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Research Paper

Adaptive Multi-Sensor Fusion for Autonomous Navigation Based on Bayesian Networks: An Application-Oriented Study

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Abstract. This paper proposes an adaptive multimodal sensor fusion framework aimed at improving the positioning accuracy and robustness of intelligent systems in dynamic and harsh environments. This paper studies the integration of heterogeneous sensor data, sensor faults, modal loss, and environmental interference. The fusion strategy will be dynamically adjusted based on the reliability of the sensors. By using Bayesian reliability weighting, a scalable architecture can be created to handle large volumes of high-dimensional and diverse sensor data. Simulated tests were conducted in both indoor and outdoor environments. In order to compare the performance of the proposed system with traditional methods (such as weighted fusion, simple averaging, and neural network fusion). The above results indicate that the average positioning error for structured tasks is sub-decimeter. Moreover, even if 40% of the sensor channels are damaged, the accuracy of this framework will still remain above 0.9, and it outperforms other algorithms in terms of mean error and error variance. According to the analysis of heat maps and radar charts, this method performs well under various faults and environmental changes. Scalability tests indicate that adding more sensors is still beneficial; however, after five additions, the performance improvement is almost negligible. The new technology runs in real-time, averaging less than 25 milliseconds per frame. The framework significantly improves positioning accuracy, robustness, and efficiency through adaptive sensor fusion, and is now used in complex applications such as robotics, autonomous driving, and smart factories.

Keywords: *Sensor Networks, Sensor Fusion, Reliability Assessment, Autonomous Systems, Localization, Bayesian Methods, Fault Tolerance, Real-Time Processing*

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Introduction

Many robotic technologies and other intelligent systems have recently begun developing autonomous driving technology. Establishing a system capable of collecting and processing data from various sensors (such as vision systems, inertial measurement units, global positioning systems, LiDAR, and ultrasonic sensors) in complex or unknown environments is necessary [1]. The aforementioned multi-sensor platform collects a large number of redundant signals, but sensor noise, bias, faults, and environmental influences still exist [2]. Even if the initial sensors have high accuracy [3], traditional sensor data fusion methods cannot address the issues of high uncertainty and non-linearity. The initial heuristic or fixed-weight fusion methods lead to poor or unsafe navigation performance [4], as they do not take into account the continuous changes in the reliability of each sensor. In recent studies, end-to-end fusion and deep learning models have also been used, but their interpretability and generalizability in safety-critical applications have not yet been validated [5]. In many fields, such as urban traffic management, underground mining, and disaster rescue, there is an urgent need for high-precision, interpretable, and customizable probabilistic sensor fusion frameworks in the context of developing systems in uncertain environments [6]. Therefore, Bayesian networks are now used to simulate the dynamics, uncertainty, and interconnectivity of sensor data [7]. Probabilistic graphical models can clearly display

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uncertainty and dependencies, and they are suitable for online reasoning and decision-making because they can handle complex measurement correlations and disturbances [8].

In the field of Bayesian-based multi-sensor fusion, extensive research has recently been conducted to address the shortcomings of deterministic methods and purely data-driven approaches. According to the aforementioned research, Bayesian networks excel at handling complex conditional dependencies and can integrate data from UAVs and wheeled robot autonomous driving systems [9]. Since Bayesian networks are much more complex than parameter filters and deep neural networks, they can adapt to changes in sensor reliability, damage, and other factors online. Dynamic Bayesian networks [10] can quickly respond to changes in sensor quality or task conditions [11]. By combining hierarchical Bayesian models with adaptive learning mechanisms, the handling of sensor errors in multi-source data and environments can be improved [12]. Joint learning of network structure and parameters is a method to achieve good integration. Reduce the impact of model prior bias and enhance robustness in the presence of partial missing or observed data [13]. Applications in infrastructure-free navigation, mobile robots, and autonomous driving indicate that adaptive Bayesian fusion systems can enhance positioning accuracy, perception reliability, and operational safety [14]. Despite these achievements, there are still some unresolved issues regarding computational efficiency, scalable architecture optimization, and the integration of formal and modern planning and control modules [15].

This paper proposes an adaptive multi-sensor fusion framework based on Bayesian networks for autonomous driving. Based on the aforementioned reasons, as well as the following content. Use probabilistic models for inference to achieve stable and high-speed fusion of multiple sensor streams. Sensors also have noise and are unreliable in different environments. The main content of this paper is as follows: (1) A novel sensor fusion architecture based on Bayesian methods, with online reliability assessment; (2) A reasonable reasoning scheme that supports adaptive weighting and sensor fault tolerance; (3) Comprehensive experimental validation of the robustness, performance, and adaptability of the above methods in simulated and real navigation scenarios. This paper will provide recommendations for future intelligent and secure navigation systems.

Related Work and Background

Multi-Sensor Fusion Techniques

Over the past 20 years, more and more sensors have been integrated into intelligent navigation systems to enhance the overall performance and reliability of autonomous vehicles. Integrating multiple sensor data sources to address the issues of single sensor data source systems and leveraging the different advantages of various sensors to enhance functions such as scene recognition, localization, and decision-making. [16] The earliest and most popular methods are the Kalman filter family based on the recursive Bayesian framework, such as the Extended Kalman Filter and the Unscented Kalman Filter. These frameworks use known process and observation models to integrate noisy and incomplete sequence measurements [17]. Kalman filter-based algorithms are suitable for approximately linear and Gaussian systems, and they are computationally convenient. However, if there is significant nonlinearity, sudden environmental changes, or non-Gaussian noise components, their accuracy and stability will be greatly reduced [18]. Particle filters and other sequential Monte Carlo methods have been developed, which estimate the probability density function of the system state by propagating and updating a set of random samples with importance weights, achieving better performance in mobile robot localization and simultaneous localization and mapping (SLAM) under uncertainty [19].

Deterministic fusion uses rule-based algorithms with fixed weights, achieving lower latency results in structured environments or constrained systems [20]. However, in high-risk scenarios, they may experience performance degradation because they cannot respond promptly to changes in sensor or environmental reliability. Deep learning-based sensor fusion models have rapidly developed in research and practice recently, with the emergence of large-scale labeled datasets and high-performance computing [21]. Currently, CNNs and RNNs are the main types of neural network architectures used to learn features from sensor data and solve various complex problems, such as aerial robots, autonomous driving, and industrial automation. End-to-end fusion models often lack interpretability, face domain transfer issues, and are sensitive to rare or unexpected outliers. Therefore, although they perform well in practice, they may not be suitable for safety-critical systems or deployment. The general trend in the literature is to use fusion schemes in practical autonomous systems to

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combine statistical accuracy with adaptability and interpretability in order to manage the non-stationarity and randomness of sensor data.

Bayesian Networks for Uncertainty Modeling

Bayesian networks are increasingly used in robotic perception and multi-sensor data fusion systems to model and propagate uncertainty [22]. These models simultaneously display the relationships between system variables, sensor readings, and hidden contextual factors in the form of graphs and probability distributions. This enables people to systematically reason and make decisions under uncertainty. Since Bayesian networks can simultaneously integrate domain knowledge and the latest evidence, reasonable estimates can still be made even if data is lost or corrupted [23]. Especially in multi-robot systems, typical static network structures have been widely used for sensor anomaly detection, reliability assessment, and efficient integration of data from multiple sensors.

Dynamic and hierarchical Bayesian networks capable of handling large-scale, complex multi-sensor arrays have recently emerged, and these networks can be used for modeling sequential processes [24]. Dynamic variants are more suitable for handling issues such as drift, degradation, and sudden context switching of navigation sensors, as they can support recursive reasoning on new data. Moreover, the new learning method has self-optimization capabilities, allowing it to adjust the network's parameters and structure based on changes in the system and environment, thereby reducing manual tuning and improving the system's long-term stability. Bayesian networks are suitable for safety-critical applications both indoors and outdoors because they offer better robustness and adaptability, and allow for interpretable results and formal verification. These networks are not black-box fusion mechanisms.

Design of the Adaptive Sensor Fusion Algorithm

Framework Architecture

The adaptive multi-sensor fusion system developed in this paper adopts a hierarchical modular architecture, featuring relatively stable and scalable characteristics. It is also capable of real-time operation and drawing conclusions under adverse weather conditions. At the bottom layer, multiple different sensor modules (such as LiDAR, cameras, IMU, GPS, ultrasonic sensors, etc.) collect data in a distributed manner. By utilizing various physical phenomena and error characteristics, these modules continuously acquire raw data to enhance perception coverage and redundancy. The central data acquisition unit synchronizes all incoming data streams, aligns timestamps, and standardizes formats. This is done to preserve the time and context of multimodal inputs.

Let the synchronized sensor vector at time t be denoted as

$$\boldsymbol{s}_t = \left[s_t^{LiDAR}, s_t^{camera}, s_t^{IMU}, s_t^{GPS}, s_t^{ultra}\right] \qquad \text{Eq.(1)}$$

The preprocessing module will receive the aforementioned multidimensional vectors. Here, the data undergoes a series of processing steps to achieve various purposes. First, use state-aware filtering coefficients to filter noise in real-time based on signal changes. Next, each modality will be dynamically normalized using Min-Max or Z-score, and the features will be standardized for comparison. Then, subsequent advanced integrity checks will be performed to automatically detect data drift or other synchronization issues before fusion: temporal overlap and mutual information correlation. The complete preprocessing process is as follows:

$$\boldsymbol{f}_t = \mathcal{P}(\boldsymbol{s}_t) = \mathcal{C}\left(\mathcal{N}\left(\mathcal{F}(\boldsymbol{s}_t)\right)\right) \qquad \text{Eq.(2)}$$

where $\mathcal{F}(\cdot)$ denotes noise filtering, $\mathcal{N}(\cdot)$ normalization, and $\mathcal{C}(\cdot)$ the cross-modal consistency check.

At this point, the Bayesian fusion core integrates the results of all preprocessed modalities. In most cases, the uncertainty model for each feature channel is a probability.

$$f_t^{(i)} \sim \mathcal{N}\left(\mu_t^{(i)}, \Sigma_t^{(i)}\right) \qquad \text{Eq.(3)}$$

where $\mu_t^{(i)}$ and $\Sigma_t^{(i)}$ are the mean and covariance learned or estimated from historical and contextual data. If there are multiple correlated signals, the joint feature distribution of all sensors at time t can be described as a multivariate Gaussian distribution:

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$$\boldsymbol{f}_t \sim \mathcal{N}(\boldsymbol{\mu}_t, \boldsymbol{\Sigma}_t) \quad \text{Eq.(4)}$$

where $\boldsymbol{\mu}_t$ and $\boldsymbol{\Sigma}_t$ encapsulate the fused mean vector and covariance matrix across all modalities.

The Bayesian core integrates them into a context-based, unified belief of the navigation state. During the process of creating the joint posterior distribution in the Bayesian core, inference rules are applied to the subsequent processing at the decision layer. The navigation state estimate $\hat{\mathbf{x}}_t$ is subsequently sent to the control and planning subsystems for operations such as collision avoidance and trajectory generation. As shown in Figure 1, the feedback path will continuously correct the module to address long-term issues in the system, such as sensor drift and short-term anomalies.

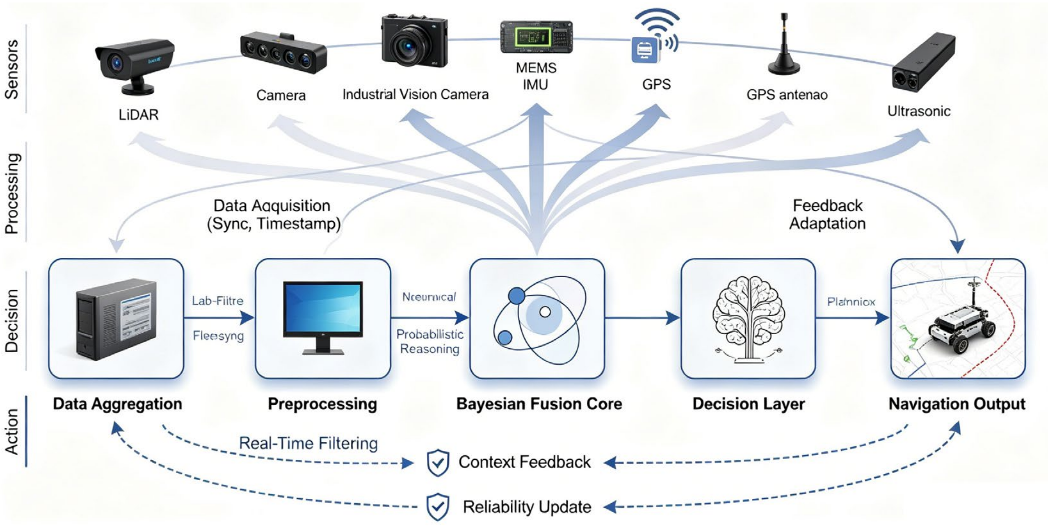

Figure 1. Overall Architecture of the Adaptive Multi-Sensor Fusion System.

Bayesian Inference Strategy

The core of the fusion system is the inference protocol based on Bayesian networks, which can reliably determine the actual navigation state even in the presence of inconsistencies and uncertainties in the sensors. Let the latent navigation state at time t be $\mathbf{x}_t$, and denote the aggregate observation history up to t as $\mathbf{Z}_{1:t}$.

The recursive Bayesian update deployed throughout the fusion core takes the general form:

$$P(\boldsymbol{x}_t \mid \boldsymbol{Z}_{1:t}) = \frac{P(\boldsymbol{z}_t \mid \boldsymbol{x}_t) P(\boldsymbol{x}_t \mid \boldsymbol{Z}_{1:t-1})}{P(\boldsymbol{z}_t \mid \boldsymbol{Z}_{1:t-1})} \quad \text{Eq.(5)}$$

where $P(\mathbf{x}_t \mid \mathbf{Z}_{1:t-1})$ acts as the prior and $P(\mathbf{z}_t \mid \mathbf{x}_t)$ reflects the aggregate likelihood from all sensor modalities. The denominator ensures normalization over the posterior.

To handle multiple sensors, they are assumed to be conditionally independent and thus can be factored:

$$P(\boldsymbol{z}_t \mid \boldsymbol{x}_t) = \prod_{i=1}^{N} P\left(z_t^{(i)} \mid \boldsymbol{x}_t\right) \quad \text{Eq.(6)}$$

where $z_t^{(i)}$ denotes the observation from sensor i at time t. This approach enables scalable computation and transparent interpretation of sensor contributions.

Introducing time-varying weights for each possibility reflects the interaction between sensors and the reliability adjustment of context awareness.

$$P\left(z_t^{(i)} \mid \boldsymbol{x}_t\right) \propto w_t^{(i)} \cdot \mathcal{L}_t^{(i)}(\boldsymbol{x}_t) \quad \text{Eq.(7)}$$

where $w_t^{(i)}$ is the contextually updated reliability coefficient for sensor i, and $\mathcal{L}_t^{(i)}(\mathbf{x}_t)$ is a Gaussian, Laplacian, or Gamma family likelihood, selected based on empirical modeling of uncertainty and outlier behavior.

The backpropagation in Bayesian networks is based on the evidence update method, and the most probable state is usually determined by the Maximum A Posteriori (MAP) estimation:

$$\boldsymbol{x}_t^{MAP} = arg\ \max_{\boldsymbol{x}_t} P(\boldsymbol{x}_t \mid \boldsymbol{Z}_{1:t}) \quad \text{Eq.(8)}$$

Finally, fused state estimation is usually regarded as the posterior expectation in order to provide smooth and continuous navigation solutions and avoid confusion:

$$\hat{\boldsymbol{x}}_t = \mathbb{E}[\boldsymbol{x}_t \mid \boldsymbol{Z}_{1:t}] \quad \text{Eq.(9)}$$

Figure 2 shows the Bayesian workflow from system data collection, reliability adaptive modeling, reasoning, and propagation stages, to context credibility assessment and fusion state output from sensor inputs.

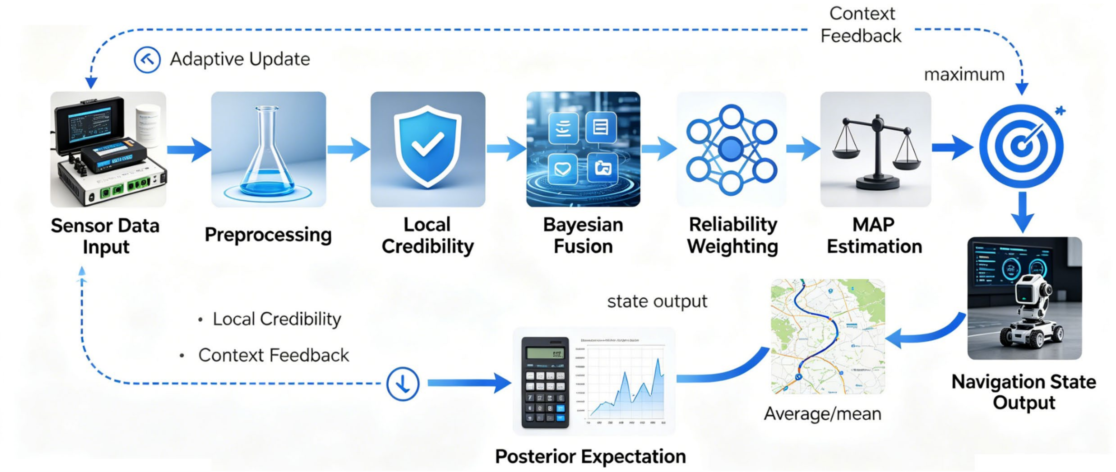

Figure 2. Data Processing and Bayesian Inference Workflow.

Adaptive Reliability Assessment

The ability to evaluate and adjust the reliability of different sensors in real-time is the foundation of a reliable multi-sensor fusion system for autonomous vehicles. Many factors can affect the reliability of sensors, such as environmental changes, interference, aging, temporary obstacles, and equipment failures. To reduce the risk of erroneous or misleading observations, adaptive reliability assessment is required. In addition, to make navigation decisions, the most reliable and relevant data available at any time must be used.

By using an online reliability model, the framework continuously evaluates the reliability of each sensor and employs statistical performance metrics and other environmental factors. Formally, for each sensor i at time t, the reliability score is denoted as $w_t^{(i)}$. Recursively update this weight based on both short-term observation anomalies and long-term consistency indicators:

$$w_t^{(i)} = \lambda \cdot w_{t-1}^{(i)} + (1 - \lambda) \cdot R_t^{(i)} \quad \text{Eq.(10)}$$

where $0 < \lambda < 1$ is a forgetting factor, and $R_t^{(i)}$ aggregates statistical indicators at the current time. Measuring variance, the innovation residual of the fusion core, inter-sensor consistency, and temporal stability statistics are some examples of the aforementioned indicators.

To quantify innovation residuals, the framework computes the difference between each incoming measurement $z_t^{(i)}$ and its predicted value $\hat{z}_t^{(i)}$ from the Bayesian estimate:

$$res_t^{(i)} = \left\| z_t^{(i)} - \hat{z}_t^{(i)} \right\| \quad \text{Eq.(11)}$$

A large residual signals a possible outlier or fault, triggering a reduction in $R_t^{(i)}$. Conversely, if the sensor's residuals remain consistently low within the sliding window, one can be assured. Therefore, the statistical reliability index can be referred to as a function:

$$R_t^{(i)} = exp\left(-\frac{res_t^{(i)2}}{2\sigma^2}\right) \quad \text{Eq.(12)}$$

where σ is tuned according to expected inlier noise characteristics.

Moreover, each sensor should produce the same results. If multiple sensors detect the same phenomenon (such as position and speed), then statistical data indicates that the measurements should be close to each other and within a reasonable range. Paired differences reduce the reliability rating, exceeding the confidence threshold. Therefore, the fusion algorithm is a collaborative adjustment method. It encourages sensors whose outputs are recognized by others and punishes sensors with persistent discrepancies.

The reliability profile of each sensor in the monitoring system is assessed to determine if there are sudden drops, persistent low reliability warnings, or related failures. In addition, the meta-reasoning module can be blacklisted to prevent faulty sensors, reallocate computational resources, and adopt redundancy measures, such as model-based predictive virtual sensors, until hardware recovery or manual intervention becomes possible.

Reliability assessment is temporal, using current and historical data. Sudden sensor dropouts, abnormal variance peaks, or sudden mean changes can quickly reduce current reliability, thereby decreasing the weight in the fusion. In this case, these will receive less attention. Nevertheless, it will gradually return to the initial value to restore trust in the sensor algorithm. The aforementioned mitigation measures are still not sufficient in practice; frequent environmental changes (such as electromagnetic interference, fog, and rain) and occasional loss of sensor data are also issues.

Finally, as shown in Section 3.2, the reliability weights of adaptive learning are smoothly integrated into the Bayesian fusion core, and the likelihood contribution of each sensor to the total posterior is as follows:

$$P\left(z_t^{(i)} \mid \boldsymbol{x}_t\right) \propto w_t^{(i)} \cdot \mathcal{L}_t^{(i)}(\boldsymbol{x}_t) \qquad \text{Eq.(13)}$$

The aforementioned structure will ensure that low-reliability or uncertain high-variation sensor data will not significantly impact the final decision. Therefore, adaptive reliability assessment can ensure the immediate response speed and long-term stability of autonomous systems. It can prevent a sharp decline in sensor accuracy while not affecting the speed required for real-time operations.

Performance Analysis

Simulation Setup and Scenarios

A large number of simulation cases were created to comprehensively verify the generality and effectiveness of the proposed adaptive sensor fusion algorithm [25]. At the same time, these simulation cases also include a large number of common problem scenarios from autonomous driving research. A physically accurate robot simulator was used to create the simulated environment. To simulate real-world interference, high-fidelity models were added, such as LiDAR, visual cameras, IMU, GPS, as well as configurable sensor noise and random fault injection mechanisms [26].

Here are examples of the three tests. First, to test the localization accuracy of multimodal data streams, structured indoor navigation tasks were set up. These tasks include narrow corridors, unevenly distributed light sources, and occasional static obstacles. Secondly, outdoor urban environments are dynamic obstacle fields that require redundant sensors and adaptive reliability mechanisms to cope with, such as pedestrian and vehicle agents, unstable GPS signals, and significant lighting changes [27]. Third, there are increased harmful environmental conditions. These environmental conditions include artificial fog, rain, sensor occlusion, and physical interference, all of which affect one or more sensor modalities. In all cases, the high-precision sub-millimeter ground tracking system in the simulator ensures the true position and orientation of the ground [28].

The evaluation also includes fault injection and normal operation. In the fault injection scenario, random sequences of sensor dropouts, out-of-range values, and noise increases are used to evaluate the system's robustness and degraded sensor fault tolerance. Independently test twenty random seeds, and then calculate the average of the results [29].

Regularly record raw sensor data, preprocessed signals, fusion module status, and performance metrics of the final navigation results at various stages of the system pipeline. Positioning accuracy, root mean square error, drift trends, event-triggered anomalies, response delays, and intervention frequency are part of the data logging. To ensure reproducibility, Appendix A includes key simulation configuration parameters, as well as typical environmental maps and example agent trajectories. These parameters adhere to the best practices described in recent literature on sensor fusion benchmarks [30].

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Comparative Evaluation Metrics

In order to evaluate the accuracy, stability, and adaptability of the new combination strategy over different time periods, a general performance metric system has been proposed [31]. To evaluate the accuracy of the initial positioning, the average Euclidean distance and mean squared error (MSE) are used as metrics. These metrics are compared by evaluating the estimated trajectory against the true values from the simulator. In the error analysis, the point-wise errors and aggregate errors of the multi-sensor fusion output were compared with the errors of the unimodal baseline [32] to further demonstrate the effectiveness of the fusion core.

Robustness can be determined by measuring the performance degradation of certain sensors being lost, noisy data, and forced sensors under unreliable conditions. Heatmaps and line graphs demonstrate the system's ability to maintain a certain level of accuracy when encountering a proportion of faulty sensors. In this case, the effectiveness of adaptive reliability assessment is also clearly visible. The success rate of resilience testing also helps determine fault tolerance; in other words, it is the proportion of test cases where navigation remains normal and collision-free despite sensor failures [33].

Add the following adaptability assessments: inference stability, recovery speed after fault injection, and the variability of fusion results with changes in sensor weights. System latency measurements recorded the average and maximum inference time per frame to verify real-time feasibility. These measurements must be used for time-sensitive robotic systems [34]. The results were compared with traditional and modern fusion algorithms, using open-source code libraries and standardized benchmarks whenever possible [35].

Results and Discussion

Empirical evaluation uses five comprehensive, multi-part chart systems to assess the performance of the proposed adaptive sensor fusion framework. These metrics include sensitivity, accuracy, robustness, scalability, benchmarks, and comparisons.

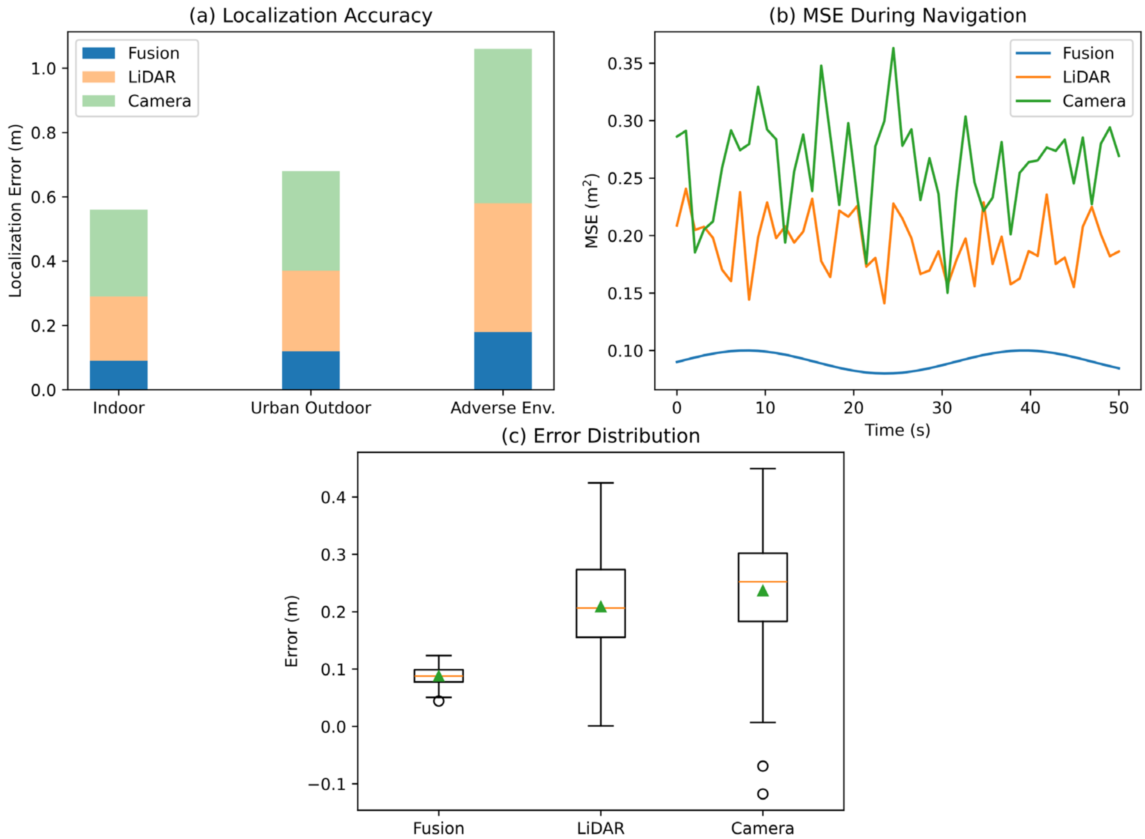

Figure 3. Fusion accuracy and errors. (a) Mean localization error in various environments. (b) MSE trends over 50 steps. (c) Box plots of error distributions.

Figure 3 shows the specific distribution of fusion accuracy and error. Figure 3(a) shows the positioning error of the fusion algorithm compared to the baseline using only LiDAR and cameras in structured indoor, urban outdoor, and harsh environments. The indoor error of the fusion method is 0.09 meters, and it remains below 0.2 meters (0.18 meters) even in adverse weather conditions. The error for the single-modal flow is 0.40 meters, and for the camera, it is 0.48 meters. Figure 3(b) shows the mean squared error (MSE) after 50 navigation steps. The fusion system maintains a low MSE (approximately 0.09) throughout the navigation process, while the MSE of the single sensor varies significantly, often increasing with changes in light or path. The fusion method is more reliable and consistent, reducing mean error and interquartile range (IQR), with significantly fewer outliers compared to the unimodal method, as shown in the error distribution box plot in Figure 3(c).

Figure 4 shows multiple robustness tests. The enhanced Figure 4(a) shows the accuracy of three fusion strategies, namely the proposed method, classical fusion, and simple averaging, as the proportion of faulty sensors increases. The proposed algorithm significantly reduced performance. In the case of 40% sensor failures, its accuracy remains above 0.9 (mean ± standard deviation shadow: 0.91 ± 0.023), but traditional methods and the average baseline drop below 0.7 under the same conditions. Figure 4(b) is a heatmap showing the robustness of various environments (indoor, outdoor, adverse conditions) and fault types, such as LiDAR, GPS, and cameras. The robustness of this method exceeds 0.73, even in the most unfavorable combination ("adverse" × "camera whiteout"). Figure 4(c) shows the fusion reliability radar chart, used for normal, single fault, and multiple fault scenarios. The area covered by the proposed framework is significantly larger, with a decrease from nominal to worst-case scenarios of only 0.98 - 0.80, indicating that the framework has good stability.

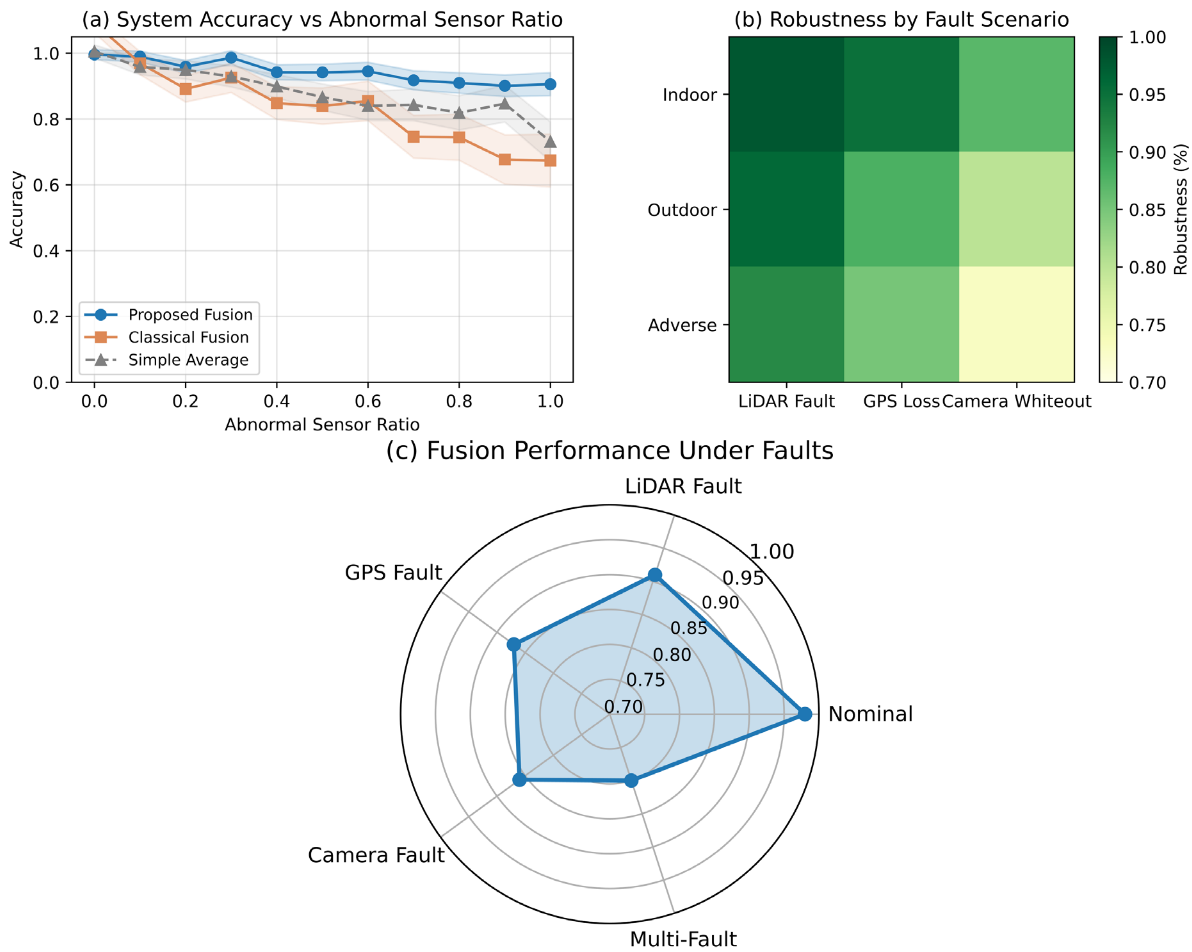

Figure 4. Robustness and fault tolerance. (a) Accuracy vs. faulty sensor ratio. (b) Robustness heatmap for environments and faults. (c) Reliability radar for typical fault cases.

The analysis of the impact of the number/type of sensors is shown in Figure 5. Figure 5(a) shows the relationship between the number of sensors (1-8) and accuracy. The accuracy of the fusion system steadily rises from 0.80 to 0.97, while the classic and simple average curves reach a plateau at a lower optimal scenario accuracy. These trends are shown in the corresponding bar charts and scatter plots, with a decline in performance after the fifth model. Figure 5(b) directly compares the accuracy of multiple sensor combinations, such as LiDAR+IMU+Cam and large heterogeneous sets. It also shows that the three-modal and four-modal cases approach the performance limit (0.945). Figure 5(c) shows the error correlation of different combination pairs in the enlarged scatter plot. The greater the sensor diversity, the less the system pairing bias and error coupling.

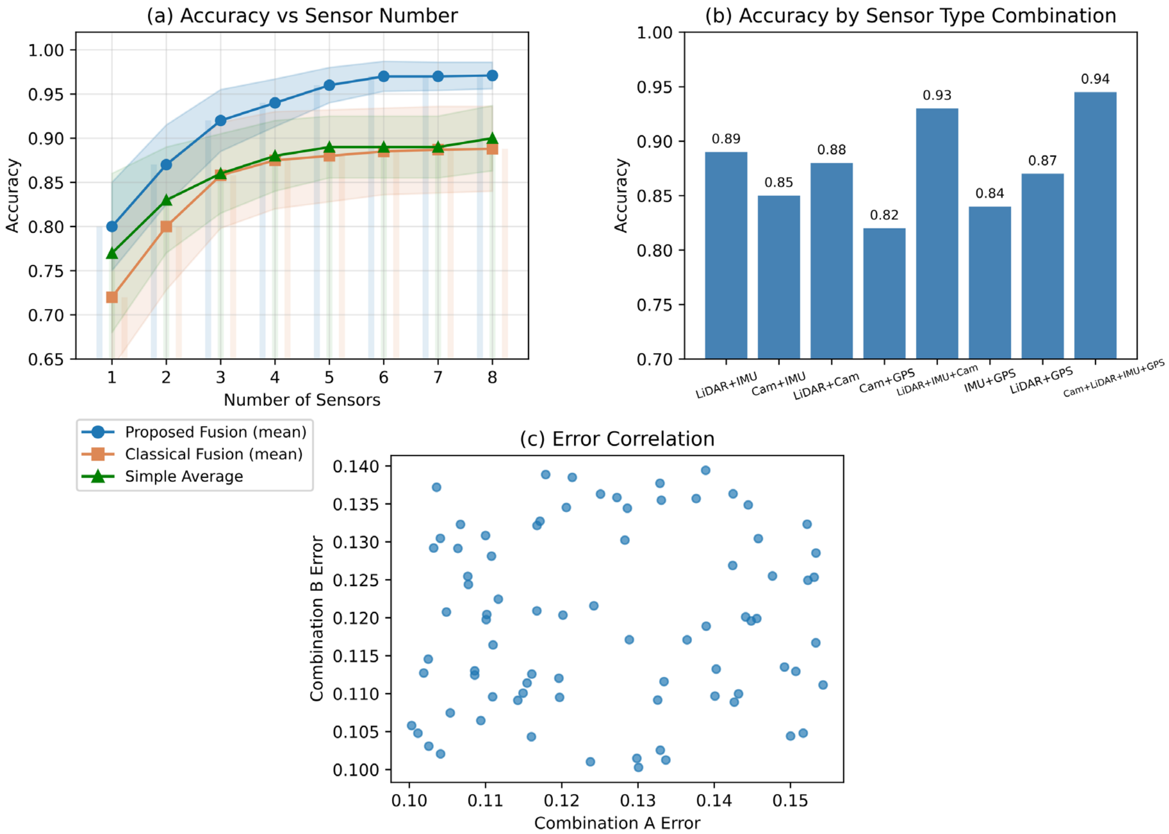

Figure 5. Sensor number and type effects. (a) Accuracy as sensor count grows. (b) Accuracy for key sensor groups. (c) Error correlation by pairing.

Figure 6 shows a comparison of the proposed fusion method with other alternative methods. As shown in Figure 6(a), the proposed method achieves the highest accuracy of 0.962, surpassing all other methods, including neural networks (0.90), average (0.84), fixed weights (0.86), EKF (0.855), and the classical baseline. As shown in Figure 6(b), in the extended data sample, our system exhibits lower mean values, smaller dispersion, and worst-case errors under complex environmental conditions. Figure 6(c) shows the detailed inference time statistics for various scenarios. The fusion method consistently outperforms the neural model, making it suitable for real-time applications in embedded and robotic systems. It maintains low latency (averaging around 16-25 milliseconds), and the extended graph now shows the minimum, maximum, and average times for each scene.

Figure 7 shows the key design elements. As shown in Figure 7(a), the bar chart displays the performance under random settings, static weighting, oracle, and without adaptive modules. The advantage of the adaptive method is 7-15 percentage points, while the advantage of other methods is 1-5%. Figure 7(b) is the relationship diagram between system accuracy and reliability weight. The robustness of this algorithm is not high and may require more accurate reliability estimation. This is because it is relatively stable within a small range near the parameter mean (0.5), but it significantly declines at the edges. Figure 7(c) is a broad scatter plot fitting of fusion performance and simulated noise, containing 90 points. It shows a gradual linear degradation with no significant loss, and the best-fit curve demonstrates noise resistance characteristics.

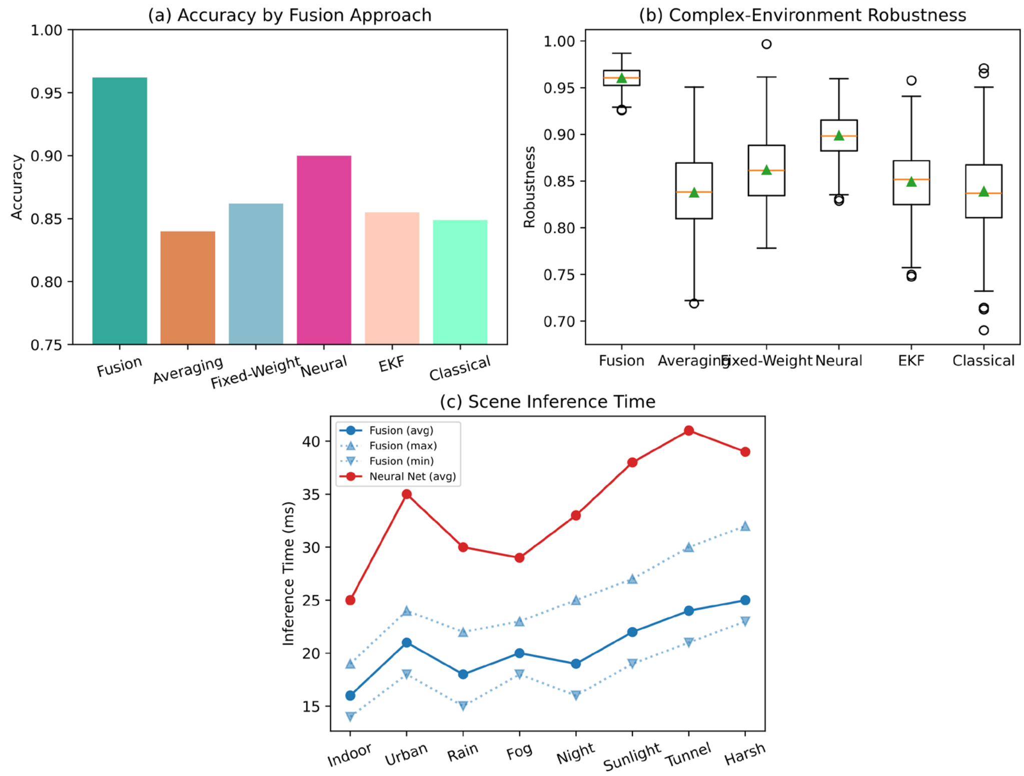

Figure 6. Comparison with fusion baselines. (a) Accuracy by fusion algorithm. (b) Accuracy and worst-case error in complex scenes. (c) Inference time comparison.

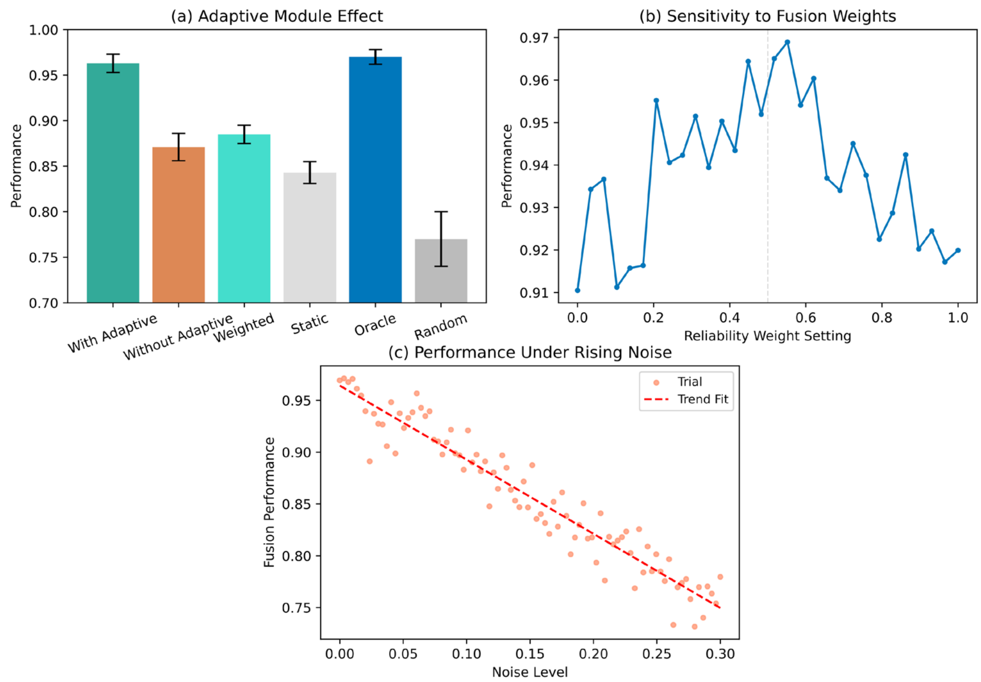

Figure 7. Ablation and sensitivity. (a) Accuracy with/without adaptivity and different weights. (b) Reliability weight sensitivity. (c) Fusion accuracy vs. noise level.

Conclusion

This paper proposes a new adaptive sensor fusion framework. It conducted a large number of simulation experiments to test various operational scenarios, changes in sensor arrangements, and various environmental or functional uncertainties. All the top performance metrics of the new methods—accuracy and stability of positioning, robustness in the presence of faults and noise, computational speed, and adaptability—have been tested. The fusion system has an average positioning error of less than a decimeter in structured environments. In the case of certain sensor failures or modal failures, the system can still operate normally. Through multi-dimensional comparison, the algorithm reduces the average error and decreases the dispersion of the error. Therefore, it has stability and reliability under both normal and extreme conditions. Due to its scalability, this framework will be used in various advanced sensor systems in modern robotics and intelligent autonomous vehicles.

Although the aforementioned research has achieved some positive results, it has not yet reached perfection. Although the simulation is very comprehensive, it has not yet been applied on a full scale in the real world, such as high-frequency real-time data streams, unpredictable anomalies, and computational constraints caused by scale. Currently, the adaptive module mainly handles static and semi-static fault patterns. The reliability reasoning mechanism still struggles to address highly uncoordinated or non-stationary adversarial attacks. In industrial-grade hardware environments, the optimization and verification of energy efficiency and real-time performance under extreme multimodal densities still need to be quantitatively achieved.

The following are three directions for future research. First, conduct field tests of the organizational system in real safety-critical environments to ensure the framework's adaptability and resilience under high-pressure operational conditions. These environments include autonomous driving, aerial robotics, and large-scale industrial monitoring. Secondly, improve the applicability of the reliability assessment layer to handle relevant and non-stationary sensor faults, as well as sensor faults caused by adversarial attacks. It may also be possible to leverage the latest advancements in trustworthy machine learning and online anomaly detection. Third, it is necessary to research the acceleration of algorithms, low-power optimization, and hierarchical fusion architectures. This will ensure that these algorithms are scalable and run smoothly in resource-constrained and latency-sensitive edge device environments. In summary, the aforementioned future efforts may lay a solid foundation for adaptive sensor fusion in the next generation of reliable autonomous driving systems.

Author Contributions

Gabriela Jarosz contributes to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision. Elżbieta Cybulska contributes to data collection, draft preparation, manuscript editing. All authors have read and agreed with the manuscript before its submission and publication.

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