Noise Reduction Techniques in ADAS Sensor Data Management: Methods and Comparative Analysis

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***Abstract*—This review examines noise reduction techniques in Advanced Driver Assistance Systems (ADAS) sensor data management, crucial for enhancing vehicle safety and performance. ADAS relies on real-time data from conventional sensors (e.g., wheel speed sensors, LiDAR, radar, cameras) and MEMS sensors (e.g., accelerometers, gyroscopes) to execute critical functions like lane keeping, collision avoidance, and adaptive cruise control. These sensors are susceptible to thermal noise, mechanical vibrations, and environmental interferences, which degrade system performance. We explore filtering techniques including KalmanNet, Simple Moving Average (SMA), Exponential Moving Average (EMA), Wavelet Denoising, and Low Pass Filtering (LPF), assessing their efficacy in noise reduction and data integrity improvement. These methods are compared using key performance metrics such as Signal-to-Noise Ratio (SNR), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Recent advancements in hybrid filtering approaches and adaptive algorithms are discussed, highlighting their strengths and limitations for different sensor types and ADAS functionalities. Findings demonstrate the superior performance of Wavelet Denoising for non-stationary signals, SMA and EMA's effectiveness for smoother signal variations, and LPF's excellence in high-frequency noise attenuation with careful tuning. KalmanNet showed significant improvements in noise reduction and data accuracy, particularly in complex and dynamic environments. Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) were especially effective for RADAR sensors, handling non-linearities and providing accurate state estimation. Emphasizing Hardware-in-the-Loop (HIL) bench testing to validate these techniques in real-world scenarios, this study underscores the importance of selecting appropriate methods based on specific noise characteristics and system requirements. This research provides valuable insights for ADAS and autonomous driving technologies development, emphasizing precise signal processing's critical role in ensuring accurate sensor data interpretation and decision-making.**

Keywords*—ADAS; sensor data management; noise reduction; KalmanNet; Wavelet Denoising; RADAR; SMA; EMA; LPF; HIL bench testing

I. Introduction

The evolution of automotive technology is rapidly transforming with the integration of Advanced Driver Assistance Systems (ADAS) and Autonomous Driving (AD) technologies, which are set to redefine vehicle safety and efficiency standards. Central to the success of these systems is the precise and reliable processing of sensor data from a variety of sources, including wheel speed sensors (WSS), inertial measurement units (IMUs), and radar systems. These sensors collectively enable the vehicle to perceive its environment, make decisions, and execute safe driving maneuvers [1], [2]. However, the performance of ADAS and AD is critically dependent on the quality of the sensor data, which can be severely compromised by noise and interference, posing significant challenges to system reliability [3]. As vehicle systems become increasingly interconnected through Vehicle-to-Everything (V2X) communication and the rollout of 5G networks, the demand for real-time, robust, and low-latency data processing solutions has intensified, underscoring the necessity for efficient noise reduction algorithms.

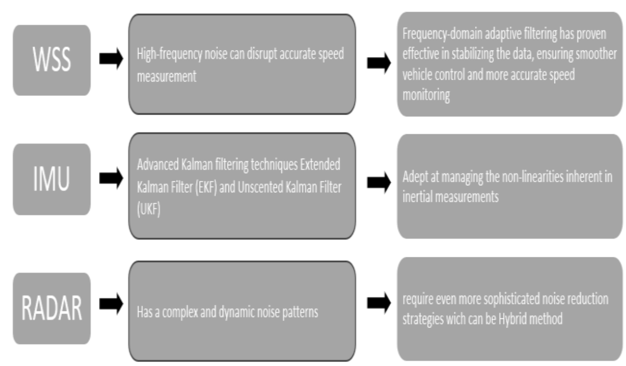


Fig. 1. Challenges encoutered by each sensor type.

As shown in the Fig. 1 and in order to mitigate these challenges, cutting-edge signal processing techniques have been developed to enhance sensor data quality, each tailored to the unique characteristics of different sensors. For instance, in WSS, where high-frequency noise can disrupt accurate speed measurement, frequency-domain adaptive filtering has proven effective in stabilizing the data, ensuring smoother vehicle control and more accurate speed monitoring [4]. IMUs, which are essential for maintaining vehicle dynamics and stability, benefit from advanced Kalman filtering techniques—particularly the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF)—which are adept at managing the non-linearities inherent in inertial measurements [3], [12]. Meanwhile, RADAR systems, tasked with obstacle detection and environmental mapping, require even more sophisticated noise reduction strategies, including multi-sensor fusion and machine learning-based methods, to effectively manage the complex and dynamic noise patterns encountered in real-world scenarios [5], [6].

To address the challenges posed by dynamic environments in ADAS applications, this Fig. 2 illustrates the increasing necessity for advanced noise reduction techniques tailored to specific driving situations.

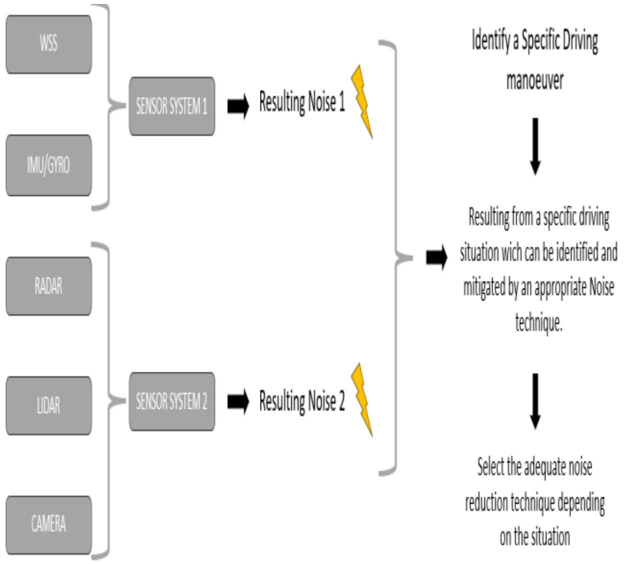


Fig. 2. The need for enhancing sensor noise reduction based on the driving situation identified.

As ADAS technology continues to advance, the integration of more complex sensor systems, such as radar and lidar, has heightened the need for innovative noise reduction techniques. These systems operate in dynamic environments filled with clutter, where conventional noise reduction approaches may fall short. To overcome these limitations, researchers are developing more sophisticated signal processing algorithms and exploring alternative modulation schemes, specifically designed to enhance data acquisition accuracy and reliability [7]. For RADAR systems, advanced Kalman filtering methods, such as the Unscented Kalman Filter (UKF), have demonstrated exceptional performance in tracking applications, particularly where noise is non-Gaussian and non-linear [12]. Simultaneously, multi-sensor fusion strategies, which integrate data from radar, lidar, and cameras, have become increasingly vital in providing a comprehensive perception of the vehicle's surroundings, compensating for the limitations of individual sensors [8]. However, the success of these approaches hinges on precise data synchronization and the development of sensor-specific noise reduction strategies, making them a critical area of ongoing research.

This Fig. 3 highlights the range of noise reduction techniques evaluated in this study, with a focus on those specifically selected for their effectiveness in various sensor types.

Recent advances in noise reduction techniques reflect a growing recognition of the need for tailored solutions across different sensors. For WSS, techniques like Simple Moving Average (SMA) and Exponential Moving Average (EMA) remain popular for their simplicity and computational efficiency, though Enhanced Simple Moving Average (ESMA) methods have emerged to address the limitations of initialization periods and stability [9], [10], [11]. IMUs, on the other hand, continue to benefit from the Kalman filtering family, with the EKF and UKF providing robust solutions for handling non-linear dynamics and improving measurement accuracy [13]. In RADAR systems, wavelet denoising has proven to be a powerful tool for managing non-stationary signals, while innovations like KalmanNet—which merges neural networks with Kalman filtering—offer significant advancements in reducing noise and enhancing signal clarity in complex operational environments [14], [15]. These innovations are critical not just for improving sensor data quality but also for enabling the high levels of performance demanded by modern ADAS and AD systems.

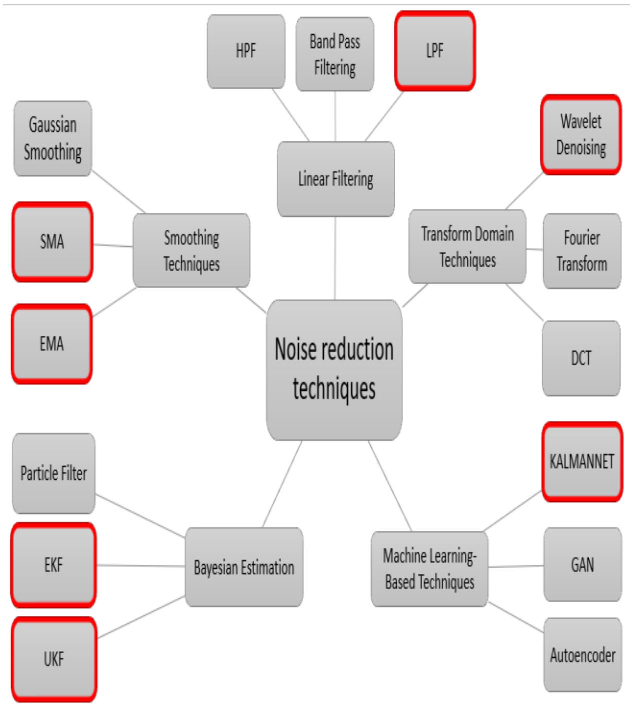


Fig. 3. Noise reduction techniques and chosen techniques shape outline are in red.

Effective noise reduction techniques are essential across WSS, IMUs, and RADAR systems, as they directly influence the reliability and safety of ADAS and AD applications. For WSS, methods like SMA and EMA continue to provide efficient solutions for mitigating speed-related noise, ensuring smoother control and accurate speed data [9], [10]. In IMUs, the advanced filtering techniques of EKF and UKF are crucial for maintaining vehicle stability by effectively handling the non-linearities in inertial data [16], [17]. RADAR systems, operating in complex environments, benefit significantly from wavelet denoising and hybrid methods like KalmanNet, which enhance signal clarity and improve the detection of critical obstacles [14], [15]. These tailored approaches are not only vital for current applications but also lay the groundwork for future advancements in automotive safety and sensor technology [18], [19], [20].

To validate the effectiveness of these advanced noise reduction techniques, we conducted a comprehensive empirical study using synthetic datasets that closely mimic the noise characteristics encountered by automotive sensors such as WSS, IMUs, and RADAR. By systematically introducing a range of noise types and levels, we rigorously evaluated the performance of each noise reduction method across key metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Signal-to-Noise Ratio (SNR), and Peak Signal-to-Noise Ratio (PSNR). This approach ensured a robust assessment of each technique's ability to enhance data accuracy and reliability under real-world conditions.

The Fig. 4 shows a summary of the key findings from existing literature, emphasizing the importance of tailored noise reduction approaches for enhancing sensor data accuracy in ADAS applications.

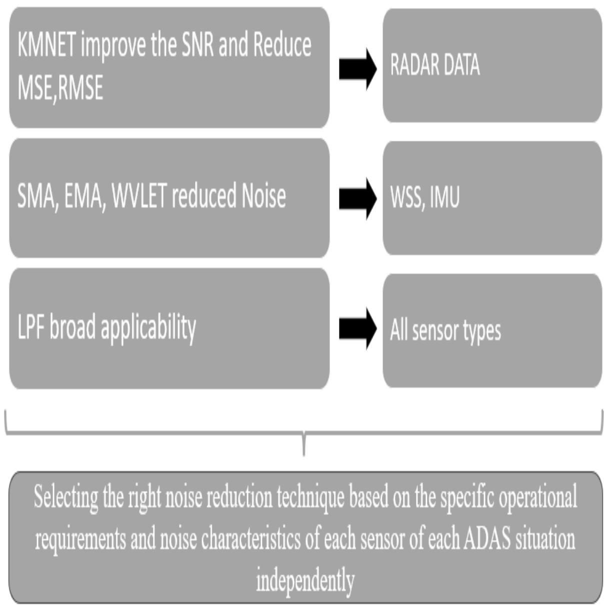


Fig. 4. Key findings of the existing literature.

The findings of this study strongly support the hypothesis that a tailored, sensor-specific approach to noise reduction can significantly improve data accuracy and system performance across various ADAS and AD applications. KalmanNet and hybrid techniques showed the greatest improvements in SNR and significant reductions in MSE and RMSE for RADAR data, while SMA, EMA, and Wavelet Denoising effectively reduced noise in WSS and IMU data, with Low Pass Filtering (LPF) providing broad applicability across all sensor types [21], [22]. These results underscore the critical importance of selecting the right noise reduction techniques based on the specific operational requirements and noise characteristics of each sensor, paving the way for enhanced automotive safety and efficiency.

In the introduction, the critical role of Advanced Driver Assistance Systems (ADAS) and Autonomous Driving (AD) technologies in enhancing vehicle safety and efficiency is examined, with an emphasis on the importance of accurate sensor data processing. The challenges associated with noise and interference in key sensors—such as wheel speed sensors (WSS), inertial measurement units (IMUs), and radar systems—are highlighted, particularly given their integral role in ADAS and AD system performance. The methodology section discusses the application of advanced noise reduction techniques, specifically tailored to the unique characteristics of these sensors, while also considering the demands of Vehicle-to-Everything (V2X) communication and 5G networks. Techniques such as Simple Moving Average (SMA), Exponential Moving Average (EMA), Wavelet Denoising, Low Pass Filtering (LPF), KalmanNet, Extended Kalman Filter (EKF), and Unscented Kalman Filter (UKF) are evaluated for their efficacy in noise reduction, with an additional focus on the necessity of real-time processing and the preference for simpler, computationally efficient algorithms over more complex ones. The results provide a detailed analysis, demonstrating the effectiveness of these methods in enhancing Signal-to-Noise Ratio (SNR) and reducing Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), while also considering the practical implications of implementing these techniques in real-time V2X and 5G environments. The discussion elaborates on these findings, underscoring the importance of sensor-specific noise reduction strategies and their implications for the future development of ADAS. The conclusion synthesizes the key contributions of the study, proposing directions for future research aimed at further optimizing these techniques and ensuring their seamless integration into comprehensive, real-time ADAS frameworks, thereby advancing the reliability and performance of automotive safety systems.

Given the critical role that precise noise reduction techniques play in the effectiveness of ADAS, it is essential to explore and build upon existing research that has laid the groundwork in this field. The following section reviews the advancements and challenges documented in recent literature, providing a context for the methodologies employed in this study.

II. RELATED WORK

Recent research has focused extensively on developing data-driven frameworks for diagnostics and prognostics across various domains, including automotive and aerospace. These frameworks typically involve sophisticated data acquisition processes from sensors and control units, often leveraging machine logs and CAN bus networks to enhance system monitoring and fault detection [23], [24]. Advanced data processing techniques, such as feature selection and extraction, have been employed to improve diagnostic accuracy, but their application in real-time systems remains a challenge due to computational limitations [23], [24].

The Fig. 5 provides an overview of the testing and validation activities critical to ensuring the reliability and performance of automotive systems, especially in the context of noise reduction.

The adoption of machine learning algorithms, including Random Forests, Bayesian estimation methods, and Cox proportional hazards models, is widespread for fault detection and remaining useful life (RUL) prediction; however, these approaches often require significant computational resources, limiting their applicability in real-time environments [25]-[26]. Despite these advancements, there is a clear need for further research into hybrid models that can efficiently balance predictive accuracy with real-time processing demands, particularly in safety-critical systems where data availability may be limited [25].

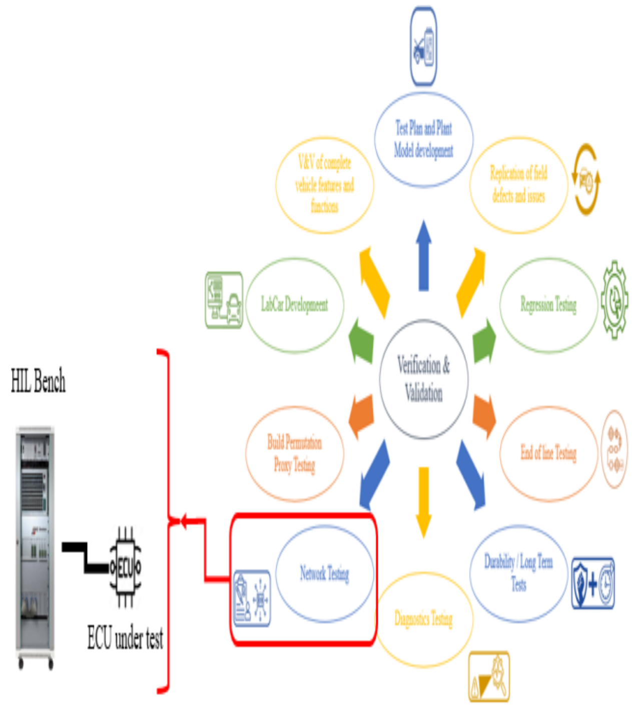


Fig. 5. Testing and validation activities in the automotive field [40].

The Fig. 6 below presents a comparison of advanced fault detection and diagnostic techniques, highlighting those selected for this study due to their relevance in noisy environments.

In the context of noise reduction in data acquisition systems, particularly for automotive applications and Hardware-in-the-Loop (HIL) testing, various noise sources have been identified, including thermal fluctuations, mechanical vibrations, and environmental interferences [27], [28]. Although conventional noise mitigation techniques, such as proper cabling, shielding, and signal modulation, provide baseline improvements, they fall short in addressing the complex, high-frequency noise patterns encountered in modern vehicle systems, especially under dynamic conditions [27], [29]. Emerging machine learning approaches, like ensemble LSTM and Random Forest, have been proposed for fault detection in noisy conditions, showing promise in controlled environments but requiring further validation under real-world conditions [30]. Moreover, the impact of noise on sensor performance, particularly in automotive camera sensors and object detection systems, has underscored the necessity for simultaneous analysis of multiple noise factors to ensure robust performance [31].

This Fig. 7 illustrates the various sources of noise and interference that impact sensor data quality in automotive systems, underscoring the need for robust noise reduction strategies.

Fig. 6. Advanced techniques for fault detection and diagnostics and selected ones for the current study in red [41].

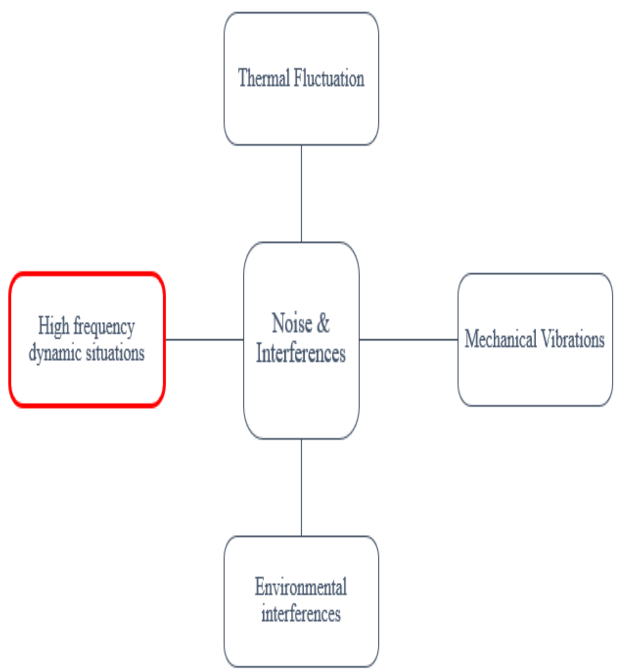


Fig. 7. Noise and interferences.

This body of work highlights the critical importance of noise reduction in the automotive and aerospace industries. Researchers have explored a wide array of techniques to minimize aerodynamic, vibroacoustic, and communication noise, yet the integration of these techniques into real-time systems remains an ongoing challenge [32], [33]. Advanced methods, such as compressive sensing-based noise radar and hybrid active noise control systems, have been developed to improve sensor performance, but their high computational requirements often hinder their implementation in embedded systems [34], [35]. As the industry moves towards more complex and interconnected systems, such as those enabled by V2X and 5G technologies, there is an increasing demand for noise reduction techniques that are both highly effective and computationally efficient [36], [28]. This demand is further amplified by the exponential growth in sensor data volume and complexity, necessitating the development of novel algorithms that can operate within the stringent constraints of modern embedded systems [37].

The Fig. 8 below -compares existing noise reduction methods with the current demands of modern automotive systems, highlighting gaps that this study aims to address.

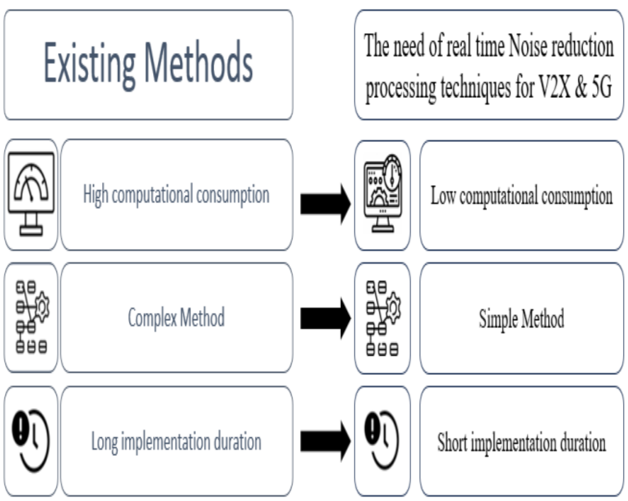


Fig. 8. Comparaison between the existent method in the literature and the current need.

In summary, the need for effective noise reduction in automotive sensor data acquisition is well-established in recent research. However, as vehicle connectivity and automation continue to expand, the challenges associated with noise in sensor systems grow more complex [37]. While existing studies have made significant strides in addressing these issues, particularly through HIL testing and the development of robust sensor models, there remains a critical need for further research that focuses on the integration of real-time noise reduction techniques within the context of V2X and 5G environments [38]-[39]. This integration is essential not only for meeting current safety standards but also for advancing the capabilities of future Advanced Driver Assistance Systems (ADAS) and autonomous driving technologies [36], [37]. Future research should prioritize the development of scalable, adaptive noise reduction strategies that can efficiently process the vast amounts of data generated by modern vehicle systems, ensuring both reliability and real-time performance [37].

III. Context and Objectives

Hardware-in-the-Loop (HIL) testing has become a cornerstone in the validation process of complex automotive and aerospace systems. By accurately simulating real-world conditions, HIL testing serves as a critical bridge between theoretical models and practical applications, ensuring that systems perform reliably and efficiently under operational constraints. Recent advancements in this domain have been pivotal in overcoming key challenges, such as the bandwidth limitations of Electronic Control Units (ECUs), while significantly enhancing diagnostic capabilities. These advancements are particularly vital as the integration of next-generation technologies, including advanced communication networks like 5G and Vehicle-to-Everything (V2X), becomes increasingly prevalent in automotive systems.

This Fig. 9 showcases a typical Hardware-in-the-Loop (HIL) test bench setup, demonstrating its critical role in validating the performance of noise reduction techniques under real-world conditions.

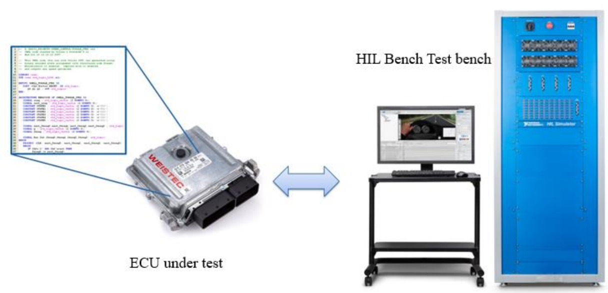


Fig. 9. An example of HIL bench test bench with an ECU [42].

The primary objectives of this research are:

- Enhancing the precision of data collection and testin through the development and implementation of advanced HIL testbeds.
- Improving fault detection and noise reduction by integrating sophisticated signal processing techniques, tailored to the unique demands of modern sensor systems.
- Optimizing HIL testing frameworks to effectively manage the complexities introduced by the integration of 5G and V2X technologies, ensuring robust performance and reliability.

Addressing these objectives is crucial for refining real-time performance in HIL testing and ensuring that simulation outcomes closely mirror real-world conditions. As HIL testing methodologies evolve, these efforts will drive the development of more reliable, efficient, and safe automotive and aerospace systems, positioning them to meet and exceed the rigorous demands of contemporary engineering challenges. This study emphasizes the strategic selection of noise reduction techniques based on sensor-specific and operational requirements, highlighting their impact on the performance and reliability of Advanced Driver Assistance Systems (ADAS). Future research should focus on further optimizing these techniques and exploring their seamless integration into comprehensive ADAS solutions, thereby advancing the frontier of automotive safety and operational efficiency.

IV. METHODOLOGY

A. General Approach

To validate the hypothesis that tailored noise reduction techniques enhance the accuracy and reliability of sensor data in Advanced Driver Assistance Systems (ADAS), a comprehensive study was conducted. This study involved the generation of synthetic datasets for Wheel Speed Sensors (WSS), Inertial Measurement Units (IMU/GYRO), and RADAR sensors, reflecting the typical data volume and noise complexity encountered in real-world scenarios. This approach ensures that the study replicates the diverse and challenging conditions that ADAS must effectively manage for enhanced performance and safety.

The following figure shows the proposed method followed for this paper:

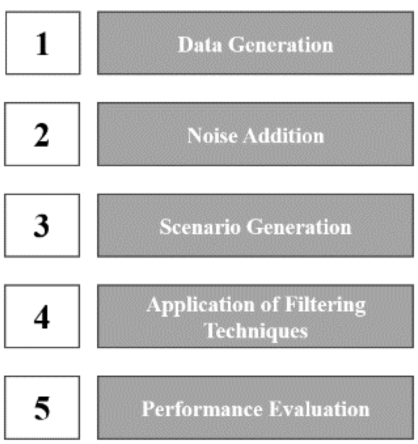


Fig. 10. Proposed method for filtering.

Fig. 10 illustrates the structured approach followed in this research, highlighting the key stages of data generation, noise addition, and performance evaluation.

The methodology followed a systematic approach as explained below:

1) Data generation: Synthetic datasets were generated to simulate sensor data under various driving scenarios. For WSS and IMU/GYRO sensors, 10 signals were created for each sensor type, capturing rapid changes in speed, motion, and orientation. For RADAR sensors, 100 signals were generated to account for the increased complexity and variability in noise patterns encountered in dynamic environments. These datasets were designed to replicate the typical challenges faced by ADAS systems, ensuring the relevance and applicability of the findings.

2) Noise addition: To replicate real-world conditions, various types and levels of noise were systematically introduced to the synthetic datasets. For instance, Gaussian noise was added to mimic thermal fluctuations, and periodic spikes simulated electromagnetic interference (EMI). The noise levels were varied to assess the robustness of each filtering technique across different conditions. Different levels of noise intensity were applied to test the robustness and adaptability of each filtering technique, ensuring comprehensive evaluation under varied conditions.

3) Scenario simulation: The study simulated a range of high-risk and typical driving scenarios, including urban intersections, highway lane changes, and emergency braking. These scenarios were derived from real-world conditions commonly tested in ADAS and Vehicle-to-Everything (V2X) systems, ensuring that the simulation covered a broad spectrum of challenges that ADAS must handle effectively. This comprehensive scenario simulation provides a rigorous testing environment, closely mirroring the operational challenges encountered in actual driving situations.

4) Filtering techniques exposition: The following Table I present a presents a comparative analysis of the noise reduction methods for WSS data in ADAS, highlighting their advantages, disadvantages, and performance metrics. This analysis is crucial for understanding the trade-offs associated with each technique, particularly in terms of computational complexity and real-time applicability.

The following Table I presents a comparative analysis of noise reduction methods specifically tailored for wheel speed sensor (WSS) data in advanced driver assistance systems (ADAS). It provides critical insight into the constraints associated with their application in real-time environments by highlighting the advantages, disadvantages and performance metrics of each method.

5) Performance evaluation criteria: The performance of each filtering technique was rigorously evaluated using metrics such as Signal-to-Noise Ratio (SNR), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The analysis provided detailed insights into the scenario-specific performance and computational complexity of each method, with an emphasis on practical implications for ADAS development. The metrics used in this study are critical for quantifying the effectiveness of each noise reduction technique, offering a clear comparison of their relative strengths and weaknesses.

To quantify the effectiveness of the noise reduction techniques evaluated in this study, the following Table II outlines the performance evaluation criteria, focusing on key metrics such as Signal-to-Noise Ratio (SNR), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). This comparison is essential for understanding the impact of each technique on data integrity and system reliability.

TABLE I. COMPARATIVE ANALYSIS OF NOISE REDUCTION METHODS FOR WSS DATA IN ADAS

Method	Advantages	Disadvantages	Performance
Simple Moving Average (SMA)	- Easy to implement	- Introduces lag - Less effective for complex noise patterns	- Significant noise reduction - Improves SNR - Higher MSE and RMSE compared to other methods during rapid signal changes
Exponential Moving Average (EMA)	- More responsive to recent changes - Smoother transition and less lag compared to SMA	- More complex to implement than SMA - May still lag in highly dynamic scenarios	- Better noise reduction than SMA - Higher SNR improvement - Lower MSE and RMSE than SMA, suitable for timely signal changes
Wavelet Denoising	- Handles non-stationary signals well - Effective at separating noise from the actual signal	- Computationally intensive - Requires careful selection of wavelet type and decomposition level	- Outperformed SMA and EMA - Highest SNR improvements - Lowest MSE and RMSE, effective for varying noise characteristics
Low Pass Filtering	- Simple and effective for high-frequency noise - Preserves low-frequency components of the signal	- Can distort signal if cutoff frequency is not appropriately set - May not be effective for low-frequency noise	- Significant high-frequency noise reduction - Improved SNR - Potential signal distortion indicated by MSE and RMSE, requires careful tuning
KalmanNet	- Neural network-aided Kalman filtering to enhance noise reduction capability using learned patterns	- Computationally intensive - Requires training data	- Demonstrated significant improvements in noise reduction and data accuracy compared to traditional Kalman filters
Extended Kalman Filter (EKF)	- Suitable for non-linear systems - Incorporates system dynamics into the filtering process	- Requires accurate system models - Computationally demanding	- Significant noise reduction - Improved SNR - Lower MSE and RMSE, effective for non-linear RADAR data
Unscented Kalman Filter (UKF)	- Superior performance for highly non-linear systems - Does not require linearization of the system model	- High computational complexity - Sensitive to initial conditions	- Outperforms EKF in highly non-linear applications - Highest SNR and lowest MSE and RMSE for complex noise patterns

TABLE II. METRICS CRITERIA EVALUATION

Metric	Increase	Decrease
Signal-to-Noise Ratio (SNR)	- **Indicates improved signal quality**: ➔ A higher SNR means the signal is clearer relative to the noise, suggesting that the filtering technique effectively reduces noise and enhances the signal's clarity.	- **Indicates poorer signal quality**: ➔A lower SNR implies that the signal is more contaminated by noise, suggesting that the filtering technique is less effective at noise reduction.
Mean Squared Error (MSE)	- **Indicates poorer filtering performance**: ➔An increase in MSE means the difference between the filtered signal and the original clean signal is larger, suggesting that the filtering technique introduces significant error or fails to effectively reduce noise.	- **Indicates better filtering performance**: ➔ A decrease in MSE means the filtered signal is closer to the original clean signal, indicating that the filtering technique effectively reduces noise with minimal distortion.
Root Mean Squared Error (RMSE)	- **Indicates poorer filtering performance**: ➔ An increase in RMSE suggests that the filtering technique is less effective, as there is a larger average magnitude of error between the filtered signal and the original clean signal.	- **Indicates better filtering performance**: ➔ A decrease in RMSE indicates that the filtering technique performs well, reducing the average magnitude of error and closely approximating the original clean signal.

B. Scope and Limitations of the Research

Fig. 11 shows the ADAS driving scenarios for which we limit the current study to identify the adequate filtering method for each situation accordingly. This focused approach ensures that the findings are directly applicable to the most critical real-world challenges faced by ADAS systems.

The scenarios used for generating WSS signals represent various high-risk and typical driving situations encountered in Advanced Driver Assistance Systems (ADAS). These include:

1) Urban intersection: Simulates driving at different speeds within an intersection, capturing low, moderate, slow, and high-speed phases.

2) Rear-end collision avoidance: Captures high-speed driving followed by rapid deceleration to avoid a rear-end collision.

3) Pedestrian crossing: Models stopping and starting for pedestrian crossings, with periods of driving and stopping.

4) Emergency braking for cyclist: Demonstrates deceleration and rapid acceleration to avoid a collision with a cyclist.

5) Blind spot detection: Simulates consistent speed with noise to represent challenges in detecting vehicles in blind spots.

6) Highway lane change: Depicts the process of lane changing on a highway, with distinct phases of driving in a lane and the lane change itself.

7) Cut-in vehicle: Illustrates a vehicle cutting into the lane, requiring a deceleration phase followed by a return to normal speed.

8) Roadworks zone navigation: Depicts navigation through a roadworks zone with varying speeds and obstacles.

9) Traffic jam assist: Represents slow driving and stopping typical of traffic jam conditions.

10)Left Turn Across Path (LTAP): Models the approach, turn, and acceleration phases of making a left turn across another path.

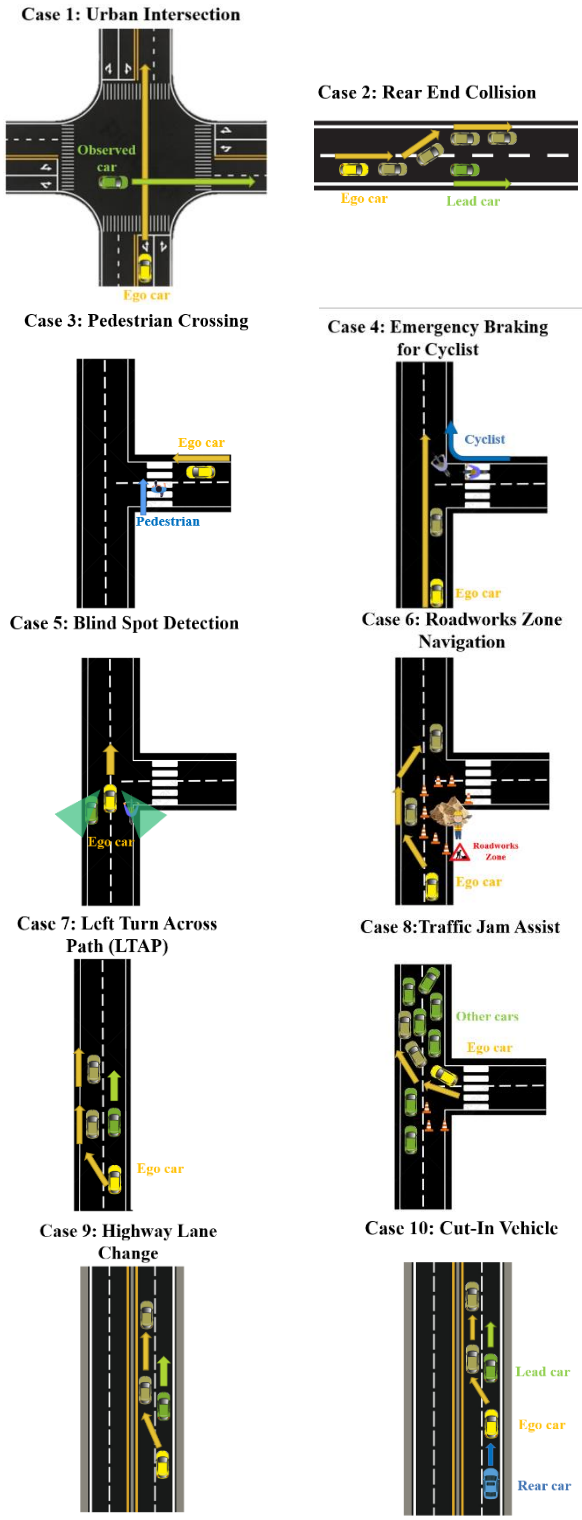


Fig. 11. ADAS driving scenarios.

These scenarios are derived from real-world situations commonly tested in ADAS and V2X (Vehicle-to-Everything) systems, as outlined in safety protocols like the European New Car Assessment Programme (Euro NCAP). The selection of these scenarios ensures the simulation of diverse and challenging conditions that ADAS must handle effectively for enhanced safety and performance. he rigorous selection and simulation of these scenarios are critical for validating the effectiveness of the noise reduction techniques in realistic and high-pressure environments.

C. *Detailed Proposed Method*

Below the detailed Method followed during this research:

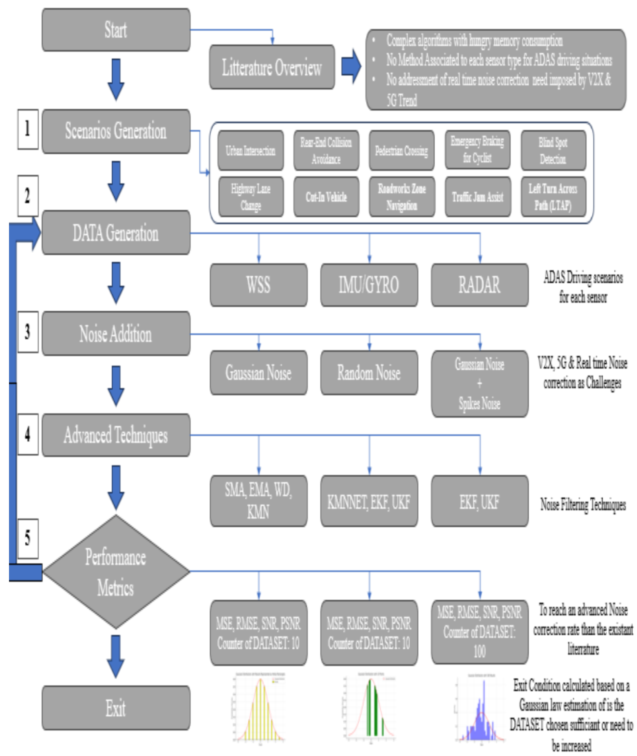


Fig. 12. Proposed method for noise filtering in the context of V2X & 5G challenges.

The proposed method (Fig. 12) is illustrated in the schema above, showcasing the systematic process of data generation, noise introduction, filtering, and evaluation across diverse driving scenarios. This approach ensures that the study addresses the specific challenges posed by V2X and 5G integration in ADAS systems.

1) Data generation and noise addition: The synthetic datasets were designed to replicate the sensor data from various automotive sensors under realistic driving conditions. For instance, WSS data was generated at high frequencies to capture rapid speed changes, while accelerometers and gyroscopes produced data representing motion and orientation in dynamic environments. This detailed approach ensures that the study comprehensively addresses the unique challenges posed by each sensor type, particularly under varied driving conditions, thus providing a robust basis for noise reduction analysis. Noise was systematically introduced to these datasets, including Gaussian noise to simulate thermal fluctuations and periodic spikes to represent electromagnetic interference (EMI). The varied noise levels ensure a comprehensive evaluation of each filtering technique's effectiveness and resilience across diverse conditions.

The filtering techniques applied in this study were selected for the ability to address the specific challenges posed by each sensor type. The selection was guided by the specific operational contexts and the complexity of the noise characteristics encountered in real-world scenarios:

2) Identification of the convenient filtering techniques: Based on the Fig. 4, the filtering techniques applied in this study were selected for their ability to address the specific challenges posed by each sensor type:

- Simple Moving Average (SMA) and Exponential Moving Average (EMA): These methods are computationally efficient and suitable for reducing short-term fluctuations and high-frequency noise in relatively stable environments. Their simplicity makes them ideal for real-time processing in scenarios where computational resources are limited, ensuring they meet the performance requirements of ADAS systems.

- Wavelet Denoising: This technique excels in handling non-stationary signals, making it effective for complex and dynamic noise patterns. Its ability to separate noise from actual signal components ensures high accuracy, especially in environments where signal integrity is critical.

- Low Pass Filtering (LPF): Simple yet effective for attenuating high-frequency noise, with careful tuning to avoid signal distortion. Although computationally lighter, LPF requires careful parameter selection to maintain signal fidelity and effectiveness.

- KalmanNet: A neural network-aided Kalman filtering technique designed to enhance noise reduction capability by learning patterns within the data. This advanced method is particularly effective in dynamic environments but requires significant computational resources and training data.

- Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF): These filters are particularly effective for non-linear systems, with the UKF offering superior performance without requiring linearization of the system model. Their robustness in handling non-linearities makes them indispensable for accurate sensor data processing in complex ADAS scenarios.

The methodology outlined provides a structured approach to evaluating and enhancing noise reduction techniques for automotive sensors in ADAS applications. By simulating diverse driving scenarios and introducing various noise types, the study identifies the most effective methods for improving sensor data integrity and reliability. This approach ensures that the findings are robust and applicable to real-world conditions, contributing to the advancement of noise reduction strategies in automotive systems.

V. Results

A. Study Overview and Hypothesis Testing

To rigorously evaluate the hypothesis that tailored noise reduction techniques enhance the accuracy and reliability of sensor data in Advanced Driver Assistance Systems (ADAS), this study conducted a comprehensive analysis across various driving scenarios. The analysis involved the generation of synthetic datasets for Wheel Speed Sensors (WSS), Inertial Measurement Units (IMU/GYRO), and RADAR sensors, reflecting the data volume and noise complexity typically encountered in real-world conditions. Various noise types and levels were systematically introduced, and multiple noise reduction techniques were applied. Their performance was measured using key metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Signal-to-Noise Ratio (SNR), and Peak Signal-to-Noise Ratio (PSNR). Fig. 13 illustrates the flow of the results section, providing a clear roadmap of the steps and analysis undertaken.

The results section is organized systematically to ensure a thorough evaluation of noise reduction techniques across various driving scenarios. Fig. 13 outlines the flow of this section, detailing each step of the analysis, from data generation to performance evaluation.

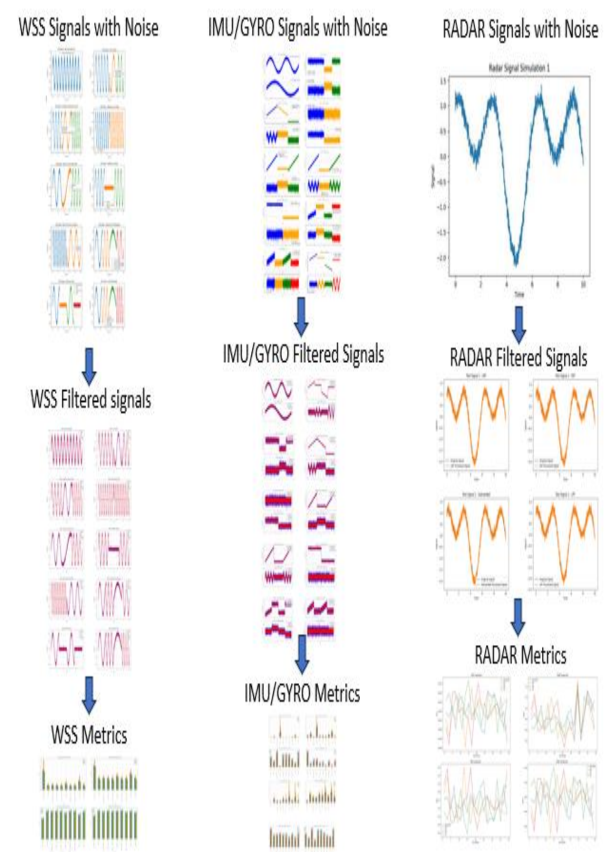


Fig. 13. Results flow chart.

This flow chart helps readers navigate the structure of the results, ensuring clarity and coherence in the presentation of the findings.

B. Synthetic Data Generation and Noise Modeling

Synthetic datasets were generated to mimic sensor data from WSS, IMU/GYRO, and RADAR sensors under diverse driving scenarios, including urban intersections, highway lane changes, and emergency braking situations. These datasets serve as the foundation for evaluating the effectiveness of various noise reduction techniques.

1) WSS signals: Fig. 14 shows the generated datasets for WSS signals with introduced noise across different ADAS scenarios.

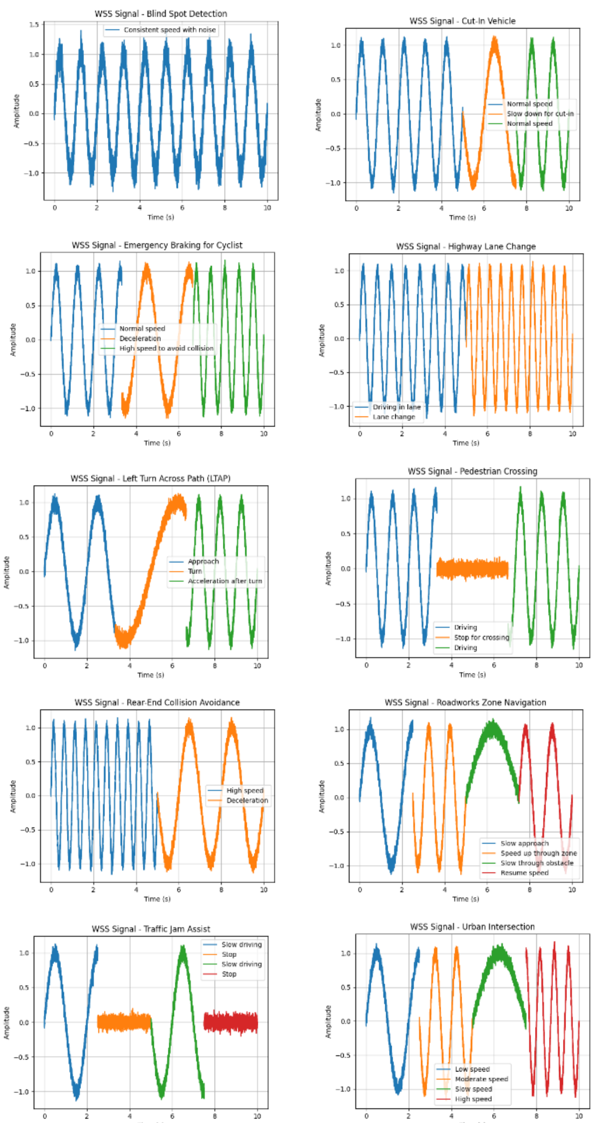


Fig. 14. DATA set generated for WSS signals with noises for each ADAS scenario.

The noise profiles depicted in this figure are crucial for assessing the robustness of the filtering techniques applied later in the analysis. Noise introduction involved adding Gaussian noise to simulate thermal fluctuations and periodic spikes to replicate electromagnetic interference (EMI). Noise levels were varied to evaluate the robustness of each filtering technique under different conditions, ensuring a comprehensive assessment across all simulated scenarios.

2) IMY/GYRO signals: The IMU/GYRO signals, as shown in Fig. 15, were generated with various noise levels to replicate real-world conditions experienced by these sensors.

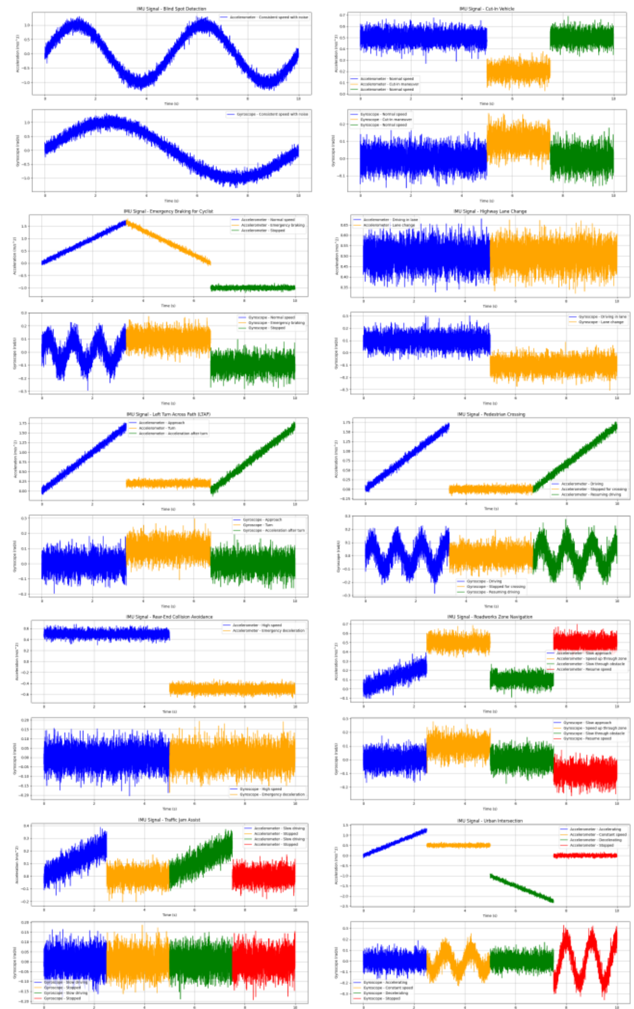


Fig. 15. DATA set generated for IMU/GYRO with noises for each ADAS scenario.

These datasets are essential for testing the effectiveness of noise reduction techniques on motion and orientation data in dynamic driving scenarios.

3) RADAR Signals: Fig. 16 presents the generated RADAR signals, highlighting the complexity of noise patterns in dynamic environments.

Given the importance of RADAR in obstacle detection and localization, this dataset plays a critical role in evaluating noise reduction techniques tailored for such complex signals. RADAR signals are dependent on obstacle localization rather than specific ADAS scenarios. Therefore, this study did not cover them under ADAS scenarios. The generation focused on real-time noise reduction with minimal time consumption to emphasize pattern recognition and the application of the appropriate noise reduction technique based on the ADAS situation encountered. For RADAR signals, the dynamic environment necessitates a different noise reduction approach than simpler sensors like WSS and IMU/GYRO.

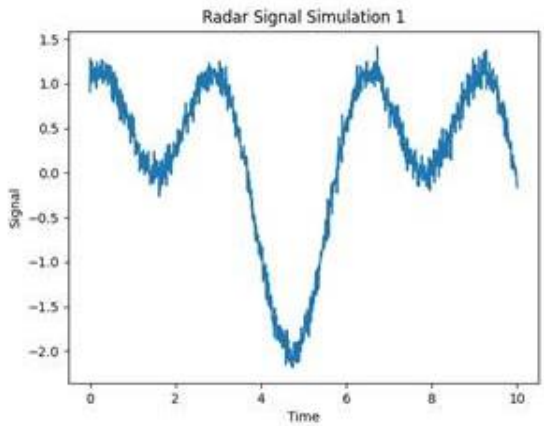


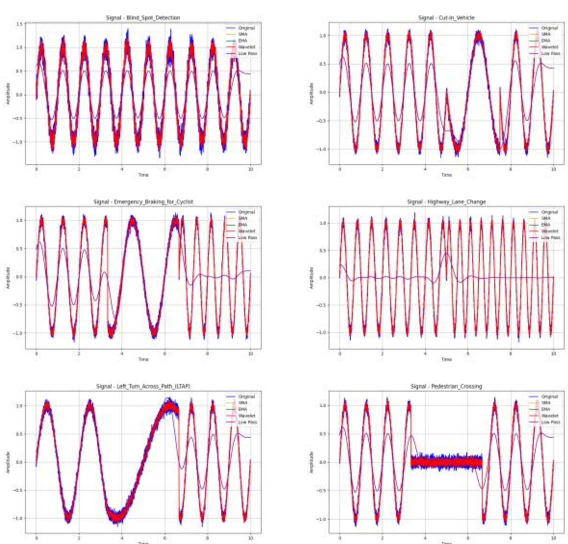
Fig. 16. DATA set for RADAR signals with noises.

C. Filtering Technique Performance on Sensor Data:

The effectiveness of the applied filtering techniques is illustrated in the following figures, showcasing the filtered outputs for each sensor type.

1) WSS Filtered signals: Fig. 17 displays the filtered WSS signals after applying the various noise reduction techniques, highlighting their impact on signal clarity.

This figure provides a visual comparison of how each technique improved the WSS data quality, making it easier to evaluate their relative effectiveness.



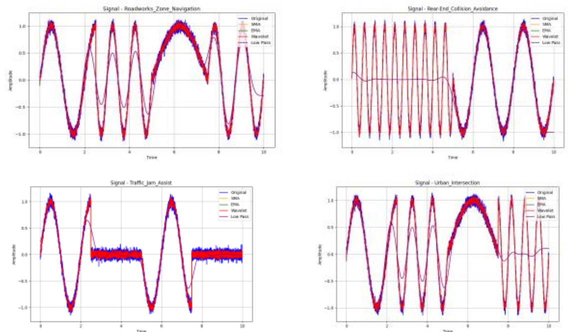


Fig. 17. Filtered signals for WSS.

2) IMU/GYRO filtered signals: The filtered signals for IMU/GYRO sensors are shown in Fig. 18, demonstrating the performance of different noise reduction methods.

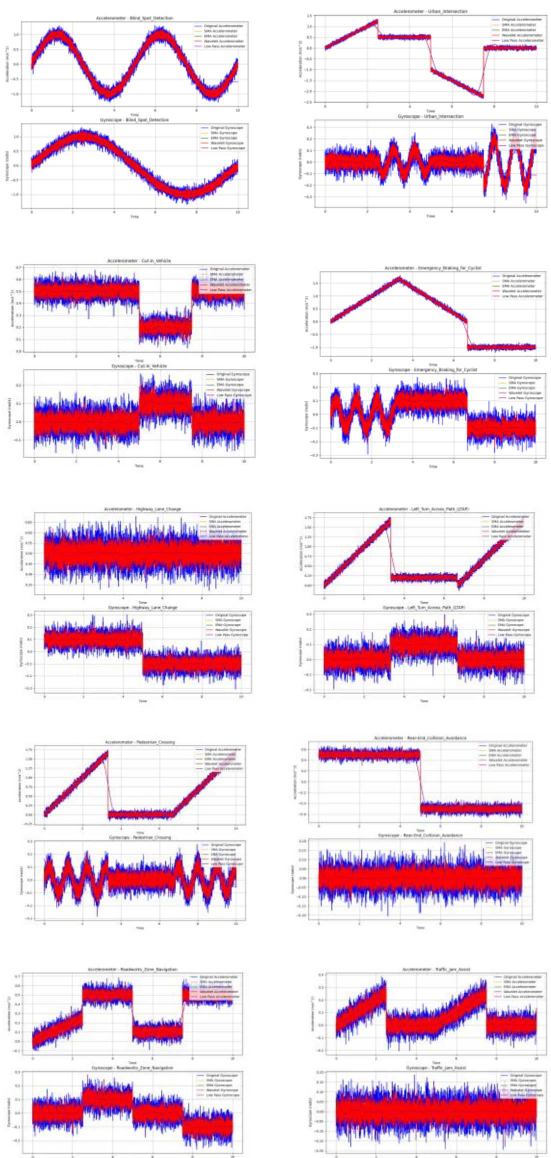


Fig. 18. Filtered signals for IMU/GYRO.

This visual representation underscores the importance of choosing the right technique based on the specific noise characteristics and sensor type.

3) RADAR filtered signals: Fig. 19 illustrates the filtered RADAR signals, reflecting the challenges and successes in noise reduction for these complex sensor types.

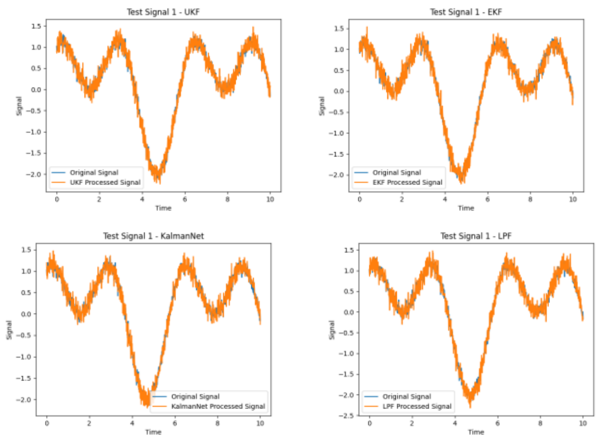


Fig. 19. Filtered signals for RADAR signals.

This figure is crucial for understanding the effectiveness of noise reduction techniques in preserving the integrity of RADAR data, which is vital for accurate obstacle detection.

D. Comparative Performance Analysis Across ADAS Scenarios

The effectiveness of each filtering technique is further analyzed across the ten scenarios, including Urban Intersection, Highway Lane Change, Pedestrian Crossing, and Rear-End Collision Avoidance, among others.

1) WSS metrics evaluation: Fig. 20 presents the metrics evaluation for WSS across various ADAS scenarios, providing insights into the performance of each filtering method.

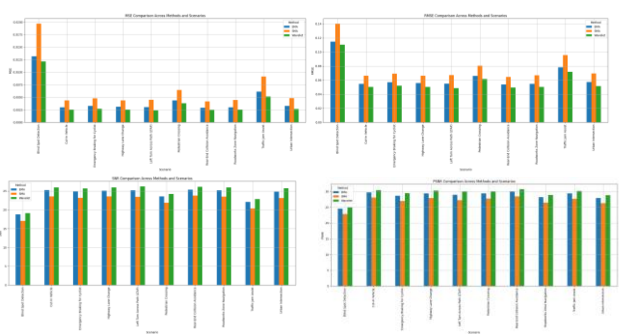


Fig. 20. WSS metrics evaluation across ADAS scenarios.

This analysis highlights how well each technique maintained signal integrity while reducing noise under different driving conditions.

2) IMU/GYRO metrics evaluation: Fig. 21 shows the metrics evaluation for IMU/GYRO signals, offering a detailed comparison of the noise reduction techniques applied.

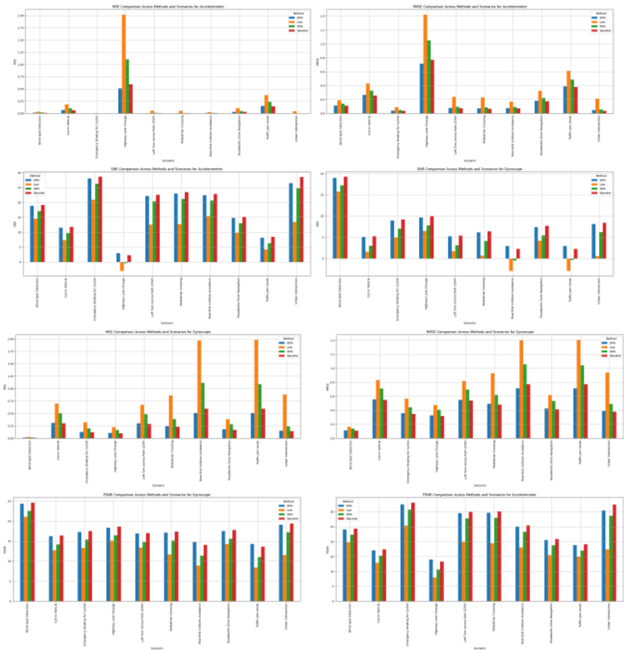


Fig. 21. IMU/GYRO metrics evaluation across ADAS scenarios.

This figure is key to understanding the effectiveness of filtering methods in handling the complexities of motion and orientation data.

3) RADAR metrics evaluation: Fig. 22 displays the metrics evaluation for RADAR signals, focusing on the ability of each technique to manage noise in dynamic environments.

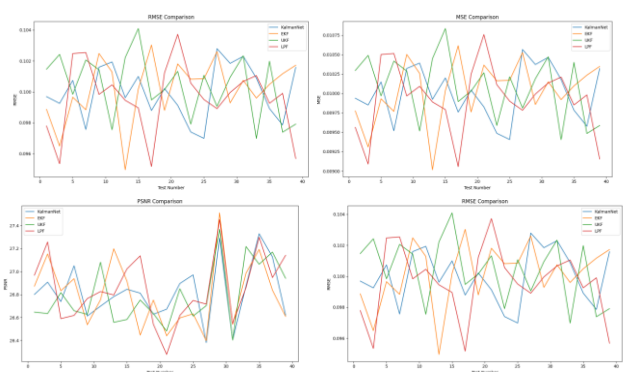


Fig. 22. RADAR metrics evaluation across ADAS scenarios.

The results from this figure are essential for determining the best noise reduction approach for RADAR data, crucial for obstacle detection and avoidance in ADAS.

The performance of each filtering technique was evaluated across the ten scenarios, focusing on how well each method reduced noise and preserved signal integrity, with a detailed analysis provided for each scenario.

The Table III summarizes the performance and results of various filtering methods across multiple ADAS scenarios, such as Urban Intersection and Highway Lane Change. It details the specific performance of each noise reduction technique, highlighting key metrics that demonstrate their effectiveness in reducing noise and preserving signal quality under different driving conditions.

TABLE III. FILTERING METHODS PERFORMANCE AND RESULTS ANALYSIS

Noise Reduction Technique	Scenario	Performance	Key Metrics
Wavelet Denoising	Urban Intersection	Achieved the highest SNR and lowest MSE/RMSE, demonstrating robust noise reduction and signal preservation. Ideal for environments with non-stationary noise, making it suitable for dynamic urban settings.	High SNR, Low MSE/RMSE
	Highway Lane Change	Performed exceptionally well in handling high-frequency noise and rapid lane changes, with significant improvements in PSNR.	High PSNR
Simple Moving Average (SMA) and Exponential Moving Average (EMA)	Pedestrian Crossing	Offered balanced performance with smoother transitions and reduced signal lag. EMA slightly outperformed SMA in SNR, especially in scenarios involving frequent stop-start motions.	Smoother transitions, Reduced signal lag, Higher SNR for EMA
	Emergency Braking for Cyclist	Provided effective noise reduction during rapid deceleration phases, though introduced some lag in more dynamic environments.	Effective noise reduction, Some signal lag
Low Pass Filtering (LPF)	Blind Spot Detection	Effective in high-frequency noise attenuation but required careful tuning to prevent signal distortion. Showed consistent results in steady-state signal processing scenarios, such as Blind Spot Detection.	Effective high-frequency noise attenuation, Requires careful tuning
	Highway Lane Change	Demonstrated substantial high-frequency noise reduction but occasionally introduced residual errors, as indicated by higher MSE/RMSE values.	High-frequency noise reduction, Higher MSE/RMSE
KalmanNet	Emergency Braking for Cyclist	Showed superior noise reduction and signal preservation capabilities, particularly in complex, dynamic scenarios. Achieved high SNR and low MSE/RMSE, effective in real-time applications where accuracy is critical.	High SNR, Low MSE/RMSE
Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF)	Cut-In Vehicle	UKF outperformed EKF in handling the non-linearities associated with sudden vehicle maneuvers, achieving the highest SNR and lowest error metrics in this scenario.	Highest SNR, Lowest error metrics
	Roadworks Zone Navigation	EKF provided robust performance in varying speeds and obstacle-rich environments, with moderate improvements in SNR and RMSE.	Moderate SNR/RMSE improvements

VI. DISCUSSION

A. Practical Implications for Real-Time ADAS Implementation

The findings underscore the importance of selecting appropriate noise reduction techniques based on specific driving scenarios and sensor characteristics. While advanced techniques like Wavelet Denoising and KalmanNet offer superior performance, their computational complexity poses challenges for real-time implementation. Conversely, simpler methods like SMA and EMA provide adequate noise reduction with lower computational demands, making them suitable for real-time processing in less dynamic environments.

B. Trends, Relationships, and Generalizations

The results from the experiments demonstrated clear trends in the performance of various adaptive signal-processing algorithms. KalmanNet and hybrid methods consistently showed the highest improvement in Signal-to-Noise Ratio (SNR) and the most significant reduction in Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). These results underscore the effectiveness of combining traditional and machine learning techniques in handling both random and systematic noise, enhancing the accuracy of sensor data in dynamic automotive environments.

C. Scenario-Specific Performance Insights

The scenario-specific analysis revealed distinct strengths and limitations of each filtering technique:

This Table IV provides an evaluation of the noise reduction methods based on scenario-specific performance, offering a detailed analysis of their suitability in various ADAS environments. The advantages and disadvantages of each technique are listed, helping to identify the most effective approaches for dynamic, high-noise, and less dynamic conditions.

TABLE IV. METHODS EVALUATION BASED ON SCENARIO PERFORMANCE EVALUATION

Noise Reduction Technique	Performance Environment	Key Scenarios	Advantages	Disadvantages
Wavelet Denoising	Dynamic, high-noise environments	Urban Intersections, Highway Lane Changes	Superior noise reduction, ideal for dynamic settings	Potentially higher computational complexity
SMA and EMA	Less dynamic conditions	General ADAS applications requiring real-time processing	Simplicity, computational efficiency	Less effective in highly dynamic environments
KalmanNet and UKF	Non-linear dynamics, high uncertainty	Emergency Braking, Cut-In Vehicle	Best for complex scenarios, accurate signal preservation	Higher computational demands

Table I summarizes the comparative analysis of noise reduction methods across all scenarios, highlighting key metrics such as SNR, MSE, and RMSE.

The following table V offers a comprehensive comparative analysis of the noise reduction techniques discussed, focusing on their application to WSS data in ADAS. It examines their overall performance, including their ability to improve Signal-to-Noise Ratio (SNR) and reduce Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), thereby providing a clear overview of their strengths and limitations.

TABLE V. COMPARATIVE ANALYSIS OF NOISE REDUCTION METHODS FOR WSS DATA IN ADAS

Method	Advantages	Disadvantages	Performance
Simple Moving Average (SMA)	- Easy to implement	- Introduces lag - Less effective for complex noise patterns	- Significant noise reduction - Improves SNR - Higher MSE and RMSE compared to other methods during rapid signal changes
Exponential Moving Average (EMA)	- More responsive to recent changes - Smoother transition and less lag compared to SMA	- More complex to implement than SMA - May still lag in highly dynamic scenarios	- Better noise reduction than SMA - Higher SNR improvement - Lower MSE and RMSE than SMA, suitable for timely signal changes
Wavelet Denoising	- Handles non-stationary signals well - Effective at separating noise from the actual signal	- Computationally intensive - Requires careful selection of wavelet type and decomposition level	- Outperformed SMA and EMA - Highest SNR improvements - Lowest MSE and RMSE, effective for varying noise characteristics
Low Pass Filtering	- Simple and effective for high-frequency noise - Preserves low-frequency components of the signal	- Can distort signal if cutoff frequency is not appropriately set - May not be effective for low-frequency noise	- Significant high-frequency noise reduction - Improved SNR - Potential signal distortion indicated by MSE and RMSE, requires careful tuning
KalmanNet	- Neural network-aided Kalman filtering to enhance noise reduction capability using learned patterns	- Computationally intensive - Requires training data	- Demonstrated significant improvements in noise reduction and data accuracy compared to traditional Kalman filters
Extended Kalman Filter (EKF)	- Suitable for non-linear systems - Incorporates system dynamics into the filtering process	- Requires accurate system models - Computationally demanding	- Significant noise reduction - Improved SNR - Lower MSE and RMSE, effective for non-linear RADAR data
Unscented Kalman Filter (UKF)	- Superior performance for highly non-linear systems - Does not require linearization of the system model	- High computational complexity - Sensitive to initial conditions	- Outperforms EKF in highly non-linear applications - Highest SNR and lowest MSE and RMSE for complex noise patterns

The Table V summarizes the performance of various noise reduction techniques across different driving scenarios, highlighting the strengths and limitations of each method in terms of key metrics like SNR, MSE, and RMSE, and providing clear insights into their suitability for specific ADAS applications. The comprehensive analysis across ten scenarios—Urban Intersection, Pedestrian Crossing, Emergency Braking for Cyclist, Highway Lane Change, Cut-In Vehicle, Rear-End Collision Avoidance, Blind Spot Detection, Traffic Jam Assist, Left Turn Across Path (LTAP), and Roadworks Zone Navigation—provided detailed insights into the suitability of each filtering technique under varied dynamic conditions. This detailed insight is crucial for tailoring noise reduction strategies to the specific operational contexts of ADAS, ensuring optimal performance under varied driving conditions.

D. *Effectiveness of Wavelet Denoising*

Wavelet Denoising was found to be the most effective method for non-stationary signals because it decomposes the signal into its frequency components, allowing for precise separation of noise from the actual signal. This method preserves important signal features while effectively attenuating noise, leading to improved SNR and lower MSE. However, the primary challenge is the computational complexity of the wavelet transform, which can be resource-intensive and may not meet the real-time processing requirements of ADAS. Optimizing the algorithms and leveraging efficient hardware solutions are necessary to address these challenges and implement Wavelet Denoising effectively in real-time applications.

E. Advantages of Kalmannet

KalmanNet integrates neural networks with traditional Kalman filtering, enhancing its capability to learn and adapt to complex, dynamic environments. This results in better noise reduction and data accuracy. In ADAS applications, KalmanNet provides robust performance in scenarios with high non-linearities and varying noise characteristics, making it suitable for handling the complex data from sensors like RADAR.

F. Importance of Hardware-in-the-Loop (HIL) Testing

HIL testing is crucial as it allows for the simulation of real-world driving conditions and noise patterns in a controlled environment. This ensures that the noise reduction techniques are tested under realistic scenarios, validating their effectiveness before deployment in actual vehicles. In our study, HIL testing was used to simulate various ADAS scenarios and noise conditions, providing a comprehensive evaluation of each filtering method's performance.

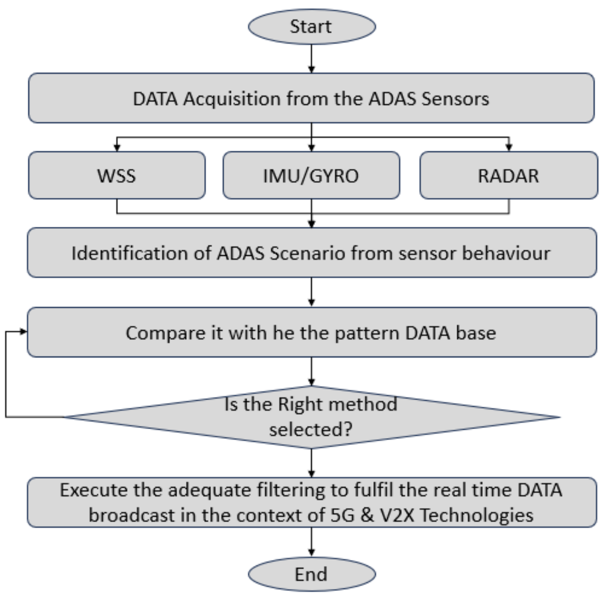


Fig. 23. Testing approach from HIL bench perspective.

Fig. 23 presents the testing approach from the HIL Bench perspective, showcasing how real-world driving conditions and noise patterns are simulated to rigorously evaluate and validate the performance of noise reduction techniques before their deployment in actual vehicles.

G. Practical Viability of SMA and EMA

Simple Moving Average (SMA) and Exponential Moving Average (EMA) provided effective noise reduction in scenarios with smoother signal variations. These methods, due to their computational simplicity, are highly viable for real-time applications where computational resources are limited. Although they introduce lag and are less effective in highly dynamic conditions, they provide reasonable noise reduction in scenarios with smoother signal variations. Combining these methods with other techniques can help mitigate their limitations and enhance overall performance.

H. Exceptions and Outlying Data

During the experiments, certain scenarios presented exceptions and outlying data points that deviated significantly from the expected performance metrics. For instance, in highly dynamic scenarios like emergency braking for cyclists, SMA and EMA struggled to adapt quickly enough, resulting in higher MSE and RMSE values. Additionally, Low Pass Filtering occasionally introduced signal distortions in scenarios with mixed frequency noise patterns, highlighting the need for precise tuning. These outliers emphasize the importance of scenario-specific adjustments and the potential for hybrid approaches to address diverse noise conditions more effectively.

I. Comparison with Previous Studies

The findings of this study align with previous research on noise reduction in ADAS sensor data management. Similar to the work by [1] and [5], our results confirm the effectiveness of advanced filtering techniques like KalmanNet and Wavelet Denoising in enhancing data accuracy and reliability. However, our study extends the existing literature by providing a more detailed comparative analysis across multiple driving scenarios and sensor types, offering practical insights for real-world applications. Furthermore, the integration of HIL testing in our methodology provides a robust validation framework, addressing a gap identified in earlier studies regarding the need for realistic testing environments.

J. Future Research Directions

Future research should focus on developing hybrid noise reduction methods that combine the strengths of traditional and advanced techniques, optimizing them for real-time applications. Expanding the dataset to include more diverse scenarios and sensor types will further validate the robustness and generalizability of these methods. Additionally, integrating machine learning algorithms and adaptive filtering techniques will be crucial in enhancing the adaptive capabilities of noise reduction methods in evolving technological environments.

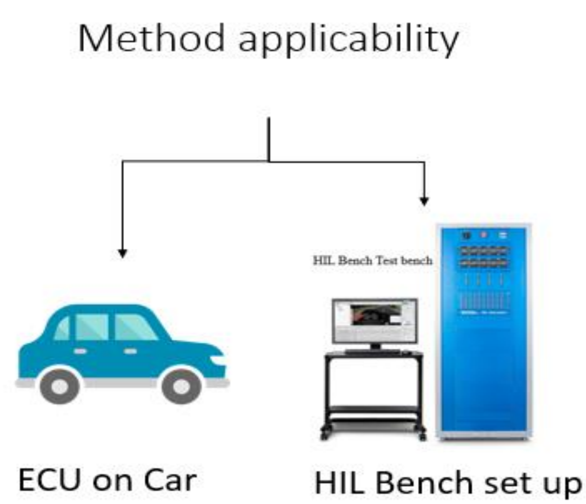


Fig. 24. Method applicability and possibility for extension on car and HIL bench.

Fig. 24 illustrates the potential for extending the proposed noise reduction methods to both automotive applications and Hardware-in-the-Loop (HIL) Bench testing, highlighting the adaptability and scalability of these techniques for broader use cases and real-time environments.

K. Consolidated Findings and Recommendations

Overall, this study provides a detailed comparison of noise reduction techniques across various ADAS scenarios, offering valuable insights for their application in real-world systems. The results highlight the necessity of a tailored approach to noise reduction, considering both the operational context and the computational resources available.

VII. Conclusion

This study demonstrated that adaptive signal processing algorithms significantly enhance the accuracy and reliability of sensor data in embedded automotive systems. The introduction highlighted the need for advanced techniques to manage the increasing complexity and volume of sensor data in modern vehicles. The experimental simulations confirmed that KalmanNet effectively reduces noise and improves data accuracy, showing the highest improvement in SNR and significant reductions in MSE and RMSE. The study also found that methods like Wavelet Denoising excel in dynamic environments with non-stationary noise, making them suitable for complex urban driving scenarios. The implications of these results are significant for the automotive industry, as implementing these adaptive algorithms can enhance the performance and safety of vehicle systems by ensuring robust and reliable sensor data handling.

Future research should focus on further optimizing these algorithms, particularly in the context of real-time processing constraints, and exploring their integration into broader automotive applications, including autonomous driving and complex sensor fusion tasks.

The integration of 5G, V2X, and IoV technologies into automotive systems significantly enhances the capabilities and performance of Advanced Driver Assistance Systems (ADAS). This study rigorously evaluated the effectiveness of various noise reduction techniques on Wheel Speed Sensors (WSS) and Inertial Measurement Units (IMUs) across a range of urban and dynamic driving scenarios. The findings underscore the necessity of selecting noise reduction techniques that are tailored to specific driving conditions and sensor characteristics, ensuring that ADAS systems can operate effectively under the diverse and challenging conditions encountered in real-world driving.

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