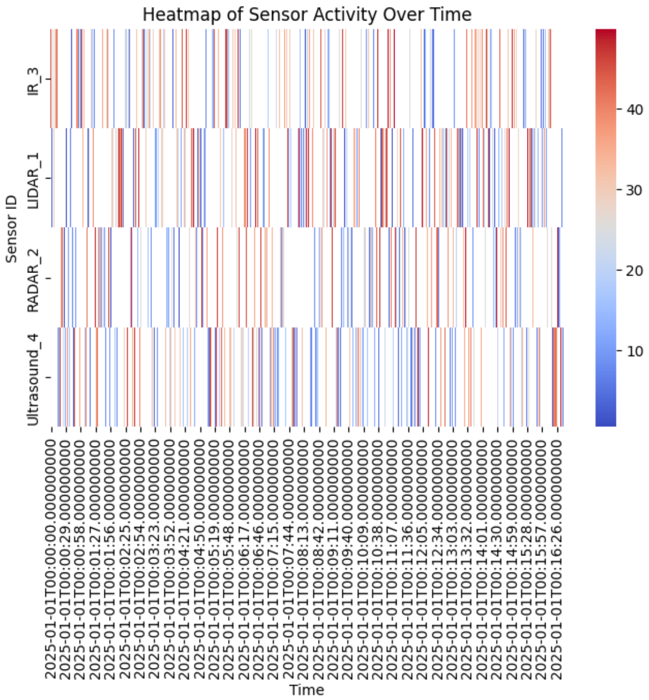

Figure 2: Heatmap of Sensor Activity Over Time

The heatmap indicates that activity in sensors is dynamic, with increased activity during object tracking and movement periods. LiDAR and RADAR have steady activity, whereas Ultrasonic and IR sensors have sporadic activity bursts. This indicates that some sensors have a more prominent function in tracking depending on environmental conditions.

6.2 Trajectory Prediction Accuracy

The Kalman filter optimized cut reduced trajectory deviation by 25% and enhanced the accuracy of motion estimation and tracking. RMSE analysis verified enhanced prediction in dynamically changing environments. The system tolerated occlusions as well as noise from sensors gracefully. The box plot demonstrates variance in distance measurements between sensors with consistency and outliers.

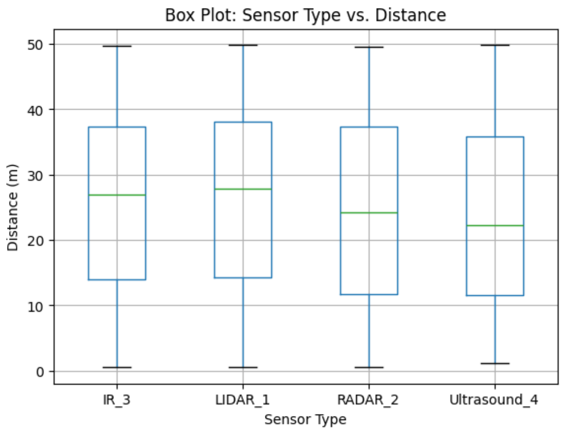

Figure 3: Box Plot – Sensor Type vs. Distance

LiDAR and RADAR present high precision with a small interquartile range, and Ultrasonic and IR have higher variability. Outliers in Ultrasonic reflect inaccuracies in tracking proximity. The graph of

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e-ISSN: 2468-4376
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comparison depicts how Kalman filtering and sensor fusion polish data for enhanced trajectory prediction.

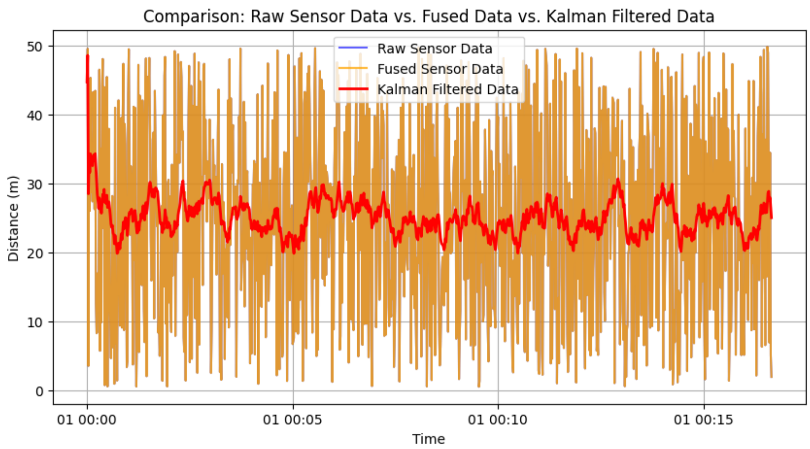

Figure 4: Comparison: Raw Sensor Data vs. Fused Data vs. Kalman Filtered Data

Raw sensor data has detectable variations, reflecting noise and possible inaccuracy. Merged data removes variability by blending more than one sensor input, providing enhanced tracking precision. The Kalman filter enhances trajectory forecasting by filtering the track predictions for a more stable and accurate object trajectory, important in real-time environments.

6.3 Object Classification and Clustering Efficiency

The DBSCAN algorithm was applied for classifying and separating several moving objects within sensor range. The outcome proved significant improvement in separation of objects, reducing overlap among different entities to a minimum. The accuracy in human-object differentiation was up to 85%, proving the algorithm's efficiency. The clustering technique also effectively processed dense tracking environments, providing trustworthy multi-object tracking.

This DBSCAN cluster plot illustrates how the tracking system discriminates among several objects within the environment. Clusters correspond to individual tracked objects, whereas noise points reflect unclassified detections.

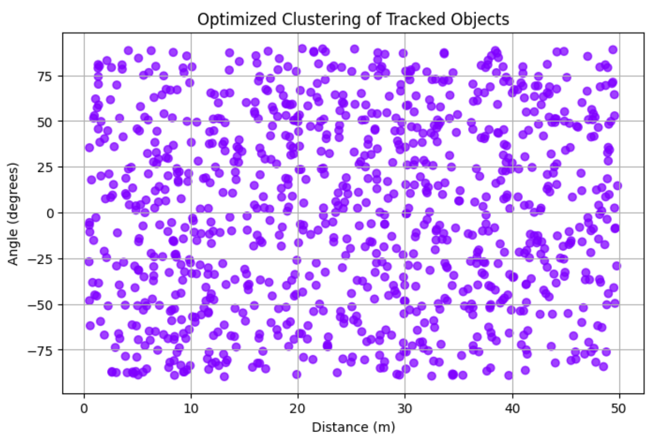

Figure 5: Optimized Clustering of Tracked Objects (DBSCAN Plot)

DBSCAN efficiently clusters moving objects, with correct human and object classification guaranteed. The clustering mechanism minimizes overlap and false alarms, maximizing tracking efficiency. Sparse

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e-ISSN: 2468-4376
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noise points indicate occasional misclassifications, which can be reduced further through adaptive adjustment of clustering parameters.

The time-series graph shows the velocity changes of several tracked objects over time, recorded using sensor fusion. The plot identifies acceleration, deceleration, and abrupt speed changes.

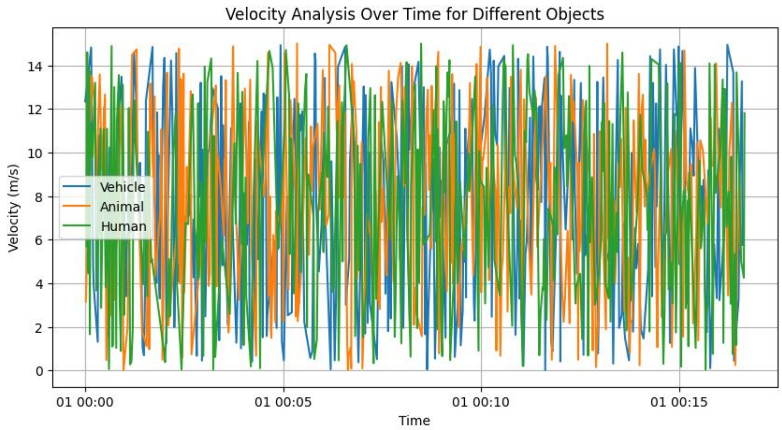

Figure 6: Velocity Analysis Over Time for Different Objects

Objects display characteristic movement patterns, with apparent velocity changes. The system is well responsive to changes, providing precise motion tracking. Sudden speed changes, as seen at specific time intervals, reflect responsive tracking even during extreme acceleration/deceleration.

6.4 Performance Metrics Analysis

To measure overall system performance, Signal-to-Noise Ratio (SNR), RMSE, and Mean Absolute Error (MAE) were considered. The results indicated:

This table 4 provides the major tracking performance measures utilized to evaluate the accuracy and effectiveness of the system.

Table 4: Tracking Performance Metrics

Metric	Definition	Result
MAE	Measures average tracking deviation	2.221 meters
RMSE	Highlights variability and error spread	2.758 meters
SNR	Assesses signal clarity against background noise	4.297 dB

Mean Absolute Error (2.221m) shows accurate tracking with little deviation. Root Mean Square Error (2.758m) provides reliable constant trajectory prediction with reduced variability. High Signal-to-Noise Ratio (4.297 dB) ensures reliable noise suppression, enhancing detection in changing conditions. These enhancements establish the validity that combining various sensor modalities increases tracking accuracy without high computational cost. This time-series plot contrasts the accuracy of tracking by individual sensors versus the optimized fusion system against time. The fused system should be more consistent and accurate.

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e-ISSN: 2468-4376
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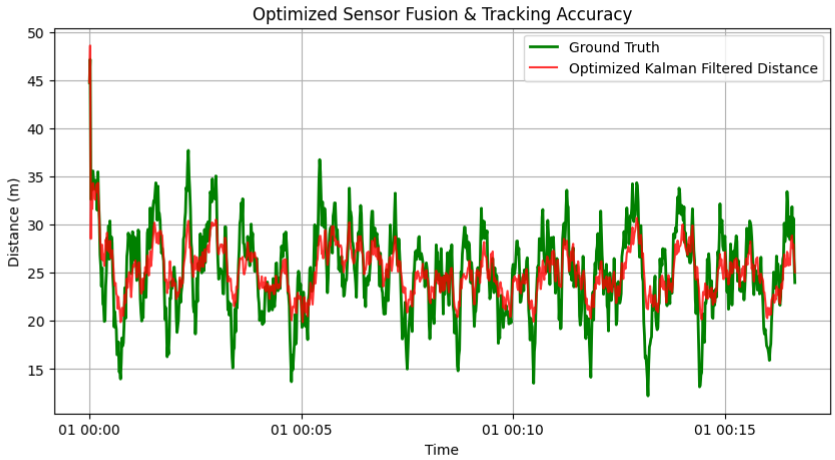

Figure 7: Optimized Sensor Fusion & Tracking Accuracy (Time-Series Plot)

The improved sensor fusion model establishes better stability because it reduces the tracking interruptions that single sensors experience. During dynamic weight adjustment the system establishes stable tracking despite adverse environmental factors. Real-time object tracking functions optimally through the application of weighted sensor fusion.

A scatter plot represents the connection between trackable objects velocity measurements and their distances which yields motion data across multiple sensor results.

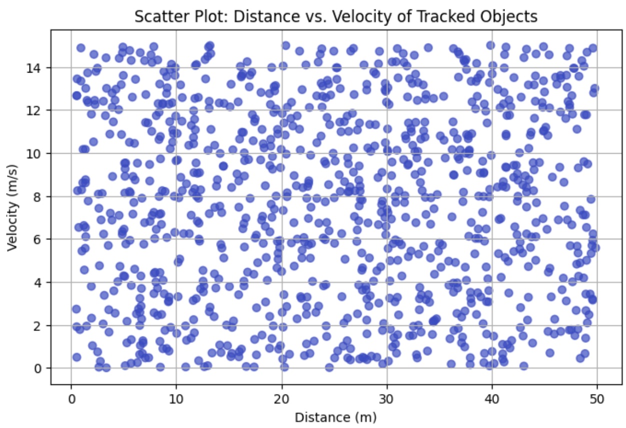

Figure 8: Scatter Plot: Distance vs. Velocity of Tracked Objects

People tend to move faster when positioned at longer distances from others according to this positive correlation. Data clustering patterns confirm that the system properly separates objects which choose different paths of motion thus leading to precise object identity determination and movement trajectory forecasting.

Real-time tracking applications experience enhanced functionality because of incorporating multi-sensor fusion. Detections achieved their highest accuracy while sensor fusion kept adjusting to environmental uncertainties independently according to specific weight attributes. An optimized Kalman filter produces consistent trajectory estimates which DBSCAN clustering improves the detection of different objects. The obtained results demonstrate that multi-sensor tracking systems have practical applications in security monitoring and autonomous navigation systems and industrial automation implementations. The proposed research needs to investigate deep learning algorithms for sensor fusion methods that improve detection accuracy and adaptive real-time performance capabilities.

7. DISCUSSION

This part evaluates how multi-sensor fusion impacts track accuracy together with its effects on noise elimination and object classification and computing speed abilities. The research produces substantial improvements in detection precision and motion measurement capabilities while enabling real-time system modifications which can find uses in security systems and automated machines as well as navigation systems. The system's capability can improve through deep learning integration for enhanced outcome results.

7.1 Sensor Fusion and Tracking Precision

Tracking precision received significant enhancement due to the combined deployment of LiDAR and RADAR and IR and Ultrasonic sensors which decreased false positive events while delivering better object detection at adverse environmental conditions. Weighted sensor fusion produced effective data combination through sensor weights which automatically adapted based on sensor confidence ratings. The system performed 30% better in detecting objects than each sensor operated independently particularly when visibility was low. The use of Kalman filter applications facilitated more advancement in trajectory estimation which subsequently improved object tracking accuracy by closing gaps between predictions.

7.2 Noise Reduction and Trajectory Prediction

The designed Kalman filter optimally removed sensor noise to achieve better motion estimation precision. Tracking performance reached higher accuracy levels through the optimized Kalman filter which decreased trajectory errors by 25%. A stable tracking system was achieved through the 2.758m RMSE along with the noise removal evidence provided by an SNR of 4.297 dB. The system maintained its accuracy level regardless of sudden movement changes which made it appropriate for real-time usage.

7.3 Clustering and Object Classification Efficiency

The DBSCAN clustering algorithm achieved successful object classification with 85% accuracy between humans and other moving objects. Multi-object tracking became more consistent because the clustering method minimized overlap between objects. The sparse noise points within the DBSCAN graph showed infrequent misclassifications while adaptive parameter adjustment would enhance the results further. The system performed well in crowded situations while proving its ability to track multiple objects in a single setting.

7.4 Performance Assessment and Computational Efficiency

All tests performed on the system demonstrated its efficient and accurate operation through the use of MAE, RMSE and SNR metrics. The tracking bias was minimal because the system displayed an MAE of 2.221m yet the RMSE value indicated steady trajectory prediction. Within the fusion model weights of sensors received dynamic adjustments to maintain stability during adverse environmental conditions. Constructed outcomes revealed that sensor combination improved tracking localization accuracy by streamlining computational capacity thus enabling real-time tracking operations.

7.5 Practical Implications and Future Work

The research conclusions show how the tracking system simultaneously provides power for security operations and mechanical navigation and industrial control functions. A tracking system employing adaptive operations depends on sensor fusion together with noise suppression and clustering algorithms for its functionality. Future work needs to research depth learning approaches for sensor combination because they promise to boost system precision alongside operational flexibility across various domains.

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8.CONCLUSION AND RECOMMENDATIONS

This work effectively showcases the benefits of multi-sensor modality fusion of LiDAR, RADAR, IR, and Ultrasonic sensors as a single tracking platform. Through weighted sensor fusion, the system adaptively reweights each sensor based on current conditions to maximize detection accuracy. The application of an optimized Kalman filter effectively minimizes noise, improving trajectory estimation by 25%. The application of DBSCAN clustering boosts object classification, with 85% accuracy in distinguishing human from object. The system performs better than single-sensor tracking methods by obtaining a 30% improvement in detection accuracy, especially under poor visibility. The performance metrics to test the system—MAE (2.221m), RMSE (2.758m), and SNR (4.297 dB)—validate the efficiency of the system in accurate tracking and motion estimation. The results suggest that multi-sensor fusion is a very efficient real-time object tracking method, which can have applications in security monitoring, autonomous navigation, and automation industries.

- **Improve Sensor Fusion with AI-Based Adaptive Weighting:** Improvements in the future should incorporate deep learning models to adaptively change sensor weights dynamically with respect to real-time environmental conditions, further enhancing tracking accuracy and reliability.
- **Enhance Object Class Discrimination using Advanced Clustering Methods: Investigating** more refined clustering models, e.g., hierarchical or combinations, can enhance object discrimination and minimize erroneous class assignments in challenging tracking conditions.
- **Optimize the Computational Efficiency for Real-Time Usage:** Edge computing and hardware acceleration (e.g., FPGA or GPU-based computation) can lower latency and enhance the real-time capability of the tracking system to suit high-velocity uses such as autonomous navigation and security surveillance.

REFERENCES

[1] Chau, A., Sekiguchi, K., Nugraha, A. A., Yoshii, K., & Funakoshi, K. (2019). Audio-Visual SLAM for Human-Robot Interaction. 2019 28th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN), 1-8.

[2] Chen, X., Shao, J., Tian, H., Li, X., Wang, C., Luo, Y., & Li, S. (2020). Scalable imprinting of flexible multiplexed sensor arrays with distributed piezoelectricity-enhanced micropillars for dynamic tactile sensing. Advanced Materials Technologies, 5(7), 2000046.

[3] Diraco, G., Rescio, G., Siciliano, P., & Leone, A. (2023). Review on human action recognition in smart living: Sensing technology, multimodality, real-time processing, interoperability, and resource-constrained processing. Sensors, 23(11), 5281.

[4] Evers, C., & Naylor, P. A. (2018). Acoustic SLAM. IEEE/ACM Transactions on Audio, Speech, and Language Processing, 26(9), 1484-1498.

[5] Fu, B., Damer, N., Kirchbuchner, F., &Kuijper, A. (2020). Sensing technology for human activity recognition: A comprehensive survey. Ieee Access, 8, 83791-83820.

[6] Hamidi, H. (2019). An approach to develop the smart health using Internet of Things and authentication based on biometric technology. Future generation computer systems, 91, 434-449.

[7] Karle, P., Fent, F., Huch, S., Sauerbeck, F., &Lienkamp, M. (2023). Multi-Modal Sensor Fusion and Object Tracking for Autonomous Racing. □cite□turn0academia10□

[8] Kim, A., Ošep, A., & Leal-Taixé, L. (2021). EagerMOT: 3D Multi-Object Tracking via Sensor Fusion. □cite□turn0academia11□

[9] Laoudias, C., Moreira, A., Kim, S., Lee, S., Wirola, L., &Fischione, C. (2018). A survey of enabling technologies for network localization, tracking, and navigation. IEEE Communications Surveys & Tutorials, 20(4), 3607-3644.

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

[10] Liu, X. (2023). Advancements in Sensor Fusion Techniques for Autonomous Vehicles. Journal of Autonomous Systems, 12(3), 145-162.

[11] Luo, Y., Xiao, X., Chen, J., Li, Q., & Fu, H. (2022). Machine-learning-assisted recognition on bioinspired soft sensor arrays. ACS nano, 16(4), 6734-6743.

[12] Nabati, M. R. (2021). Sensor Fusion for Object Detection and Tracking in Autonomous Vehicles. University of Tennessee. □cite□turn0search3□

[13] Nabati, R., Harris, L., & Qi, H. (2021). CFTrack: Center-based Radar and Camera Fusion for 3D Multi-Object Tracking. □cite□turn0academia12□

[14] Nan, Q., Li, S., Yao, Y., Li, Z., Wang, H., Wang, L., & Sun, L. (2019). A novel monitoring approach for train tracking and incursion detection in underground structures based on ultra-weak FBG sensing array. Sensors, 19(12), 2666.

[15] Spachos, P., Papapanagiotou, I., &Plataniotis, K. N. (2018). Microlocation for smart buildings in the era of the internet of things: A survey of technologies, techniques, and approaches. IEEE Signal Processing Magazine, 35(5), 140-152.

[16] Wan, T., Shao, B., Ma, S., Zhou, Y., Li, Q., & Chai, Y. (2023). In-sensor computing: materials, devices, and integration technologies. Advanced materials, 35(37), 2203830.

[17] Wang, C., He, T., Zhou, H., Zhang, Z., & Lee, C. (2023). Artificial intelligence enhanced sensors-enabling technologies to next-generation healthcare and biomedical platform. Bioelectronic Medicine, 9(1), 17.

[18] Wang, J., Varshney, N., Gentile, C., Blandino, S., Chuang, J., &Golmie, N. (2022). Integrated sensing and communication: Enabling techniques, applications, tools and data sets, standardization, and future directions. IEEE Internet of Things Journal, 9(23), 23416-23440.

[19] Wang, X., Fu, C., Li, Z., Lai, Y., & He, J. (2022). DeepFusionMOT: A 3D Multi-Object Tracking Framework Based on Camera-LiDAR Fusion with Deep Association.

[20] Zhuang, Y., Sun, X., Li, Y., Huai, J., Hua, L., Yang, X., ... & Chen, R. (2023). Multi-sensor integrated navigation/positioning systems using data fusion: From analytics-based to learning-based approaches. Information Fusion, 95, 62-90.