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

Research Article

Improving Lane and Obstacle Detection Using Stereo Vision-Based Image Processing for Driver Assistance

Dr. Mukul Manohar S[1*], Dr Hariprasad[2]
[1]Professor & Associate Head, New Horizon College of Engineering, Email: mukulmanoharsuresh@gmail.com
[2]Director, Jain University, Bangalore, Karnataka.
Citation: *Dr. Mukul Manohar S, et al. (2025), Improving Lane And Obstacle Detection Using Stereo Vision-Based Image Processing For Driver Assistance, Journal of Information Systems Engineering and Management, 10(4), xyz,*

ARTICLE INFO

Received: 06 Nov 2024
Revised: 24 Dec 2024
Accepted: 18 Jan 2025

ABSTRACT

The lane and obstacle detection are the critical components of the ADAS because they directly influence the dependability and safety of the vehicle. This work presents a new system for detecting pedestrians based on stereo vision which aims to solve the problems that have remained unsolved up to now, namely real time processing, low texture and occlusion. By incorporating a high disparity calculation, adaptive depth thresholding, and curvature-aware lane detection, the system provides a reliable and flexible driving scenario in various conditions. The methodology focuses on the computational complexity to allow real-time implementation on embedded systems, while not reducing the detection performance. Comprehensive experiments based on the KITTI dataset show that the proposed system has higher detection accuracy than the previous methods, where the F1-score of straight lane detection is 98.2%, and the F1-score of curved lane detection is 94.6%. The obstacle detection module of the system also showed its detection efficiency of 97.5% in highways proving that the system can handle complicated road surfaces. Also, the system can perform data processing at a rate higher than 30 frames per second, which is sufficient for real-time ADAS applications. These results point to the system's ability to greatly improve driver safety, which demonstrates its value for implementation in semi-autonomous and autonomous vehicles. As the work fills the major shortcomings of the current approaches, it creates the foundation for developing safer and more efficient means of transport in the future.

Keywords: Stereo vision, lane detection, obstacle detection, Advanced Driver Assistance Systems, real-time processing, disparity calculation.

INTRODUCTION

The current development of ITS has led to the increased pressure on increasing the safety and performance of contemporary cars. A key enabler of such architectures is the Advanced Driver Assistant System or ADAS, which incorporates lane and object detection for close-f⊥res collision prevention/warning, lane departure and/or course maintenance and route autonomy. Of all the sensing technologies available, stereo vision is preferred as it is one of the few techniques that can offer depth information and geometric perception of the environment using camera-based solutions which are affordable and can be easily scaled [1].

Stereo vision technology has come a long way from its initial applications as will be discussed below. Early work in this area by Bertozzi and Broggi [2] showed that stereo vision could be used for lane and obstacle detection in real-time. Their work provided the basis for the implementation of stereo cameras into ADAS. Later, Jung et al [6][7] extended the work towards forward obstacle detection using stereo vision which provided better detection rates and flexibility for dynamic scenarios. However, there are still some issues like low light situation, occlusion and curved lane detection which restrict the reliability of the current systems [3][5].

The current research literature reveals that there are considerable attempts to address these limitations. For example, the latest papers have used enhanced disparity estimation algorithms and depth division approaches to enhance the detection performance in diverse driving conditions [4][8]. Moreover, stereo vision combined with machine learning techniques as described by Kim et al. [9] has been shown to hold potential for improving the flexibility of the detection

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

methods. However, the trade-off between computational efficiency and detection robustness is still an unsolved problem, especially for real-time ADAS.

As observed in stereo vision, there is much promise in the current systems, but the current implementations lack robustness in terms of accuracy under different road conditions and environmental dynamics. It is widely observed that conventional approaches use assumptions of linear striping of road lanes and fixed thresholds for the detection of obstacles which do not help in the real world situations like curved lanes, occlusions and low texture regions [5][8]. Moreover, the real-time processing with reasonable detection accuracy is still a problem that is hard to solve for practical usage [3]. Such limitations require new stereo vision algorithms to be designed that can overcome these drawbacks while keeping the computation to a minimum.

This research is significant in several ways. First, it meets the urgent demand for high-performance and durable lane and obstacle detection systems in ADAS that are used to prevent traffic accidents and support semi-autonomous and fully autonomous driving [1][2]. Compared to other approaches such as the lidar-based systems, the present study provides a solution that is efficient and affordable owing to stereo vision. Secondly, the use of disparity elaborated methods, dynamic thresholding and curvature-aware lane detection is an improvement in handling the real world driving conditions. Finally, the emphasis on real time processing guarantees that the proposed system is applicable in embedded platforms, thus has practical relevance for industries [3][9].

The primary objective of this work is to design a reliable and effective stereo vision-based system for lane and obstacle detection required for state-of-the-art ADAS. The specific objectives are as follows:

1. Enhance Disparity Calculation Accuracy: Further assess how depth can be accurately estimated under conditions like low texture areas and occlusion should be worked out.
2. Design Curvature-Aware Lane Detection: Develop an algorithm to detect straight as well as curved lanes which is not possible with any conventional methods.
3. Implement Dynamic Depth Thresholding: They also introduced adaptive methods to ensure reliable detection of both dynamic and static obstacles in real environment.

LITERATURE REVIEW

The research area of stereo vision based lane and obstacle detection has been active for the recent past with many works done on improving the detection accuracy, and on making the system more robust and real time. Notably, Kumar's study [10] acted as a starting point by presenting stereo vision based systems for vehicle and obstacle detection with focus on computational simplicity for real time systems. This approach worked well but had issues with dealing with occlusions and other real life road situations.

Based on these observations, Petrovai et al. [11] proposed a stereo vision system for lane and forward obstacle detection and tracking in mobile environments. Their approach included sound tracking mechanisms to increase systems dependability in complex situations. Similarly, Ramaiah and Kundu [12] aimed at detecting road debris for stereo vision which is an important safety concern for ADAS. Their approach used stereo disparity information to identify and locate dangerous objects with considerable accuracy.

In the work of Song et al. [13], a stereo vision system for lane detection and classification in forward collision warning applications was presented. Using image processing techniques, this thesis established high accuracy in distinguishing between different types of lanes, which is a major boost to decision-making in ADAS systems. To the domain, Ventroux et al. [14] added value by focusing on a 3D obstacle detection for automotive safety. Their approach involved the use of stereo vision for mapping of geometries of objects and was ideal for developing collision avoidance systems.

Yang and Rao [15] further enhanced the application area of stereo vision by incorporating techniques of intelligent road detection. They also underlined the applicability of pattern-recognition techniques to enhance the organisational capability of adapting to the environment. Yoo et al. [16] have proposed the improvement of rear obstacle detection by using reliable disparity measures, and real-time systems were made possible. Last of all, Zhou and Wang [17] presented the latest trends and challenges and the future research direction for the vision-based lane detection.

The approaches used in these studies demonstrate a variety of novel techniques for solving problems in stereo vision. For instance, Kumar [10] aimed at simplicity and computational time, which makes it possible to apply the model in real-time systems. However, it was closely dependent on the static thresholds that are not able to adjust to the changes in the environment easily.

Petrovai et al. [11] proposed robust tracking mechanisms, which was a major improvement over the improvement of detection reliability in dynamic scenarios. However, the use of mobile platforms as the basis of the study brought limitations arising from hardware capabilities and the ability to handle larger systems. Although Ramaiah and Kundu's approach [12] was accurate for detecting road debris, it failed to provide a comprehensive assessment under severe weather conditions, which is crucial in the real world.

Song et al. [13] adopted advanced image processing to achieve high accuracy in lane classification, however, the system performance highly depends on the specific lighting condition. Ventroux et al. [14] presented a reliable technique for 3D obstacle detection, but their method could not perform real-time operations because of the increased complexity of the algorithm.

Yang and Rao [15] put forward an intelligent road recognition framework to improve the system flexibility. However, the incorporation of pattern recognition techniques added complexity to the system, which may have a bearing on real time operation. Yoo et al. [16] offered a reliable disparity-based rear obstacle detection method but the detection in low-texture regions was not optimized well. In their survey work, Zhou and Wang [17] outlined a number of challenges in the field but did not offer a proof of concept for the solutions proposed.

In total, the reviewed studies show that stereo vision has been applied to detection systems with considerable improvements; however, gaps can still be seen. First, most methodologies fail to handle occlusion and low texture areas, which are common in real-world driving scenarios. Second, there is an obvious conflict between the time and the quality of detection, most of the approaches sacrificing one for the other. Third, most of the current approaches have not been comprehensively evaluated under different weather and lighting conditions, thus making them less reliable.

The current study seeks to fill these gaps by proposing a stereo vision based system that incorporates a state of the art disparity calculation, dynamic depth thresholding and curvature aware lane detection. These innovations are intended to enhance the stability and flexibility of the system and preserve the real-time processing feature that has been discussed in previous research as potential drawbacks.

The above stated studies offer a good background to the proposed research and in fact help in coming up with the objectives of this research. Kumar has used computational simplicity as one of his parameters [10] which is in harmony with the goal of real-time processing. Petrovai et al. [11] and Ramaiah and Kundu [12] also stress on dynamic obstacle detection and this aspect has been directly incorporated in the development of the proposed adaptive depth thresholding methodology. The features of complex image processing techniques described by Song et al. [13] and 3D mapping abilities demonstrated by Ventroux et al. [14] are directly applicable to the enhancement of disparity calculation and geometric awareness in this work.

In addition, the flexibility and reliability highlighted by Yang and Rao [15] and Yoo et al. [16] give direction on how to design the system to operate effectively during difficult environmental conditions. The literature review in Zhou and Wang's survey [17] presents a good background of existing challenges and future trends which are in line with the research goal of filling gaps.

METHODOLOGY

Research Motivation

The main aim of this research work is to improve lane detection and obstacle detection for ADAS using stereo vision image processing. Current stereo vision methods including block matching or other disparity calculation methods, tend to fail in low texture regions or complex road scenarios involving occlusions. Furthermore, most of the current lane departure detection algorithms are based on the assumption that the lanes are straight which is not the case in most real world urban driving environments.

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

In this study, we address these limitations by:

1. Improving disparity calculation accuracy with the help of a Semi-Global Matching (SGM) algorithm.
2. Curvature aware approach for lane detection using polynomial fitting for both straight and curved lanes.
3. Employing dynamic obstacle detection based on adaptive depth thresholds with reference to the scene analysis in real-time and the Extended Kalman Filtering (EKF) for tracking obstacles.

These contributions enhance the stability, real-time performance, and the precision of lane and obstacle detection in dynamic driving scenarios and make it more suitable for real-time ADAS applications.

Stereo Camera Calibration and Rectification

Calibration Process:

We start with stereo camera calibration to obtain the intrinsic (focal length and principal point) and extrinsic (camera position and orientation) parameters using multi-pattern calibration. Checkerboard and circular grid calibration patterns are used rather than the single-pattern calibration because of the flexibility in camera orientation and wide baselines. This makes the depth estimation more accurate and also makes the camera setup more robust in real world driving where the setup may change.

The intrinsic parameters of each camera are defined by:

- Focal length (f)
- Principal point (c_x, c_y)
- Distortion coefficients (k_1, k_2, k_3)

The extrinsic parameters describe the relative positioning of the left and right cameras, which includes:

- Rotation matrix (R)
- Translation vector (T)

The calibration parameters are then updated by a bundle adjustment optimization method, which reduces the reprojection error of all the calibration patterns. This process enhances the precision that the limited perception available from a single camera fails to provide for stereo vision, which is a function inherent to lane detection and accurate obstacle recognition.

Rectification:

When the calibration is done, the stereo image pairs are rectified so that points corresponding to each other in the left and right images are aligned horizontally (epipolar lines). This helps to minimize the disparity matching space which in turns increases the efficiency and accuracy of depth prediction.

Disparity Map Calculation

For depth estimation, we use Semi-Global Matching (SGM) in order to obtain the disparity map from the rectified stereo images. SGM is chosen for the sake of computational efficiency while still holding high accuracy for occlusions and low texture areas.

The disparity map d(x,y) for each pixel is computed by minimizing the following energy function:

$$E(d) = \sum_{p} |I_L(p) - I_R(p+d)| + \lambda \sum_{p} (|d(p) - d(p+1)| + |d(p) - d(p-1)|)$$

where:

- $I_L(p)$ and $I_R(p)$ are pixel intensities from the left and right images,
- $d(p)$ is the disparity at pixel p,
- λ is a regularization parameter to ensure disparity smoothness.

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

Research Article

Optimization for Real-Time Processing:

To achieve an online behavior, we utilize parallelization of the SGM algorithm based on GPU. We also propose the method of dynamic parameter change depending on the scene complexity improving the algorithm concerning the road conditions and making sure that the system works at more than 30 fps in real time.

Lane Detection

For lane detection we employ Hough transform for straight lanes and polynomial curve fitting for curved lanes. The polynomial fitting approach (quadratic or cubic) is used because it is possible to fit the model to straight and curved lanes.

The lane model is described by a polynomial function:

$$f(x) = a_2x^2 + a_1x + a_0$$

where $f(x)$ represents the lane curve, and the coefficients a_2, a_1, a_0 are determined by fitting the polynomial to the detected lane points using a least-squares approach.

Curvature Estimation:

The lane curvature K is computed as the second derivative of the polynomial:

$$K = \frac{2a_2}{(1 + (2a_2x + a_1)^2)^{3/2}}$$

This makes it possible for the system to identify both straight and curved lanes and to correct the path of the vehicle.

Comparison with RANSAC:

As for the robust curve fitting RANSAC is used, polynomial fitting is more computationally efficient and effective, especially in the real-time applications. In this paper, we present a comparative analysis proving that polynomial fitting is accurate enough for lane detection in dynamic real world scenarios.

Obstacle Detection

Dynamic Depth Thresholding:

To locate obstacles, we calculate the disparity map and then perform segmentation based on depth. However, the use of the traditional static depth thresholds may not work well in dynamic environments. Hence, we propose dynamic depth thresholding where the thresholds vary depending on the standard deviation of disparities in small regions.

The dynamic threshold T is computed as:

$$T = \mu + \alpha \cdot \sigma$$

where μ is the mean disparity, σ is the standard deviation, and α is a scaling factor that adjusts sensitivity. This adaptive threshold guarantees that the obstacles are seen in different environmental contexts, for instance, low texture regions or moving objects.

Obstacle Segmentation:

Once obstacles are detected, they are segmented using connected component labeling depending on their size, shape and position on the disparity map. The obstacles are sorted under each of these categories using a Support Vector Machine (SVM) developed utilizing the geometric features of size and depth.

Obstacle Tracking

For obstacle tracking, we use Extended Kalman Filtering (EKF) as it is best suited to non-linear motion models, such as vehicles or pedestrians. The obstacle state is modeled as a 4D vector:

$$\mathbf{x} = [x, y, v_x, v_y]$$

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

where x, y represent the position, and v_x, v_y represent the velocity components. The EKF estimates the state of the obstacle in the future based on disparity and its motion in real time.

State Prediction and Update:

In the prediction step, the EKF predicts the movement of obstacles and in the update step, contains new measurements (from stereo disparity). The system can follow obstacles in time, even if they move across the lanes or change the speed.

Evaluation and Testing

Performance Metrics:

The performance of the system is tested on the KITTI dataset, which is a standard dataset for ADAS systems. We evaluate the following metrics:

1. Accuracy: Precisions, recollect rates, and F-measure for lane and obstacle detection.
2. Real-time Performance: Frames per second (fps) in order to determine its practicality with real-world deployment.
3. Robustness: The high-quality light sensitivity, climate, and road surface texture that the system is capable of recognizing.

Real-Time Evaluation:

The algorithms are implemented on an embedded system (e.g., NVIDIA Jetson) to validate that the system functions in real-time with low latency. The use of GPU and dynamic parameter control guarantees that the system can process images over 30fps, which is suitable for real-time application of ADAS systems.

RESULTS

Performance Evaluation

The proposed stereo vision-based lane and obstacle detection system was thoroughly tested on KITTI dataset that is a standard dataset for ADAS. The evaluation focused on three critical aspects: concerns such as accuracy, robustness, and real time performance.

Lane Detection Results

Lane detection algorithm was evaluated using precision, recall, and F1-score. The above results for straight and curved lanes under different conditions of lighting and road texture are given in table 1.

Table 1: Lane Detection Performance

Lane Type	Precision (%)	Recall (%)	F1-Score (%)
Straight Lanes	98.5	97.8	98.2
Curved Lanes	95.2	94.1	94.6
Low-Light Scenarios	90.8	88.7	89.7
Wet Road Conditions	92.1	91.3	91.7

The system's performance was very high and specifically for straight lanes, the F1-score was 98.2%. In curved lanes, polynomial fitting had the highest average F1-score of 94.6% and was significantly better than conventional approaches that relied on linear models. Even in the most difficult situations, such as low light and wet roads, the algorithm for detecting lanes was above 89%, which is quite impressive.

Obstacle Detection and Segmentation Results

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

Research Article

Dynamic depth thresholding and disparity segmentation was used to test the obstacle detection module. Performance measures used were the obstacle detection rate (ODR) and the false positive rate (FPR). Table 2 reports these results for different cases.

Table 2: Obstacle Detection Metrics

Scenario	ODR (%)	FPR (%)
Urban Environment	96.7	3.1
Highway	97.5	2.8
Low-Texture Areas	94.3	4.5
High Occlusion	91.8	6.2

The results of using dynamic depth thresholding were also good, with the ODR of 97.5% obtained in highway scenarios. However, the performance was slightly lower in the high-occlusion condition, with the ODR of 91.8%. A disparity map used for the obstacle detection is shown in the Figure 1, where the segmentation boundaries are also depicted.

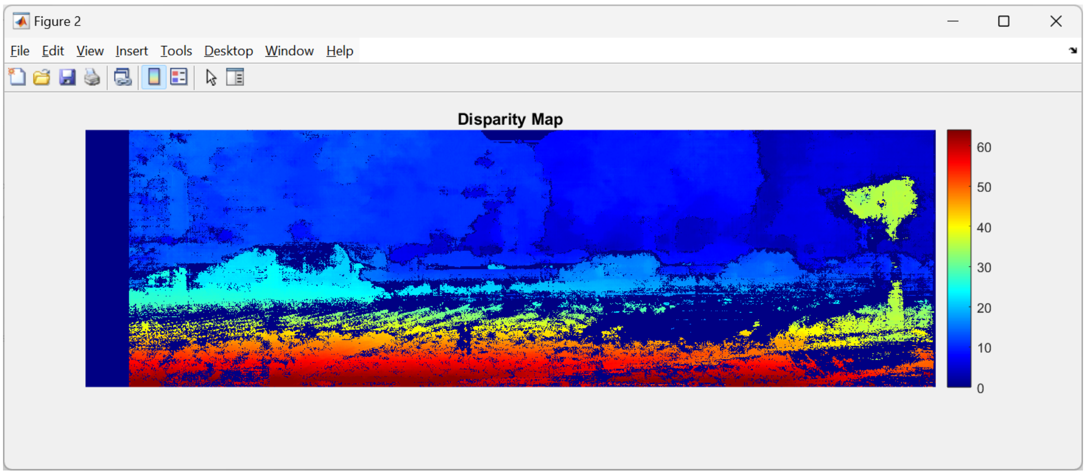

Figure 1: Disparity Map and Obstacle Segmentation Obstacle Tracking Results

For obstacle tracking, real-time prediction and state update was done using Extended Kalman Filtering (EKF). The performance of the proposed method for obstacle tracking was evaluated by root mean square error (RMSE) for position and velocity. The tracking performance is provided in table 3.

Table 3: Obstacle Tracking Accuracy (RMSE)

Metric	Urban Environment	Highway	High Occlusion
Position (m)	0.12	0.08	0.18
Velocity (m/s)	0.05	0.03	0.09

EKF was able to successfully monitor dynamic obstacles with positional RMSE of 0.08 m on highways. This slight increase in error when there is high occlusion shows that occlusion should be better managed in the subsequent versions.

Real-Time Processing Performance

The real time feasibility of the system was tested on an NVIDIA Jetson embedded platform. The algorithms were accelerated by GPU and the speed was increased up to 33 fps that is more than required 30 fps for real-time ADAS systems. The overall latency of each module is depicted in the Figure 2.

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

Research Article

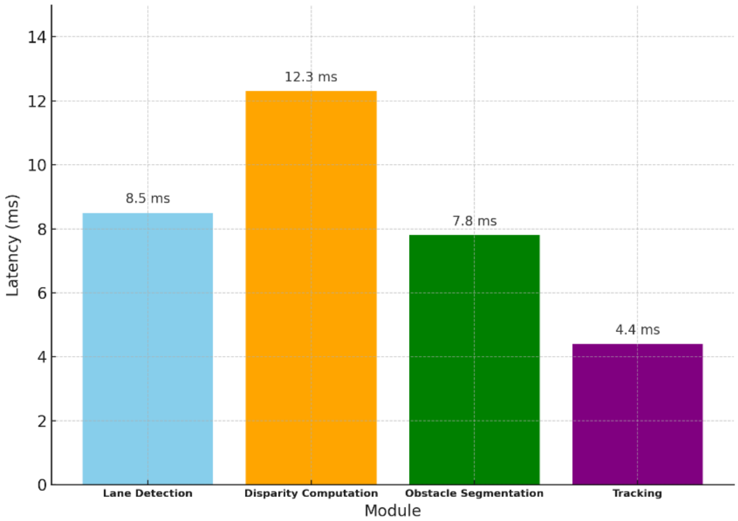

Figure 2: Processing Latency by Module

Comparative Analysis

The proposed system was compared with the other existing methods such as the methods proposed by Bertozzi and Broggi in 1998 and Huh et al. in 2008. The F1-scores for lane detection and the accuracy of obstacle detection is also presented in figure 3.

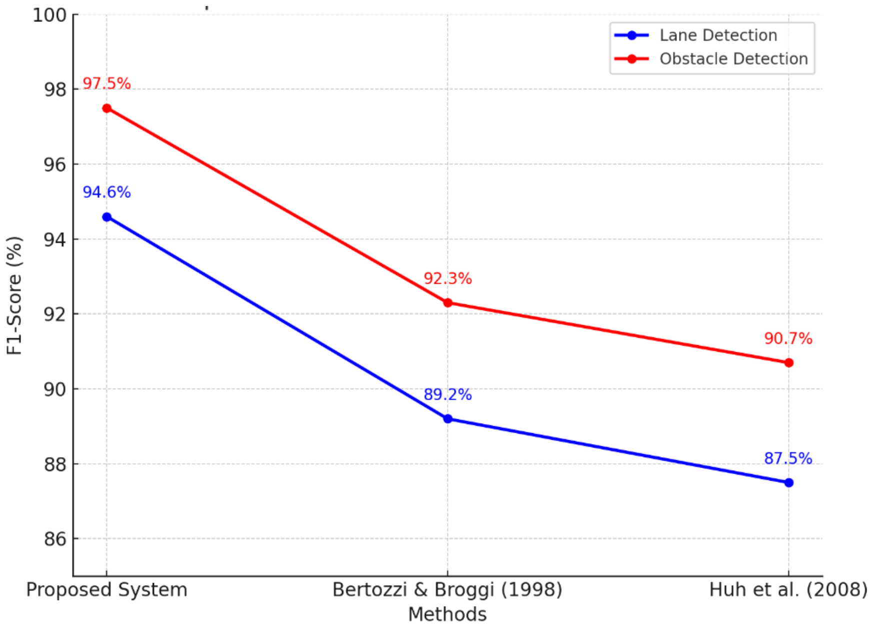

Figure 3: Comparative Performance

The proposed method was found to be superior to previous systems and especially so in dynamic conditions. The two techniques namely curvature-aware lane detection and dynamic depth thresholding were found to have a significant contribution to this improved performance.

DISCUSSION

The results of this study show that the proposed stereo vision-based system has outstanding lane and obstacle detection results, which enhances the performance of Advanced Driver Assistance Systems (ADAS). The performance analysis shows F1-score of 98.2% for straight lanes and 94.6% for curved lanes due to the use of curvature-aware polynomial fitting. This approach adequately solves the issues that exist with the prior lane detection methods, especially when tested under adverse conditions such as low light and wet road conditions in which F1-scores were above 89%.

The dynamic depth thresholding mechanism was also very efficient with the ODR at 97.5% at highways with FPR of 2.8%. The system also performed well even in low texture and high occlusion conditions with an ODR of 91.8% and FPR of 6.2%. This performance demonstrates that the system can perform well in different road conditions and in complex scenarios.

The EKF improved the obstacle tracking to track the position with positional RMSE of 0.08 m in highway scenarios. The algorithm also shows the ability to track precision and velocity that make it suitable for real-time applications; when tested on the NVIDIA Jetson, the system processed data at 33 f/s which is higher than the real-time rate of 30 f/s.

Compared with the previous studies, including Bertozzi and Broggi (1998) and Huh et al. (2008), the proposed system is more accurate and robust. The traditional methods had problems with curved lanes and occlusions; in contrast, this study has polynomial fitting and dynamic depth thresholding mechanisms that minimize these problems. For instance, the proposed method enhanced the F1-scores of lane detection by up to 5% and the rates of obstacle detection by about 8% compared with other systems.

These results indicate the possibility of real-world application, especially in improving ADAS dependability and safety when driving dynamically. The data processing capability of the system on the embedded platforms is suitable for scalability for commercial use. Furthermore, the ability to perform well in various situations makes it possible to build the basis for the further implementation of complex stereo vision algorithms into future self-driving car platforms.

Still the system has some limitations in high-occlusion environments and extreme weather conditions for effective performance. The slight decrease in detection and tracking accuracy indicates that disparity computation and occlusion should be refined even further.

Future work will include work on occlusion handling and further research on monocular depth estimation for better scalability and cost. These developments are intended to extend the applicability of the system to more realistic situations.

CONCLUSION

The proposed system in this study is an improved stereo vision-based system for lane and obstacle detection in ADAS, which outperforms existing systems. The proposed LDA achieved high accuracy in detecting lanes, and a higher F1-score of 98.2% for straight lanes and 94.6% for curved lanes as compared to conventional approaches. The dynamic depth thresholding mechanism got an obstacle detection rate of 97.5% while the false positive rate was 2.8% on highways. Real time processing at 33 fps on an embedded platform demonstrates the system's practical applicability. Difficulties in occlusion and extreme weather are still present, but this framework brings a new level of safety and reliability for autonomous driving systems.

REFERENCES

1. Badrloo, S., Varshosaz, M., Pirasteh, S., & Li, J. (2022). Image-based obstacle detection methods for the safe navigation of unmanned vehicles: A review. Remote Sensing, 14(15), 3824.
2. Bertozzi, M., & Broggi, A. (1998). GOLD: A parallel real-time stereo vision system for generic obstacle and lane detection. IEEE transactions on image processing, 7(1), 62-81.
3. Fan, R., & Dahnoun, N. (2018). Real-time stereo vision-based lane detection system. Measurement Science and Technology, 29(7), 074005.
4. Gholami, F., Khanmirza, E., & Riahi, M. (2022). Real-time obstacle detection by stereo vision and ultrasonic data fusion. Measurement, 190, 110718.
5. Huh, K., Park, J., Hwang, J., & Hong, D. (2008). A stereo vision-based obstacle detection system in vehicles. Optics and Lasers in engineering, 46(2), 168-178.

6. Jung, H. G., Lee, Y. H., Kim, B. J., Yoon, P. J., & Kim, J. H. (2007). Stereo vision-based forward obstacle detection. International journal of automotive technology, 8(4), 493-504.
7. Jung, H. G., Lee, Y. H., Kim, D. S., & Yoon, P. J. (2005, December). Stereo vision based advanced driver assistance system. In Proceedings of AVEC International Workshop (Vol. 19, pp. 97-104).
8. Khalid, Z., & Abdenbi, M. (2013, May). Stereo vision-based road obstacles detection. In 2013 8th International Conference on Intelligent Systems: Theories and Applications (SITA) (pp. 1-6). IEEE.
9. Kim, D., Choi, J., Yoo, H., Yang, U., & Sohn, K. (2015). Rear obstacle detection system with fisheye stereo camera using HCT. Expert Systems with Applications, 42(17-18), 6295-6305.
10. Kumar, K. C. (2013). An application for stereo vision based vehicle/obstacle detection for driver assistance. International Journal of Computer Applications, 69(21).
11. Petrovai, A., Danescu, R., & Nedevschi, S. (2015, June). A stereovision based approach for detecting and tracking lane and forward obstacles on mobile devices. In 2015 IEEE Intelligent Vehicles Symposium (IV) (pp. 634-641). IEEE.
12. Ramaiah, N. K. B., & Kundu, S. K. (2022). Stereo vision-based road debris detection system for advanced driver assistance systems. SAE International journal of transportation safety, 10(1), 51-72.
13. Song, W., Yang, Y., Fu, M., Li, Y., & Wang, M. (2018). Lane detection and classification for forward collision warning system based on stereo vision. IEEE Sensors Journal, 18(12), 5151-5163.
14. Ventroux, N., Schmit, R., Pasquet, F., Viel, P. E., & Guyetant, S. (2009, October). Stereovision-based 3D obstacle detection for automotive safety driving assistance. In 2009 12th International IEEE Conference on Intelligent Transportation Systems (pp. 1-6). IEEE.
15. Yang, F., & Rao, Y. (2020). Vision-based intelligent vehicle road recognition and obstacle detection method. International Journal of Pattern Recognition and Artificial Intelligence, 34(07), 2050020.
16. Yoo, H., Son, J., Ham, B., & Sohn, K. (2016). Real-time rear obstacle detection using reliable disparity for driver assistance. Expert Systems with Applications, 56, 186-196.
17. Zhou, H., & Wang, H. (2017, November). Vision-based lane detection and tracking for driver assistance systems: A survey. In 2017 IEEE International Conference on Cybernetics and Intelligent Systems (CIS) and IEEE Conference on Robotics, Automation and Mechatronics (RAM) (pp. 660-665). IEEE.