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Adaptive Sensor Fusion Algorithms for Autonomous Systems in Adverse Weather Conditions

Milad Rahmati1

1Independent Researcher, Los Angeles, California, United States

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Abstract: This paper presents an adaptive sensor fusion algorithm designed to enhance the performance of autonomous systems operating under adverse weather conditions. Traditional sensor fusion methods struggle with data inconsistencies caused by environmental factors such as fog, rain, and snow, which compromise the reliability of LiDAR and radar inputs. To address this challenge, we propose a novel fusion framework integrating machine learning-based adaptive weighting to dynamically adjust sensor contributions based on weather conditions. The proposed algorithm is validated using simulated and real-world datasets, demonstrating superior robustness, accuracy, and computational efficiency compared to state-of-the-art methods. Experimental results show an 18% improvement in obstacle detection accuracy and a 23% reduction in false positives under adverse conditions. These findings suggest significant potential for improving the safety and reliability of autonomous systems in real-world scenarios.

Keywords: **Adaptive sensor fusion, autonomous systems, adverse weather conditions, LiDAR, radar, machine learning, sensor data weighting, environmental perception.**

*Corresponding author.
E-mail address: mrahmat3@uwo.ca (Ivan Mendoza-Bravo).
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1. Introduction

Autonomous systems, including self-driving vehicles, unmanned aerial systems, and robotic platforms, depend on sensor fusion to interpret and navigate their environments. Sensors such as LiDAR and radar are integral due to their capability to generate detailed spatial and temporal information. However, their performance is significantly disrupted by adverse weather conditions like fog, rain, and snow, which introduce noise and degrade signal quality. These environmental challenges hinder the reliable operation of autonomous systems in practical settings (Zhang & Liu 2021; Smith & Chen, 2020).

Sensor fusion algorithms combine data from multiple sensors to create a cohesive understanding of the surroundings. Conventional approaches, such as Kalman filters and particle filters, generally rely on fixed assumptions about sensor reliability, often neglecting variations caused by environmental factors. This limitation makes them less effective in dynamically changing weather conditions (Xu et al., 2022). In contrast, advances in machine learning (ML) provide opportunities to create adaptive fusion algorithms that dynamically adjust the contributions of sensors based on contextual information (Liu et al., 2021).

This study focuses on bridging the gap in adaptive sensor fusion by introducing an innovative algorithm that applies ML techniques to dynamically reweight sensor inputs according to weather conditions. Unlike traditional methods—such as Kalman filtering, Dempster-Shafer theory, and fuzzy logic fusion—which often rely on rigid, rule-based sensor reliability assumptions, the proposed framework integrates real-time adaptive weighting driven by machine learning. This flexibility allows the system to adjust dynamically to environmental disturbances.

The main contributions of this research are as follows:

1. A novel adaptive sensor fusion framework employing ML-based weighting for improved performance in adverse weather.
2. Comprehensive validation of the proposed approach using both simulated and real-world datasets.
3. Comparative analysis with existing methods, demonstrating substantial advancements in robustness and accuracy.

2. Related Work

Sensor fusion has become a cornerstone of autonomous systems, enabling these systems to interpret complex environments by integrating data from multiple sensors. Traditional methods like Kalman filters and particle filters have been extensively used due to their simplicity and efficiency in static conditions (Zhang & Liu 2021; Smith & Chen, 2020). However, these approaches lack the flexibility to handle dynamic changes in sensor reliability caused by environmental factors, making them inadequate for adverse weather scenarios.

Recent advancements in machine learning (ML) have paved the way for adaptive sensor fusion techniques. For instance, deep learning models have been applied to dynamically adjust sensor weights based on contextual information. Xu et al. (2022) proposed a convolutional neural network (CNN) for sensor fusion in autonomous vehicles, which demonstrated improved accuracy in urban environments. However, the approach required extensive computational resources, limiting its real-time applicability.

Another notable development is the use of reinforcement learning (RL) for sensor fusion optimization. Liu et al. (2021) developed an RL-based framework to adjust sensor contributions dynamically, achieving promising results in terms of obstacle detection accuracy. Despite its effectiveness, the model struggled with generalization to unseen weather conditions, highlighting the need for more robust training techniques.

Hybrid methods combining traditional algorithms with ML enhancements have also gained attention. Zhao et al. (2020) integrated a Bayesian framework with a neural network to improve object tracking in foggy environments. This approach demonstrated improved robustness but required careful tuning of model parameters, which is not always feasible in real-time applications.

Adverse weather conditions pose unique challenges to sensor performance. LiDAR sensors are highly sensitive to rain and fog, leading to data degradation, while radar sensors, although more resilient, produce lower-resolution data (Chen & White, 2021).

Several studies have explored weather-specific sensor fusion methods. For example, Fang et al. (2021) developed a weather-adaptive fusion system that selectively prioritizes radar over LiDAR during heavy rain. While this system addressed specific weather conditions, it lacked generalizability across diverse scenarios.

Despite significant progress, key challenges remain in the domain of adaptive sensor fusion. These include developing lightweight algorithms that can operate in real-time, ensuring robustness across diverse environmental conditions, and achieving efficient integration of new sensors. The proposed research builds upon these findings by introducing a machine learning-based adaptive fusion framework capable of real-time sensor weighting under varying weather conditions. This framework aims to address the identified gaps and advance the state of the art.

3. Methods

This section provides an overview of the methodology for the proposed adaptive sensor fusion framework, which employs machine learning (ML) to adjust sensor contributions dynamically based on environmental conditions. The framework is designed to maintain robust performance in adverse weather conditions.

3.1 System Architecture

The proposed system consists of three primary components that work cohesively to achieve adaptive sensor fusion:

Preprocessing Module

Raw data from LiDAR and radar sensors are processed to enhance their usability. For LiDAR, a voxel grid filter is applied to downsample the dense point cloud, ensuring computational efficiency without losing essential spatial features. Radar data is processed using clutter suppression techniques to filter out irrelevant reflections and enhance signal quality (Zhang & Liu, 2021).

Environmental Condition Classification

An environmental classifier is used to identify prevailing weather conditions, such as clear skies, fog, rain, or snow. This classifier relies on inputs from external APIs or additional environmental sensors. The identified condition guides the adaptive fusion mechanism by indicating the likely reliability of each sensor (Smith & Chen, 2020).

3. Fusion Module

The core of the system is the fusion module, which assigns dynamic weights to each sensor's output. These weights are determined by a machine learning model trained to assess sensor reliability under different environmental contexts. The final fused output is calculated using:

$$O_f = w_l \cdot O_l + w_r \cdot O_r \tag{1}$$

Here, O_f represents the fused result, O_l and O_r are outputs from LiDAR and radar, and w_l and w_r are the respective adaptive weights (Xu et al., 2022).

The reliability scores α_i used in the softmax function are predicted by a multilayer perceptron (MLP), trained to estimate each sensor's contextual performance based on historical data and environmental conditions. The full structure and training process of the MLP are described in Section 3.2.

The sensor weight w_i is computed using a softmax function, ensuring that all weights are normalized and sum to one:

$$w_i = \frac{\exp(\alpha_i)}{\sum_{j=1}^{n} \exp(\alpha_j)} \tag{2}$$

Where:
w_i = weight of the *i-th* sensor,
α_i = reliability score predicted by the ML model for the *i-th* sensor,
n = total number of sensors.

3.2 Machine Learning Model

A multilayer perceptron (MLP) model is employed to predict optimal sensor weights dynamically. The MLP receives a feature vector containing preprocessed sensor quality metrics. Specifically, radar signal-to-noise ratio (SNR) is normalized using min-max scaling to the [0,1] range, and LiDAR point density is computed as the average number of points per square meter and standardized. Additionally, environmental condition labels (e.g., fog, rain) are one-hot encoded. To capture prior system behavior, rolling averages of recent detection accuracy and false positive rate are also included.

The MLP consists of two hidden layers with 64 and 32 neurons, respectively, and uses ReLU activations. A learning rate of 0.001 and a batch size of 32 were used during training. Early stopping based on validation loss was applied to prevent overfitting.

The MLP has two hidden layers with ReLU activations and a softmax output layer for generating normalized weights. Training is conducted using a mean squared error loss function, aiming to align the predicted weights with ground truth weights derived from labeled datasets.

Since the MLP is trained to predict sensor weights rather than final fusion outputs, the loss function directly compares predicted weights with reference weights derived from optimal fusion outcomes observed in labeled datasets. This surrogate supervision approach avoids requiring end-to-end labels and allows stable training.

Loss is calculated as follows:

$$\text{Loss} = \frac{1}{N}\sum_{i=1}^{N}\left(w_i^{\text{true}} - w_i^{\text{pred}}\right)^2 \tag{3}$$

Where:
w_i^{true} = ground truth weight of the i—th sensor,
w_i^{pred} = predicted weight by the ML model for the i—th sensor,
N = total number of training samples.

Signal to noise ratio is calculated as:

$$\text{SNR} = 10 \cdot \log_{10}\left(\frac{P_{\text{signal}}}{P_{\text{noise}}}\right) \quad (4)$$

Where:
SNR = signal-to-noise ratio,
P_{signal} = power of the signal,
P_{noise} = power of the noise.

3.3 Experimental Setup

The framework was evaluated using both simulation-based and real-world datasets:

1. Simulated Dataset
A simulation environment was created using CARLA, a platform for autonomous system testing. Scenarios were designed to emulate challenging weather conditions, such as heavy rainfall, dense fog, and snowfall.

2. Real-World Dataset
Publicly available datasets, including KITTI and nuScenes, were utilized for real-world validation. These datasets were filtered to focus on adverse weather scenarios, enabling comprehensive testing of the framework (Liu et al., 2021).

3. Evaluation Metrics

The performance of the framework was assessed using:
- **Obstacle Detection Accuracy:** The percentage of objects correctly identified.
- **False Positive Rate (FPR):** The rate at which non-existent objects were mistakenly detected.
- **Processing Time:** The time required to generate the fused output.

3.4 Implementation Details

The framework was implemented in Python using TensorFlow for developing the ML model. Data preprocessing was performed using the Point Cloud Library (PCL), and CARLA was employed for simulation. Experiments were executed on a high-performance workstation equipped with an NVIDIA RTX 3080 GPU and 32 GB of RAM, ensuring computational efficiency.

4. Results

This section presents the outcomes of the evaluation conducted on the proposed adaptive sensor fusion framework. Tests were carried out using simulated and real-world datasets, focusing on key metrics such as obstacle detection accuracy, false positive rate (FPR), and computational efficiency.

4.1 Performance on Simulated Dataset

The framework was evaluated in a simulated environment generated using CARLA, with scenarios designed to emulate challenging weather conditions (Table 1):

1. Heavy Rain:
- **Obstacle Detection Accuracy:** Achieved 85.2%, reflecting a 20% improvement compared to traditional static fusion methods (Zhang & Liu, 2021).
- **False Positive Rate:** FPR was reduced to 7.4%, outperforming baseline methods with an FPR of 12.8%.
- **Processing Time:** Maintained an average frame processing time of 35 milliseconds, ensuring real-time performance.

2. Dense Fog:
- **Obstacle Detection Accuracy:** Recorded at 81.6%, exceeding static fusion methods by 18%.
- **False Positive Rate:** Achieved an FPR of 9.1%, indicating improved reliability.
- **Processing Time:** Processing time remained efficient at 37 milliseconds per frame.

3. Snow:
- **Obstacle Detection Accuracy:** Reached 83.9%, showcasing enhanced detection capability.
- **False Positive Rate:** Reduced to 8.5%.
- **Processing Time:** Averaged 36 milliseconds per frame, maintaining consistency across tests.

Table 1. Simulated dataset performance.

Condition	Accuracy (%)	FPR (%)	Processing Time (ms)
Heavy Rain	85.2	7.4	35
Dense Fog	81.6	9.1	37
Snow	83.9	8.5	36

As shown in Tables 3 and 4, the proposed framework significantly outperforms both baselines in detection accuracy and false positive rate across diverse weather conditions.

4.2 Performance on Real-World Datasets

The framework was further validated using curated subsets of the KITTI and nuScenes datasets, specifically focusing on adverse weather conditions (Table 2):

1. KITTI Dataset (Rain Subset):

- **Obstacle Detection Accuracy:** Reached 88.4%, representing a 17% improvement over state-of-the-art methods.
- **False Positive Rate:** Achieved an FPR of 6.9%.
- **Processing Time:** Demonstrated real-time capability with a frame processing time of 33 milliseconds.

2. nuScenes Dataset (Fog Subset):

- **Obstacle Detection Accuracy:** Recorded 86.2%, outperforming baseline methods by 15%.
- **False Positive Rate:** Maintained an FPR of 7.2%.
- **Processing Time:** Achieved an average frame processing time of 34 milliseconds.

Table 2. Real-world dataset performance.

Condition	Accuracy (%)	FPR (%)	Processing Time (ms)
KITTI (Rain Subset)	88.4	6.9	33
nuScenes (Fog Subset)	86.2	7.2	34

4.3 Comparative Analysis

To evaluate the framework's effectiveness, its performance was compared with two baseline approaches:

1. Static Fusion:

- A conventional method that assigns fixed weights (e.g., 0.5 to each sensor) regardless of external conditions. This baseline represents systems that do not adapt to weather or signal quality changes.

2. State-of-the-Art ML Fusion:

- An existing deep neural network-based model trained to classify obstacle presence directly from concatenated LiDAR and radar inputs. It is not weather-aware and lacks dynamic weight adaptation.

To provide a comprehensive comparison, Tables 3, 4, and 5 present the obstacle detection accuracy, false positive rate (FPR), and processing time respectively for all three approaches: Static Fusion, State-of-the-Art ML Fusion, and the proposed framework. These results are shown across both simulated and real-world datasets.

Table 3. Obstacle detection accuracy comparison across three methods.

Condition	Static Fusion	State-of-the-Art ML	Proposed Method
Heavy Rain	71.0	77.2	85.2
Dense Fog	69.2	74.5	81.6
Snow	71.8	76.1	83.9
KITTI (Rain Subset)	75.5	81.4	88.4
nuScenes (Fog Subset)	72.3	79.3	86.2

Table 4. False positive rate (FPR) comparison across three methods.

Condition	Static Fusion	State-of-the-Art ML	Proposed Method
Heavy Rain	12.8	9.6	7.4
Dense Fog	13.4	10.8	9.1
Snow	13.0	10.2	8.5
KITTI (Rain Subset)	11.9	9.1	6.9
nuScenes (Fog Subset)	12.4	9.8	7.2

Table 5. Average processing time comparison across three methods.

Condition	Static Fusion	State-of-the-Art ML	Proposed Method
Heavy Rain	26	49	35
Dense Fog	28	51	37
Snow	27	50	36
KITTI (Rain Subset)	25	48	33
nuScenes (Fog Subset)	26	49	34

4.4 Robustness Analysis

The adaptability of the proposed framework was evaluated by observing its performance under dynamically changing weather conditions. Results indicated that the adaptive weighting mechanism effectively adjusted sensor contributions, enabling consistent and accurate obstacle detection.

4.5 Computational Efficiency
The system demonstrated high computational efficiency, achieving an average GPU utilization of 70% during real-time operation. This ensured sufficient resources for additional processes while maintaining the framework's performance.

Table 5 further confirms the computational efficiency of the framework compared to the other methods, maintaining real-time performance while ensuring low processing delay.

5. Discussion

The proposed adaptive sensor fusion framework demonstrates substantial improvements in the performance of autonomous systems under adverse weather conditions. This section analyzes the results, discusses their implications, and highlights the strengths and limitations of the approach.

5.1 Key Findings
The results reveal that the adaptive sensor fusion framework consistently outperforms baseline methods across all tested metrics:

1. Improved Accuracy:
The framework achieved higher obstacle detection accuracy across simulated and real-world datasets, particularly in heavy rain and foggy conditions. This improvement is attributed to the dynamic weighting mechanism, which effectively prioritizes reliable sensor inputs based on environmental conditions.

2. Reduced False Positives:
By dynamically adjusting sensor contributions, the proposed method significantly reduced the false positive rate (FPR) compared to both static and state-of-the-art fusion methods. This improvement enhances the reliability of autonomous systems in detecting critical objects.

3. Real-Time Performance:
The framework maintained real-time processing capabilities with low computational overhead, making it suitable for deployment in resource-constrained environments.

5.2 Implications
The findings highlight the potential of machine learning (ML)-based adaptive sensor fusion in overcoming the limitations of traditional methods. By leveraging environmental context to adjust sensor weights, the framework ensures robust performance in diverse weather scenarios, addressing a critical barrier to the widespread deployment of autonomous systems.

Applications of this framework extend beyond autonomous vehicles to include:

- **Drones:** Enhancing navigation and obstacle avoidance in challenging weather.
- **Surveillance Systems:** Improving reliability in security operations under adverse conditions.
- **Robotics:** Supporting operations in unstructured and dynamic environments.

5.3 Strengths and Contributions
Key strengths of the framework include:

- **Scalability:** The modular design allows integration with additional sensors, such as cameras or ultrasonic sensors.
- **Robustness:** The ML-based adaptive weighting mechanism ensures adaptability to a wide range of environmental conditions.
- **Efficiency:** The lightweight architecture supports real-time operation, crucial for time-sensitive applications.

5.4 Limitations and Challenges
Despite its strengths, the framework has certain limitations:

1. Limited Dataset Coverage:
While the results are promising, the validation relied on publicly available datasets and simulations. Expanding the evaluation to include more diverse real-world conditions is essential for broader applicability.

2. Training Data Dependency:
The ML model requires extensive labeled data for effective training. Collecting high-quality data for rare weather conditions, such as extreme snowstorms, remains a challenge.

3. Edge Cases:
The framework may face difficulties in edge cases, such as sudden sensor malfunctions or highly dynamic weather changes, where rapid adaptation is critical.

4. Lack of Rare Weather Testing:
The current framework has not been tested under rare or extreme weather conditions such as hailstorms or sandstorms due to the lack of publicly available datasets simulating such phenomena. Future work should focus

on synthetic data generation or field experiments to improve robustness in these scenarios.

5.5 Future Improvements

To address these limitations, the following enhancements are recommended:

1. **Expanding Dataset Diversity:** Incorporating datasets from varied geographical regions and weather conditions to improve generalizability.
2. **Hybrid Sensor Integration:** Adding visual or thermal sensors to complement LiDAR and radar inputs in extreme scenarios.
3. **Model Optimization:** Exploring lightweight neural network architectures to further reduce computational requirements.
4. **Edge Case Handling:** Implementing redundancy mechanisms or fallback strategies for sensor failure scenarios.
5. **Embedded Deployment Readiness:** To ensure applicability on embedded or low-power platforms, future development should consider compact architectures such as quantized neural networks (QNNs) or mobile-optimized variants like MobileNet, enabling deployment on edge devices without dedicated GPUs.

Conclusion

This study introduced an adaptive sensor fusion framework designed to enhance the robustness and reliability of autonomous systems under adverse weather conditions. By leveraging a machine learning-based approach to dynamically adjust sensor weights, the framework addresses the inherent limitations of static and traditional sensor fusion methods.

The proposed method demonstrated significant improvements across key performance metrics:

- **Obstacle Detection Accuracy:** Achieved up to a 20% improvement compared to baseline methods in simulated adverse weather scenarios.
- **False Positive Rate:** Substantially reduced false detections, ensuring more reliable environmental perception.
- **Computational Efficiency:** Maintained real-time processing capability, enabling deployment in practical applications.

The findings underline the potential of adaptive fusion techniques in enhancing the performance of autonomous systems in challenging environments. The modular design of the framework ensures scalability, making it suitable for a wide range of applications, including autonomous vehicles, drones, and robotics.

While the results are promising, certain limitations, such as dataset diversity and edge-case handling, highlight opportunities for further research. Future work will focus on integrating additional sensors, optimizing neural network architectures, and validating the framework in diverse real-world scenarios. These advancements aim to establish the proposed system as a cornerstone for reliable and scalable autonomous operation in unpredictable environments.

7. Future Work

This study lays a foundation for adaptive sensor fusion in autonomous systems, but there remain several promising areas for future exploration:

1. Incorporation of Additional Sensors:
Expanding the framework to include other sensor modalities, such as cameras, thermal imaging, and ultrasonic sensors, could further improve its adaptability. These additional inputs could compensate for scenarios where LiDAR and radar face limitations, such as heavy fog or low light.

2. Addressing Edge Cases and Fault Tolerance:
Developing strategies to handle rare edge cases, such as abrupt sensor malfunctions or sudden environmental changes, is essential. Implementing redundancy measures and backup systems could ensure uninterrupted operation in these situations.

3. Optimizing Model Efficiency:
Reducing the computational load of the framework by employing optimization techniques, such as pruning and quantization of the neural network, could make the system more efficient. Lightweight neural networks would be particularly useful for applications in resource-constrained settings.

4. Broader Dataset Development:
Enhancing the diversity of training datasets by including more real-world environments and rare weather conditions, such as hail or sandstorms, would improve model generalizability. Collaborative efforts with data-sharing platforms could provide access to such datasets.

5. Real-Time Learning Capabilities:
Introducing real-time learning mechanisms to enable the framework to adapt dynamically to new weather conditions and environments would enhance its flexibility. This approach would minimize the need for extensive retraining, allowing continuous improvement.

6. Applications in Multi-Agent Systems:
Extending the framework to support collaborative sensing in multi-agent systems, such as fleets of autonomous vehicles or drone swarms, could enhance situational awareness. Information sharing among agents may lead to better decision-making and efficiency.

7. Validation in Real-World Applications:
Testing the framework in various practical scenarios, such as agriculture, mining, and emergency response, would validate its robustness. These fields often involve extreme conditions where reliable sensing is critical, providing valuable insights into the system's performance.

Exploring these areas in future research could lead to a more robust and versatile sensor fusion framework, addressing the challenges faced by autonomous systems in complex and dynamic environments.

Data Availability Statement

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Competing Interests

The authors declare that they have no conflicts of interest to disclose.

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