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Cooperative Lane Keeping Assist: Design and Evaluation of a V2V Lane Perception Sharing Approach

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***Abstract*—Even autonomous vehicles are becoming very advanced. Adverse weather conditions, unclear lane markings, and unexpected obstacles can still pose challenges, especially to lane keeping assist systems. The performance of these systems varies between vehicles depending on sensor quality, environmental conditions, and data processing algorithms. A focused solution to improve lane keeping capability is vehicle-to-vehicle (V2V) communication. V2V enables vehicles to share real-time information on speed, position, direction, etc. In this paper, V2V is used specifically to share lane marking data from a front vehicle to a following vehicle. These data are fused with local perception using a confidence-weighted averaging method, where each lane position input is assigned a confidence score. When local perception degrades, such as during poor weather, this approach improves lane keeping by relying on the more reliable lane marking positions of the front vehicle. We validate our V2V-enhanced LKA system using MATLAB/Simulink simulations with one front vehicle. Results show up to a 92.75% reduction in mean error compared to standard LKA and smoother steering. Since the system shares only lane marking positions for lane keeping purposes, the communication load remains low. However, attention must still be given to cybersecurity aspects, as even limited data exchange via V2V is vulnerable to threats such as spoofing or tampering, which could compromise the safety of the lane keeping function.**

Keywords*—Lane Keeping Assist; Vehicle-to-Vehicle Communication; Autonomous Vehicles; Sensor Fusion; Confidence-weighted Averaging; Adverse Weather; Cybersecurity

I. Introduction

In the last decade, automated vehicles (AVs) have rapidly transitioned from concept to reality due to advances in perception, control, and communication technologies that promise significant improvements in road safety and traffic efficiency [1]. Early developments such as Carnegie Mellon University's NavLab5 in the 1990s and Google's self-driving car in 2010 demonstrated the feasibility of autonomous driving. Carnegie Mellon University started building the first self-driving cars, called NavLab5, in 1990 by using neural networks in image processing and steering controls. In 1995, the NavLab5 car traveled from Pittsburgh to San Diego (2,797 miles). The researchers controlled the speed and braking, but the car was otherwise autonomous. Enthusiasm about autonomous vehicles really began with the announcement of the Google car, which in 2010 was already able to move without a driver in urban conditions. Since then, all major car manufacturers have initiated autonomous vehicle development programs with their own prototypes. However, these early systems focused mainly on basic automation tasks and lacked advanced lateral control and collaborative features such as V2V communication, which are critical for higher levels of autonomy.

Automated vehicles (AVs) have become the focus of study for academic researchers and industry due to their potential to enhance safety by helping humans through advanced algorithms that can analyze the environment, manage risks, and take control [2]–[7]. According to the SAE J3016 standard, AVs are classified from Level 0 (no automation) to Level 5 (full automation) with most current systems, including commercial lane-keeping assist and adaptive cruise control, fall under Level 2 or 3, where the driver still plays a supervisory role. However, to fully replace the driver, the system must be intelligent enough to handle different driving scenarios, including obstacles and road regulations [8]–[10].

Over the past decade, the Lane Keeping Assist (LKA) system has garnered significant interest from the automotive and computer vision industries. Based on input images, the perception unit detects lanes and vehicle's position, then calculates the position error to adjust the vehicle trajectory by controlling the brake and steering [7].

The perception is critical, where the environment is recognized. To detect lane markings, image processing can be performed using various filters including Gaussian blurring, Sobel edge detection, and median filtering. In [11], a Gaussian blurring filter is used to remove noise and smooth the sharp edges, followed by sliding windows to detect lane edges in the binary image produced by Canny Edge Detection. While these conventional techniques can be effective under normal conditions, they often struggle in adverse scenarios such as rain, or low lighting, limiting their robustness.

Despite using conventional image processing to detect lane markings [12]–[15], modern systems leverage artificial intelligence. particularly deep learning, which revolutionized image processing by enabling systems to learn complex patterns and features directly from sensor data, such as cameras and LIDAR [16]–[29]. Based on large datasets, deep learning algorithm are trained to detect lane markings and other road signs under various conditions. However, deep learning models may suffer from high computational costs and can be sensitive to adversarial conditions such as spoofed lane markings or sensor occlusion, which pose challenges for real-time applications.

While deep learning is powerful in perception and decision-making, it remains vulnerable when visibility is limited due to weather conditions or sensor limitations. Vehicle-to-vehicle (V2V) communication can mitigate these gaps by providing the data about the environment that may not be captured by onboard sensors or by getting the data earlier to have a faster response. Nonetheless, the use of V2V introduces challenges such as communication latency, packet loss, and the need for efficient and reliable data fusion to ensure the consistency and safety of decisions based on shared data.

The research contribution is the development and simulation based evaluation of a Collaborative Lane Keeping Assist (C-LKA) system to improve lane detection and control using V2V received data. The idea is to fuse the data provided by the front vehicle about the detected road lanes and obstacles with onboard data using a confidence-weighted averaging method that accounts for both sensor reliability and communication quality. Based on the fused data, the C-LKA system adjusts its trajectory to mitigate the effects of sensor limitations and reduced visibility. This method builds on existing LKA systems by integrating shared perception from leading vehicles and addressing the limitations of standalone sensing systems. The main contributions of this work are summarized as follows:

- Propose a V2V-enabled Collaborative Lane Keeping Assist (C-LKA) system architecture that enhances lane perception by incorporating shared lane data from a front vehicle.
- Develop a confidence-weighted data fusion algorithm that combines onboard and received lane information based on detection confidence and communication reliability.
- Implement a trajectory replanning and lateral control strategy that leverages fused perception to improve lane-keeping performance under degraded visibility conditions.
- Validate the effectiveness of the proposed C-LKA system through simulations, demonstrating improvements in lane detection accuracy and lateral control over conventional LKA.

This paper is organized as follows. Section 2 presents the vehicle dynamics control implemented for Lane Keeping Assist. Section 3 introduces the onboard lane detection approach based on image processing techniques. Section 4 details the V2V data integration method for collaborative lane perception. Section 5 discusses the experimental results and system evaluation. Finally, Section 6 concludes the paper and outlines future research directions.

II. Research Method

This section outlines the research design, centered on the development of a Cooperative Lane Keeping Assist (C-LKA) system. The proposed C-LKA enhances traditional Lane Keeping Assist by integrating Vehicle-to-Vehicle (V2V) communication for real-time data sharing. Through the exchange of lane marking and environmental information from leading vehicles, the system fuses V2V inputs with onboard sensor data to improve robustness and decision-making accuracy (Fig. 1). This cooperative approach not only mitigates the limitations of individual sensors but also contributes to safer and more reliable autonomous driving in complex scenarios.

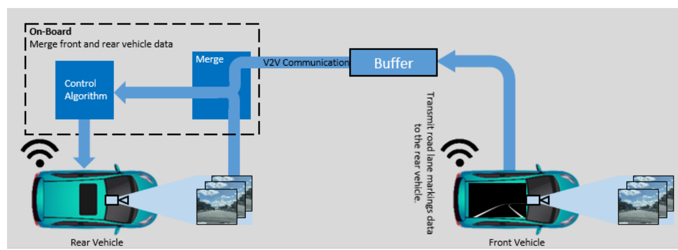


Fig. 1. The overview of our proposed V2V based Lane Keeping Assist, where the front vehicle sent lane marking to rear vehicle to enhance lane tracking control

The research pipeline is designed as a three-stage framework aimed at enhancing lane detection and steering control in autonomous vehicles Fig. 2. The proposed methodology is structured as follows:

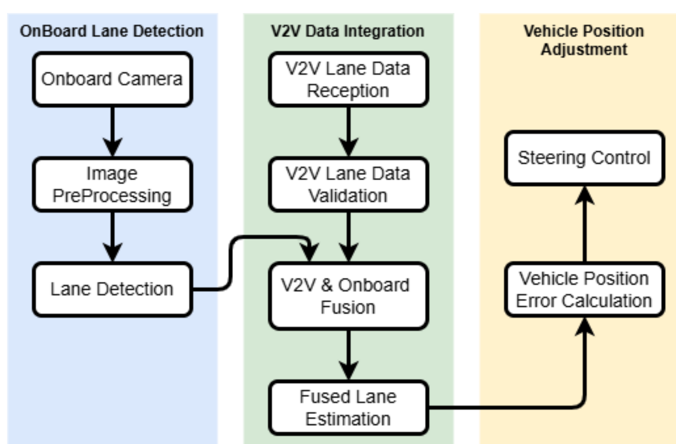


Fig. 2. Cooperative Lane-Keeping Assist (C-LKA) system flowchart

- **Onboard Lane Detection** : The vehicle performs real-time perception by detecting road lanes using input images from a front camera. Computer vision techniques (e.g. edge detection, Hough transform, or deep learning-based segmentation) process the raw image data to extract lane markings.
- **V2V Data Integration** : Locally detected lanes are merged with additional road lane data received via Vehicle-to-Vehicle (V2V) communication. This fusion refines lane estimation, improving environmental perception accuracy and robustness under challenging conditions.
- **Vehicle Position Adjustment** : The enhanced lane data feed into a control algorithm (e.g. PID) to adjust the vehicle's steering angle, ensuring that it remains within the detected road boundaries.

In the following sections, we will detail each of these three stages.

A. Vehicle Dynamics Control

In this research, we employ the dynamic bicycle model for vehicle dynamics representation, which simplifies the system to a two-wheel abstraction while preserving essential lateral and yaw dynamics Fig. 3. The model is defined through the equations of motion (1)–(6), capturing both inertial and force-based behaviors, as well as the global position and orientation of the vehicle. Although often referred to as a ”bicycle model,” this formulation includes dynamic effects such as lateral tire forces, yaw moment, and vehicle mass distribution, making it more accurate than purely kinematic models, especially at moderate to high speeds.

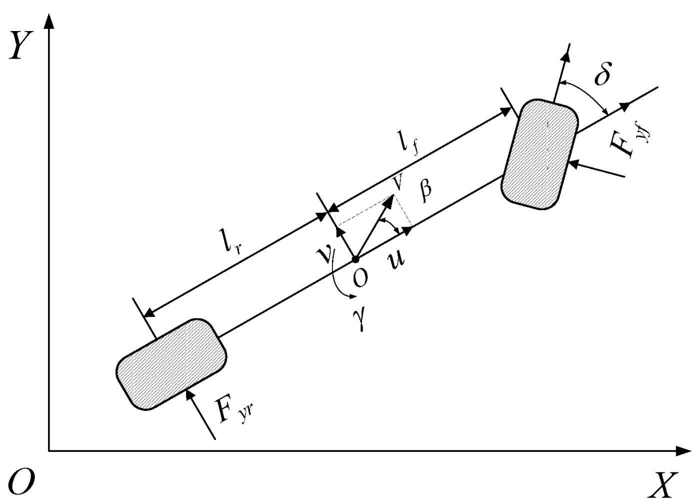


Fig. 3. Dynamic bicycle model [30]

The dynamic bicycle model is governed by the following equations:

$$m(\dot{u} - vr) = F_{xT} \quad (1)$$

$$m(\dot{v} + ur) = F_{yf} + F_{yr} \quad (2)$$

$$I_z\dot{r} = l_f F_{yf} - l_r F_{yr} \quad (3)$$

$$\dot{\theta} = r \quad (4)$$

$$\dot{X} = u\cos\theta - v\sin\theta \quad (5)$$

$$\dot{Y} = v\cos\theta + u\sin\theta \quad (6)$$

A linear tire model is used for lateral tire forces. The vehicle model employs a front steering system, and the lateral forces for the front and rear tires are given by:

$$F_{yf} = C_f\alpha_f = C_f\left(\delta - \frac{v + l_f r}{u}\right) \quad (7)$$

$$F_{yr} = C_r\alpha_r = C_r\left(-\frac{v - l_r r}{u}\right) \quad (8)$$

The model's validity for lane-keeping applications is well-established, with prior studies demonstrating its effectiveness when paired with various control strategies, including PID [31], fuzzy-PID [32], MPC [33], and Pure Pursuit [34], as well as advanced methods such as sliding mode control [35], [36] and robust H-infinity control [37]. Furthermore, the accuracy of the model has been experimentally validated in [38], which confirms its suitability for real-world applications.

In this work, we implement a PID-based steering controller to regulate the lateral position error $e = Y_{\text{ref}} - Y$, where Y_{ref} is the desired lane center. The PID parameters (proportional K_p, integral T_i, and derivative T_d) were systematically determined using the Ziegler-Nichols tuning method to ensure optimal transient response and stability margins. The PID control law is given by equation (9):

$$\delta(t) = K_p e(t) + K_i \int_0^t e(\tau)d\tau + K_d\frac{de(t)}{dt} \quad (9)$$

The PID controller is selected for its simplicity, ease of tuning, and widespread use in automotive control systems. Although more advanced controllers such as MPC and adaptive PID offer enhanced performance under varying conditions, the PID controller provides a strong baseline and facilitates direct comparison with existing literature.

The vehicle model parameters (Table I) are derived from a 2023 Ford F-150 SuperCrew 4x4 to ensures the model replicates real-world vehicle behavior.

B. Onboard Lane Detection

Lane detection is a vital component of lane keeping assist systems. The process begins with capturing the road environment through a front camera. The perception unit then processes these images to extract road markings and estimate the vehicle's lateral position, enabling steering control adjustments to maintain vehicle lateral position. The perception pipeline consists of :

TABLE I. VEHICLE DYNAMICS PARAMETERS

No.	Parameter	Symbol	Value	Unit
1	Front tire cornering stiffness	C_f	112000	N/rad
2	Rear tire cornering stiffness	C_r	112000	N/rad
3	Front axle distance from CG	L_f	1.2	m
4	Rear axle distance from CG	L_r	1.8	m
5	Yaw moment of inertia	I_z	4382	kg·m²
6	Vehicle mass	m	2812	kg
7	Front/Rear slip angles	α_f, α_r	–	rad
8	Lateral tire forces (front/rear)	F_{yf}, F_{yr}	–	N
9	Yaw rate	r	–	rad/s
10	Longitudinal/Lateral velocity	u, v	–	m/s
11	Global X/Y position	X, Y	–	m
12	Vehicle heading angle	ϕ	–	rad
13	Steering angle	δ	–	rad
14	Proportional (P)	K_p	0.015	–
15	Integral (I)	K_i	0.02	–
16	Derivative (D)	K_d	0.012	–

- **Pre-processing**: Image enhancement (e.g., contrast adjustment, noise reduction) to highlight lane features
- **Lane Detection**: Identification of lane markers using edge detection or segmentation algorithms

The locally detected path serves as the baseline for subsequent fusion with V2V data (Section II-C) to improve robustness in challenging scenarios.

1) Preprocessing: Preprocessing aims to prepare raw images received from the camera for lane identification by enhancing relevant features and reducing noise and irrelevant information. The first step is selecting the region of interest (ROI). It's a critical step to eliminate unnecessary information and focus only on the area where the road lanes are located. The ROI can be fixed or dynamic.

a) Fixed ROI: This is a simple technique to select a predefined area of the captured image, which covers the lower part where lanes are most likely to be detected. The fixed ROI is effective in straight road but present limitation for curves

b) Dynamic ROI: This is a powerful method to select the region of interest (ROI), it is adjusted dynamically based on the vanishing point (VP), which is detected using various techniques based on edge detecton such as Canny or Sobel, and others rely on image gradient or texture information. The extracted features are then processed to infer the vanishing point by using methods such as Hough Transform-Based Methods, Edge Orientation Histograms, Gradient Orientation Clustering or Texture Flow Analysis.

Despite its higher computational cost, dynamic ROI is chosen for its critical advantage: adaptive performance in both straight and curved roads. By contrast, fixed ROI's limitations in curves, where lanes often exit the predefined region, outweigh its simplicity.

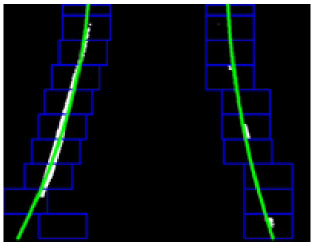
2) Onboard Lane Detection: After ROI selection, the captured images will be converted to grayscale to simplify processing, then smoothed using Gaussian blur to reduce noise for edge detection using techniques such as Canny edge detection or Sobel edge detection. Next, lane detection is done using various techniques, such as sliding windows, RANSAC, or deep learning-based lane detection.

a) Sliding Windows Algorithm: This algorithm determines road lane positions. It takes as input a binary image representing the two lane markings (the original image contains a large amount of information, thus converting it to binary can help reduce complexity and enhance processing speed). The first step is to extract the coordinates of all white pixels in the image, which correspond to the lane lines. Next, these coordinates are separated into two arrays: one for the right lane marking and one for the left. To achieve this, a sliding windows approach is used along the lane lines to identify the relevant pixels within each section [39]–[43]. Once the coordinates are classified, polynomial interpolation is applied to compute the polynomial coefficients that best fit the points for each lane marking. The lane marking is approximated using a second-order polynomial curve Fig. 4a.

Finally, the vehicle's position relative to the center of the lane is determined by calculating the offset between the midpoint of the detected lane and the vehicle's reference point (typically the midpoint of the captured images from the camera).

b) RANSAC Algorithm: RANSAC (Random Sample Consensus) is a robust estimation algorithm widely applied in road lane detection for handling noisy and occluded lane markings. RANSAC samples subsets of lane points randomly, fits them with a mathematical model (e.g., linear or polynomial), and determines the best-fit model as one that maximizes the number of inliers within a given threshold [44]–[46]. This technique effectively removes shadows, faded lane markings, and road artifacts-generated outliers, hence making it extremely relevant in practical driving conditions. The ability of RANSAC to handle straight and curved lane models and being robust to environmental noise makes it an essential pillar in ADAS and autonomous vehicles. However, it depends on parameter optimization and computational power, which may be improved with adaptive or deep learning-based techniques Fig. 4b.

While traditional methods such as sliding windows and RANSAC-based approaches provide foundational solutions, artificial intelligence (AI) techniques have emerged to address their limitations in complex scenarios [19], [47]–[49]. Deep reinforcement learning, particularly DQN and DDPG algorithms [50], has shown promising results in lane-keeping assist systems. Comprehensive evaluations [51] and [52] demonstrate how deep learning methods surpass conventional algorithms in handling environmental challenges. Recent advancements include lightweight CNNs like LLDNet [53] for real-time performance and hybrid architectures such as RS-Lane [54] that combine attention mechanisms with multi-task learning. Optimization techniques like SBBOA-CNN [55] further enhance these models, while hybrid RNNs [56] improve trajectory prediction.



(a)

(b)

Fig. 4. Road lane detection with polynomial fitting using sliding windows (a) and RANSAC algorithm (b)

Table II resumes a comparison between RANSAC, sliding window, and deep learning for lane detection. Deep learning achieves the highest accuracy ($> 95\%$) and robustness but requires substantial computational resources. RANSAC excels in geometric modeling ($> 90\%$ accuracy) but lacks contextual awareness, while the sliding window method balances accuracy ($> 90\%$) and computational efficiency, making it suitable for real-time embedded systems with limited hardware. For onboard lane detection in this paper, we select the sliding window method due to its deterministic performance and lower resource requirements, despite its lower robustness compared to deep learning.

TABLE II. PERFORMANCE COMPARISON OF LANE DETECTION METHODS

Method	Accuracy	Robustness	Computational Efficiency
RANSAC	$> 90\%$	Medium	High
Sliding Window	$> 90\%$	Low to Medium	Medium
Deep Learning	$> 95\%$	High	Low

C. V2V Data Integration

Vehicle-to-Vehicle (V2V) communication is an emerging technology involving real-time wireless data such as speed, location, and environmental conditions using dedicated short-range communication (DSRC) or Cellular-Based systems (C-V2X). V2V is a cornerstone for intelligent transportation systems (ITS) and an essential technology for road safety, traffic flow, and autonomous mobility [57]–[64].

This technology has a wide range of applications in autonomous and connected vehicles, particularly in Advanced Driver Assistance Systems (ADAS) by improving critical safety functions such as collision avoidance [65], [66] and intersection management [67], [68]. Through Vehicle-to-Vehicle (V2V) communication, it improves road safety by issuing early warnings about hazards like sudden braking, collisions, or slippery road conditions while also optimizing traffic flow by reducing congestion via cooperative driving strategies such as Cooperative Adaptive Cruise Control (C-ACC) [69]–[77].

This technology plays a pivotal role in autonomous and connected vehicles, significantly enhancing Advanced Driver Assistance Systems (ADAS) by improving critical safety functions such as collision avoidance, lane-keeping assistance, and intersection management. Leveraging Vehicle-to-Vehicle (V2V) communication, it proactively mitigates risks by providing real-time alerts about potential hazards, including sudden braking, imminent collisions, and adverse road conditions. Furthermore, it optimizes traffic efficiency by reducing congestion through cooperative driving mechanisms like Cooperative Adaptive Cruise Control (CACC), enabling smoother vehicle coordination and improved roadway throughput.

In this research, we address a critical limitation of current Lane Keeping Assist (LKA) systems, which rely solely on onboard sensors (e.g., front cameras) for lane detection. While effective under normal conditions, these sensors can suffer from reduced reliability due to technological constraints or adverse weather. Although Vehicle-to-Vehicle (V2V) communication holds significant potential to enhance driving systems, its adoption in commercial vehicles remains limited.

To bridge this gap, the proposed solution introduces a state machine that dynamically integrates V2V data into the LKA system (Fig. 5). Initially, the vehicle operates in Normal Mode, depending exclusively on onboard sensors. When adverse weather is detected and V2V data becomes available, the system transitions to Prepare Mode, where it rigorously validates the received V2V data through three checks:

- Message freshness (<100 ms, per NHTSA 2005 latency requirements and SAE J2945/1),
- Lane offset tolerance (±0.25 m), and
- Curvature consistency (<0.01 m^{-1}, per AASHTO standards).
- Time gap validation (typically within 0.9–2.5 s, depending on system mode and traffic density per NHTSA)

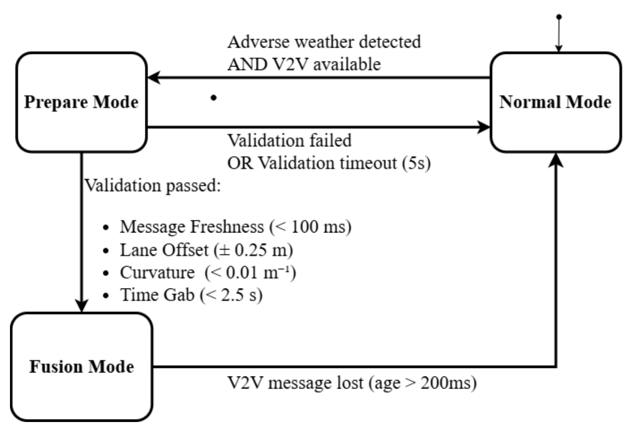


Fig. 5. V2V based lane keeping assist state machine

If validation succeeds within a 5-second timeout (ISO 26262 ASIL B), the system enters Fusion Mode, merging onboard sensor data with V2V inputs via a weighted averaging method (equation (10)) to improve lane-keeping accuracy. If validation fails, the timeout elapses, or V2V data is lost (e.g., data age > 200 ms), the system reverts to Normal Mode, ensuring robust fallback behavior.

The estimated lane position is computed using the following weighted averaging method:

$$x_{\text{fused}} = \frac{C_{\text{onboard}} \cdot x_{\text{onboard}} + C_{\text{V2V}} \cdot x_{\text{V2V}}}{C_{\text{onboard}} + C_{\text{V2V}}} \tag{10}$$

where x_{onboard} and x_{V2V} are the lane position estimates from the onboard camera and V2V data, respectively. The weights C_{onboard} and C_{V2V} represent dynamic confidence scores reflecting the reliability of each input based on data freshness, signal quality, and temporal consistency.

In the baseline implementation, equal weights ($C_{\text{onboard}} = C_{\text{V2V}} = 1$) are used, simplifying equation (10) to equation (11):

$$x_{\text{fused}} = \frac{x_{\text{onboard}} + x_{\text{V2V}}}{2} \tag{11}$$

The control architecture was modeled using MATLAB/Simulink to simulate the integration of V2V data within the Lane Keeping Assist (LKA) system. The simulations were executed on a PC equipped with an Intel Core i7-1165G7 processor, running at 2.80 GHz, with 16 GB of RAM, using MATLAB version R2018b. The Simulink model was configured with a fixed simulation timestep of 10 ms, and solver settings were adjusted to ensure real-time performance and numerical stability.

The perception subsystem responsible for lateral position error detection is illustrated in Fig. 6

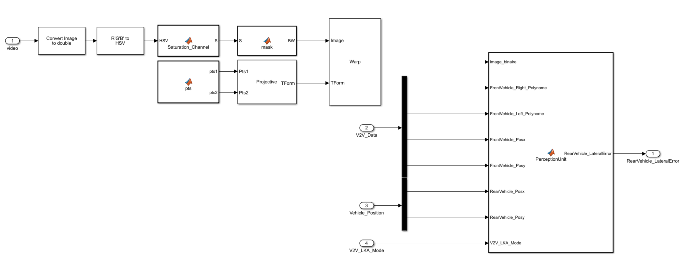


Fig. 6. Perception unit modeling in Matlab/Simulink

III. Results and Discussion

A. Experimental Validation

The developed V2V-based LKA strategy is tested in a MATLAB simulation environment using Simulink's 3D virtual driving scenarios. The vehicle dynamics are modeled using a bicycle model, and steering control is handled by a PID controller, with a constant speed of 30 m/s. The test scenarios simulate highway driving conditions, including both straight and curved road segments, under daytime lighting with adverse weather conditions. The V2V-based LKA system was activated at 1.25 seconds and deactivated at 8 seconds, during which it effectively maintained the vehicle's lateral position. Fig. 7 shows a comparison of vehicle lateral position with the V2V strategy activated and deactivated.

- **Pre-V2V Phase (0-1.25 s)**: (Normal Mode) The vehicle exhibited lateral deviations (±0.15 m) due to reliance on onboard sensors alone, highlighting limitations in perception.
- **V2V-Active Phase (1.25-8 s)**: (Prepare and Fusion Mode) Lane-keeping stability improved significantly, error and deviations reduced, demonstrating the impact of lane marking data from the lead vehicle on path correction.
- **Post-V2V Phase (8-10 s)**: (Normal Mode) Error variability increased upon V2V deactivation, confirming its critical role in enhancing system performance.

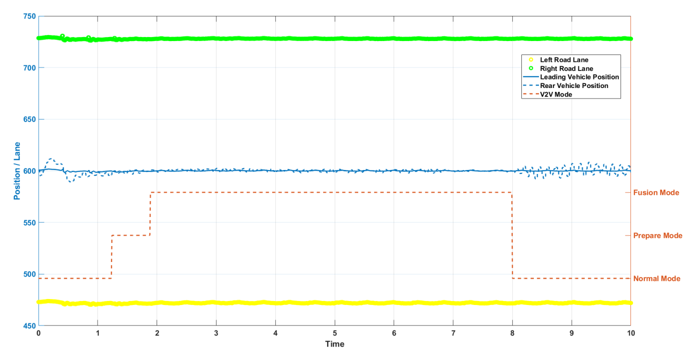


Fig. 7. Vehicle Lateral Keeping Assist Performance

The time-series snapshot (Fig. 8) confirms V2V-based LKA's superior performance, maintaining errors within a tight ±0.01 m compared to Standard LKA's ±0.06 m deviations. The system eliminates hazardous spikes while demonstrating smoother corrections and lower oscillation amplitude. These dynamic improvements align with the histogram's distributional metrics (Section III-B) .

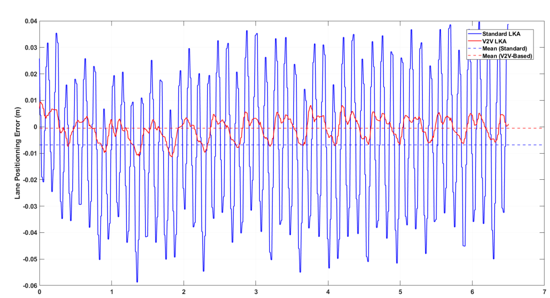


Fig. 8. Time-domain performance: V2V-LKA (blue) maintains consistent ±0.02 m tracking versus standard LKA (red) showing ±0.06 m deviations

Steering angle commands for the standard Lane Keeping Assist (LKA) and the proposed V2V-enhanced LKA are shown in Fig. 9. The standard LKA reveals frequent and high-amplitude steering oscillations, reaching saturation limits of ±1.5 rad. This behavior suggests a more aggressive control strategy that can lead to actuator saturation, reduced system stability, and decreased passenger comfort. The V2V-Based LKA operates within a lower range of approximately ±0.5 rad exhibiting smoother transitions and significantly fewer abrupt changes. This improvement in control effort reflects the improved accuracy of lane estimation enabled by V2V data fusion, particularly under degraded perception conditions, resulting in improved control performance, stability, and driving comfort.

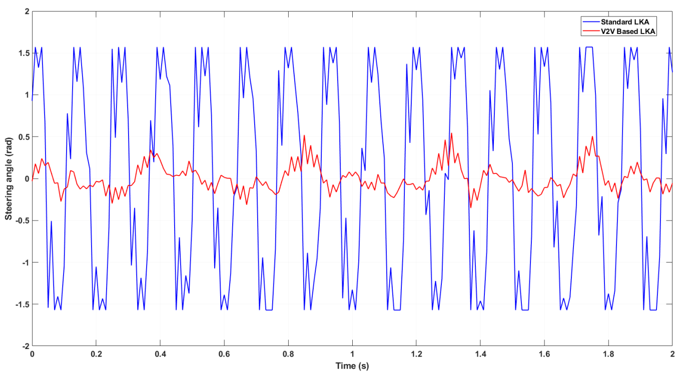


Fig. 9. Steering command comparison between Standard LKA showing ±1.5 rad saturation and V2V-LKA demonstrating smoothed ±0.3 rad control

B. Statistical Analysis

The error distribution histogram of Fusion Mode (Fig. 10b) demonstrates a marked improvement in precision, with all errors contained within ±0.02 m, surpassing the standard LKA's performance (Fig. 10a, 41.8%) by a factor of 2.4.

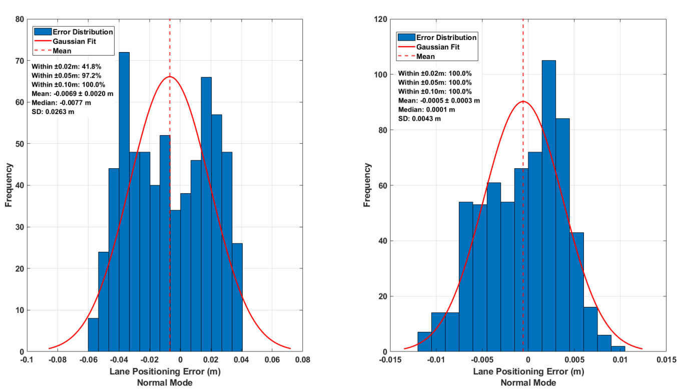


Fig. 10. Comparative error distributions: (a) Standard LKA showing broad dispersion, (b) V2V-enhanced system demonstrating concentrated error distribution within ±0.02 m

Statistical analysis in Table III confirms that these improvements are both statistically and practically significant:

- **Mean error reduction**: An independent samples t-test indicates a statistically significant reduction in mean error for the V2V system compared to the baseline ($t(1300) = -6.03$, $p < 0.001$), with a 95% confidence interval of $[-0.0084, -0.0043]$ m, corresponding to a 0.43–0.84 cm improvement.
- **Effect size**: Cohen's $d = -0.33$ reflects a small to moderate effect size, suggesting a meaningful improvement in accuracy.
- **Distribution shift**: The Kolmogorov-Smirnov test ($p < 0.001$) confirms a significant difference in the distribution of errors. Additionally, changes in skewness and kurtosis in Table IV (Fusion: skewness = -0.30, kurtosis = -0.71; Normale: skewness = 0.00, kurtosis = -1.27) indicate a more symmetric and less heavy-tailed error profile in the Fusion Mode, with fewer extreme deviations.

TABLE III. STATISTICAL COMPARISON BETWEEN NORMAL MODE AND FUSION MODE

Test	Result
Independent samples t-test	$t(1300) = -6.03$, $p = 0.000 < 0.001$
95% Confidence Interval	[-0.0084, -0.0043] m
Effect size (Cohen's d)	-0.33
Kolmogorov-Smirnov test	$p = 0.000 < 0.001$

TABLE IV. ERROR DISTRIBUTION CHARACTERISTICS COMPARISON

System	Skewness	Excess Kurtosis
Normal Mode	0.00	-1.27
Fusion Mode	-0.30	-0.71

C. Comparative Benchmarking

To evaluate our V2V-based Lane-Keeping Assistance (LKA) system, we benchmark it against state-of-the-art lane detection methods optimized for adverse weather conditions. This includes:

- *LaneScanNET* [78], which achieves 75.28% obstacle detection and 91.36% lane detection accuracy through parallel convolutional networks for unmarked roads,
- And a fuzzy inference system (FIS) [79] that dynamically adapts geometric parameters to weather conditions, enabling CLRNet to achieve 94.22% ± 2.49% lane detection accuracy.
- A Cross-Layer Refinement Network (CLRN) with image augmentation [80], which improves lane detection under adverse weather by 12.1% in F1@50 and 6.3% in overall F1 score on CULane and TuSimple.

While these deep learning methods achieve high accuracy, they face three key limitations in real-world deployment:

- **Computational Overhead**: The neural network architecture increases processing time by 15-20ms per frame, requiring GPU support for real-time operation.
- **Initialization Latency**: Systems require 5-8 frames to stabilize parameters when encountering new conditions.

- **Extreme Condition Sensitivity**: Rapid illumination changes (e.g., tunnel entries) can reduce accuracy by 30-40% until system re-stabilizes.

Our V2V approach addresses these limitations by:

- Reducing computational load (12 ms/frame) through co-operative perception
- Eliminating initialization delays through immediate lane data sharing
- Maintaining consistent performance regardless of illumination changes

D. Limitations and Future Directions

This study's simulation-based methodology, while effective for initial validation of the V2V system's improved precision (demonstrated by 100% error containment within ±0.02 m and statistically significant reductions in mean error), necessarily excludes certain real-world complexities. Future research should investigate system performance under more challenging conditions, including intermittent V2V connectivity (e.g., packet loss, latency), varying traffic densities, and dynamic environmental factors, to fully assess operational robustness while maintaining the demonstrated precision advantages.

IV. Conclusion

This paper investigates the integration of front vehicle lane marking data received via Vehicle-to-Vehicle (V2V) communication within Lane Keeping Assist (LKA) systems, demonstrating its potential to improve lateral positioning accuracy, particularly in challenging scenarios such as degraded sensor performance or ambiguous road markings. Experimental results show that V2V-enhanced perception can significantly enhance the robustness of LKA compared to standalone onboard sensor-based approaches. In our simulation, the system achieved 100% containment of lateral error within ±0.02 m and reduced the mean lateral deviation by 92.75% compared to the baseline.

However, the study has limitations that require more research. The current framework assumes reliable V2V communication and does not fully consider edge cases like signal dropout, low vehicle density, or conflicting data from heterogeneous vehicle fleets. Additionally, the computational overhead from data merging, cybersecurity risks, and latency in real-time control remain practical challenges. The system's ability to scale in heavy traffic and adapt to changing road conditions, such as construction zones, also needs more validation.

Despite these limitations, this work adds to collaborative driving research by: First, defining a V2V-augmented perception framework for LKA; second, measuring its benefits in lateral control precision during sensor degradation; and third, analyzing trade-offs between data reliability and system responsiveness. Future research should prioritize advanced multi-vehicle coordination strategies, AI-enhanced data fusion techniques, and rigorous adversarial testing in extreme operating conditions.

By addressing these gaps, this study lays a foundation for more resilient autonomous systems, motivating further research into V2V-enhanced perception as a pathway toward safer and more adaptive vehicle control.

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