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PAPER

Detect Lane Line for Self-Driving Car Using Hue Saturation Lightness and Hue Saturation Value Color Transformation

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ABSTRACT

Self-driving vehicles require the ability to perceive and understand their surroundings, just like human drivers. It entails navigating efficiently on roads, obeying traffic signs and signals, and avoiding collisions with other vehicles and pedestrians. To address the challenges associated with object detection in self-driving cars, an effort was made to demonstrate lane detection using the OpenCV library. To achieve this goal, the well-established probabilistic Hough transform technique is used for line detection. Before applying Hough transforms, several pre-processing techniques are used, including converting the image to grayscale, camera calibration, and implementing a masking filter. In addition, edge detection is performed using the edge detection method. The study also indicates a preference for the use of HSL (Hue, Saturation, and Lightness) and HSV (Hue, Saturation, Value) color spaces. When HSL is applied, white lines appear purer and brighter, resulting in superior performance compared to using HSV specifically to detect white. This algorithm proved particularly effective in detecting straight lanes, which achieved an accuracy ratio of 96.06%. By incorporating these methodologies, the lane detection algorithm implemented with the OpenCV library addresses the challenges of self-driving vehicles, providing them with improved perception capabilities similar to human drivers.

KEYWORDS

autonomous vehicle, lane detection, OpenCV, Hough transform

1 INTRODUCTION

The worst thing that can happen when driving is a road collision. They occur frequently, and most of the time, it is due to human error. Autonomous vehicles are being manufactured today in which a computer is used to drive the car. The general populace exhibits reluctance towards embracing the idea of self-driving automobiles due to its scepticism regarding the ability of machines to ensure safety.

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Self-driving cars are characterized by their analytical behavior, which is akin to that of intelligent computers. This is because computers are faster and more efficient than human minds in their operations and lack the emotional and distracting elements inherent in human decision-making [1]. A self-driving car can sense its surroundings without human help [2]. At no point is it essential to have a human driver drive the automobile; it does not even need a inside the vehicle. A conventional car can go wherever an autonomous vehicle is capable of going, and an autonomous vehicle can execute any duty that a trained human driver would [1]. The main benefits of autonomous driving include lowering traffic congestion and pollution and increasing safety. Introducing autonomous vehicles (AVs) will transform the transportation industry [2], along with improving the mobility for the young, the old, and those with disabilities [3].

Recognizing nearby objects such as pedestrians, signs, cars, lanes, animals, and curves in real-time is a crucial aspect of roadway environment perception. This task is aimed at enhancing the safety and efficacy of autonomous vehicles. The advancement of AI has facilitated the comprehension of the dynamic driving milieu in real time [2]. Autonomous vehicles (AV) can eliminate many current parking issues. Passengers won't need to park near their destination as AVs become more commonplace. Instead, after dropping off the passengers at their destination, the autonomous vehicles (AVs) drive to the nearest or most affordable parking spot to park without any occupants inside [4].

On the other hand, the disadvantages of AVs may be more exposure to network hacks due to the current computer-controlled functions, and the legal formulation of obligations may prevent the use of AVs, as well a lot of jobs will be lost as a result of AVs in the transportation sector. Furthermore, AVs are costly, but once they are more widely used, their price will decrease [5].

The autonomous vehicle is classified into five levels of automation, according to the Society of Automotive Engineers (SAE) International [6]: Level 0 means the car is completely controlled by the driver, who performs all functions of acceleration and braking, even if they are reinforced by warning systems or interference [6]. Level 1 represents the lowest possible degree of automation. The vehicle has a solitary autonomous driving assistance mechanism capable of steering and regulating speed through cruise control. Adaptive cruise control is categorized as Level 1 because it assists solely with maintaining a safe distance behind the preceding vehicle. At the same time, the human driver remains responsible for other driving tasks, like steering and braking [1]. Level 2 represents a reference to advanced driver assistance systems (ADAS). The driver has control over the steering as well as the acceleration and deceleration of the vehicle. This automation falls short of self-driving because a human is seated in the driver's seat and can take over the vehicle at any time. For example, Cadillac (General Motors) and Tesla Autopilot qualify as Level 2 supercruise systems [7]. Then, Level 3 denotes the transition from Level 2 to Level 3 and holds considerable significance in terms of technology but has little to no impact from a human standpoint. Level 3 vehicles can detect their surroundings and make their own choices, such as speeding up to go around a stationary obstacle.

Nevertheless, human overrides remain necessary. The driver must maintain vigilance and be ready to assume control if the system cannot fulfil the task [8]. While Level 4 represents the automated driving system, which is capable of executing all components of the dynamic driving task, subject to the conditions for which it was designed, irrespective of the human driver's ability to respond suitably to a prompt for intervention [9]. Finally, Level 5 means that throughout the entire journey, the driver does not need to take any action. The system's ability to accomplish the driving task is not constrained by traffic or environmental factors. It is not necessary for the driver to always be in charge of the car. All they decide is the final destination. The vehicle's operating readiness needs to be verified before operation. Someone other than the passenger may be inspecting operational preparedness. Whether or not to use the automated driving system is still up to the driver. The ADS is responsible for ensuring safe functioning once activated [10]. Autonomous vehicles are typically outfitted with various sensors due to the intricate and ever-changing nature of the on-road driving environment, particularly concerning navigation and control systems. The fusion techniques employed by driver assistance systems allow for the optimization of sensor capabilities, resulting in heightened precision in environmental perception. The sensors in this category comprise a camera, lidar, radar, GPS, and sonar [11]. Most camera activities, including lane detection, traffic light detection, and pedestrian identification, include object recognition and tracking. Multiple cameras are typically mounted all around the vehicle in current implementations to find, identify, and track things [12]. The sensor is designed to scan the car's surroundings by moving along its surface and rotating in a full circle, enabling it to capture a comprehensive view. The ability to detect thousands of laser pulses every second ensures a clear and accurate perception of the environment. This sensor utilizes RS technology to detect the light ray reflected from the surrounding environment and measure the reflected light's corresponding value. A light ray illuminates the object and is subsequently reflected, providing sensory input to detect the presence of things in the vehicle's vicinity [13]. Radar is a technological system that employs radio waves to determine various objects' distance, angle, and velocity. The operational mechanism of this technology is based on the utilization of electromagnetic radiation across different frequency spectrums [14]. The US Department of Defense established the Global Positioning System (GPS) in 1973; it has been used by civilians since 1980 [15]. The GPS receiver has the ability to acquire geolocation and time information from GPS satellites located in any part of the world, provided that there is an unobstructed line of sight to at least four GPS satellites. In autonomous cars, GPS is a common sensor for localization and navigation since it can give precise position data. A GPS sensor starts sending position data as soon as it is powered on [16–19].

Kanagaraj, et al. [20] proposed a presentation that suggests utilizing Convolutional Neural Networks (CNNs) with Spatial Transformer Networks (STNs) and real-time lane detection to improve the effectiveness of self-driving cars. The approach being considered involves using the Adam Optimizer on the LeNet-5 framework. In this study, the architecture of the LeNet-5 was analyzed and compared with the Feed Forward Neural Network approach. The LeNet-5 architecture showed a 97% accuracy rate, while the Feed Forward Neural Network had a 94% accuracy rate. Tran and Le [21] introduced a novel approach for identifying road lane markings, which can be utilized to facilitate surveillance and self-driving capabilities. The present study utilizes a front-facing camera to acquire images, which are then subjected to processing by a semantic segmentation network to extract pertinent characteristics to identify road lane markings. The network is built using the U-Net architecture, a convolutional neural network originally developed for biomedical image segmentation.

The system utilizes the Hough transform technique to determine the lines in the outcomes of the segmentation network. Rudregowda, et al. [22] presented a method for detecting lanes using image processing techniques. The video is subjected to frame extraction and image processing techniques to identify the lanes in this context. The extracted frame from the video undergoes a Gaussian filter for noise reduction. As a direct result, color masking has been included into the frame processing to identify the road lanes alone. The canny edge detection technique is then used to deduce the edges of these lanes. Next, the Hough transform was utilized on the area of focus in order to elongate the lines. The path is ultimately charted by tracing along the lines, and directional changes are anticipated by utilizing the vanishing point principle. Noman, et al. [23] utilized the IROADS database as the primary data repository. The prescribed technique is productive in diverse daylight conditions, encompassing bright, snowy, wet weather and underground environments. As the implementation results indicate, the proposed methodology exhibits a detection accuracy of 96.78% and processes each frame in an average time of 28 milliseconds.

The presence of multiple dispersed shadow regions can lead to erroneous lane line detections by the algorithm of lane line detection, as shown in previous researches [21, 22, 24]. Therefore, we want to solve this limitation by the lane line detection algorithm to detect accurately in dispersed shadow regions.

However, this study aims to improve the lane line detection of the roadway and reduce the erroneous detection from the scattered shadow areas and in foggy, cloudy and sunny environments.

This study is structured in the following manner: Section 2 describes the materials and methods for improving the lane detection of the roadway and reducing the erroneous from unfavorable environmental circumstances. Section 3 introduces the experimental results of lane line detection. And finally, section 4 discusses the conclusion.

2 MATERIALS AND METHODS

The proposed system comprises three stages: images of the roadway are obtained through a camera affixed to the vehicle, and image preprocessing includes decreasing the processing time by converting the images into a grayscale representation. Furthermore, the presence of disturbances depicted in the image can impede the precise identification of edges, necessitating the utilization of filters to eliminate noise. Several types of filters that can be employed include the bilateral filter, the Gaussian filter, and the trilateral filter. Figure 1 shows the proposed system's block diagram, which can produce two distinct segments of the lane boundary, one on the left and one on the right.

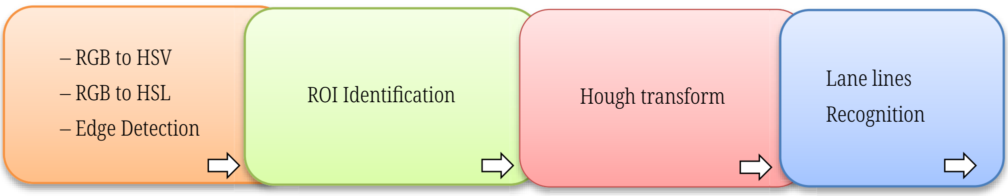

Fig. 1. Block diagram of the proposed system

2.1 Dataset

The proposed method was evaluated by analyzing datasets captured in various environments and under different lighting conditions. Various factors, such as vehicle lights, street features, weather conditions, and time of day, can contribute to alterations in artificial lighting. Conversely, the characteristics of the road impact the functionality of the driving assistance system. Well-defined and linear lane markings typically distinguish normal roads, whereas urban roads exhibit curved configurations accompanied by markings designed to mitigate high noise levels. The system underwent testing under various experimental conditions that simulated realistic limitations. For instance, factors contributing to the complexity of driving include the presence of traffic lights, obstacles, and pedestrians, as well as the diverse array of road types, such as highways, local city roads, and tunnels. Tusimple video frame datasets that are publicly available were used [25].

2.2 Image enhancement

Image enhancement is a fundamental technique within the realm of image preprocessing. Using imagery is a highly effective means of conveying visual information [26]. Digital images are occasionally corrupted by intrusive signals known as noise. In digital image processing, eliminating noise is a highly sought-after research topic. Typically, noise deteriorates images during the training and acquisition processes; noise-affected images are present in many of today's imaging applications [27]. The system that recognizes lanes on the road can detect the markers through image processing techniques like color enhancement, Hough transform, and edge detection. Subsequently, the utilization of path planning and control logic is implemented to facilitate the appropriate adjustment of the steering angle for the vehicle. The success of lane detection is strongly dependent on the extraction of visual features and how those features are interpreted. Errors may also build from one processing step to the next, resulting in less accurate control output at the end of the operation [28, 29].

2.3 Color selection

Figure 1 displays the structure of the minimalistic method for lane detection. This research employs color segmentation to identify objects or portions of the image with a specific color. After the procedure, the algorithm examines only the image sections with the designated hues. This technique is advantageous in obtaining data about lane markings since such markings are mostly painted in yellow or white globally. In Figure 2, implement a color selection technique on RGB images to isolate exclusively white and yellow lane lines while blacking out the remaining portions. However, for optimal color selection, the HSV color space is preferred. The utilization of Hue, Saturation, and Value is deemed more convenient primarily because the Hue value inherently encompasses the chromaticity of every pixel. Color selection techniques on the HSV images obscures all elements except for the white and yellow lane lines. Subsequently, the primary RGB color space of the image was converted to HSL (Hue Saturation Lightness), and segregated into distinct color bands comprising H, L, and S. This technology is employed to identify objects or image components that exhibit a particular Hue. Targeted Color Selection: The goal of identifying lane lines in images is typically to focus on specific colors like white and yellow. HSL can provide more precise control over color selection by allowing for independent adjustment of the Hue, Saturation, and Lightness thresholds. This flexibility can help isolate the desired lane line colors more accurately. Less Sensitive to Lighting Conditions: The HSL color space is generally considered less sensitive to changes in lighting conditions compared to HSV. Since the Lightness component in HSL represents the overall brightness, it can help mitigate the effects of varying lighting conditions on color selection).

2.4 Edge detection

An edge in an image refers to a region with a noticeable contrast or abrupt transition in intensity or color between neighboring pixels. A steep gradient denotes a significant and abrupt change, while a shallow slope indicates a gradual modification. Consequently, it is possible to characterize an image as an assemblage of matrices that comprise rows and columns of intensity values. Representing an image in a two-dimensional coordinate space is feasible, whereby the horizontal axis corresponds to the image's width in terms of columns, and the vertical axis corresponds to the image's height in rows. The canny function executes a derivative on the x and y axes, thereby measuring the change in intensities relative to neighboring pixels. Put another way, compute the gradient, or the difference in brightness, in every direction. Next, the computer draws the contours of the slopes using a string of white pixels. Adjusting the low-threshold and high-threshold parameters makes locating the pixels close to the gradient with the most intensity possible. If the gradient is greater than the higher threshold, the pixel in question is evaluated to see if it is an edge pixel, and if so, it is chosen. Otherwise, it is rejected. It is obtained if the gradient is connected to a robust edge if it falls between the thresholds. Completely black regions correspond to minor changes in intensity between adjacent pixels, whereas the white line represents an image region with a significant change in intensity that exceeds the threshold.

The goal of edge detection is to recognize the boundaries of objects in images. The detection process is employed to identify areas within an image that exhibit a sudden alteration in intensity. Recognizing an image as a matrix or array of pixels is possible. Each pixel in an image represents the amount of light at a specific location. The intensity of a pixel is shown by a numerical value between 0 and 255. 0 indicates no intensity or complete blackness, while 255 indicates maximum intensity or complete whiteness. Gradient refers to the variation in luminance or brightness across a sequence of adjacent pixels. A significant slope denotes a considerable alteration, whereas a minor gradient signifies a gradual modification.

Original image **RGB image**

Fig. 2. *(Continued)*

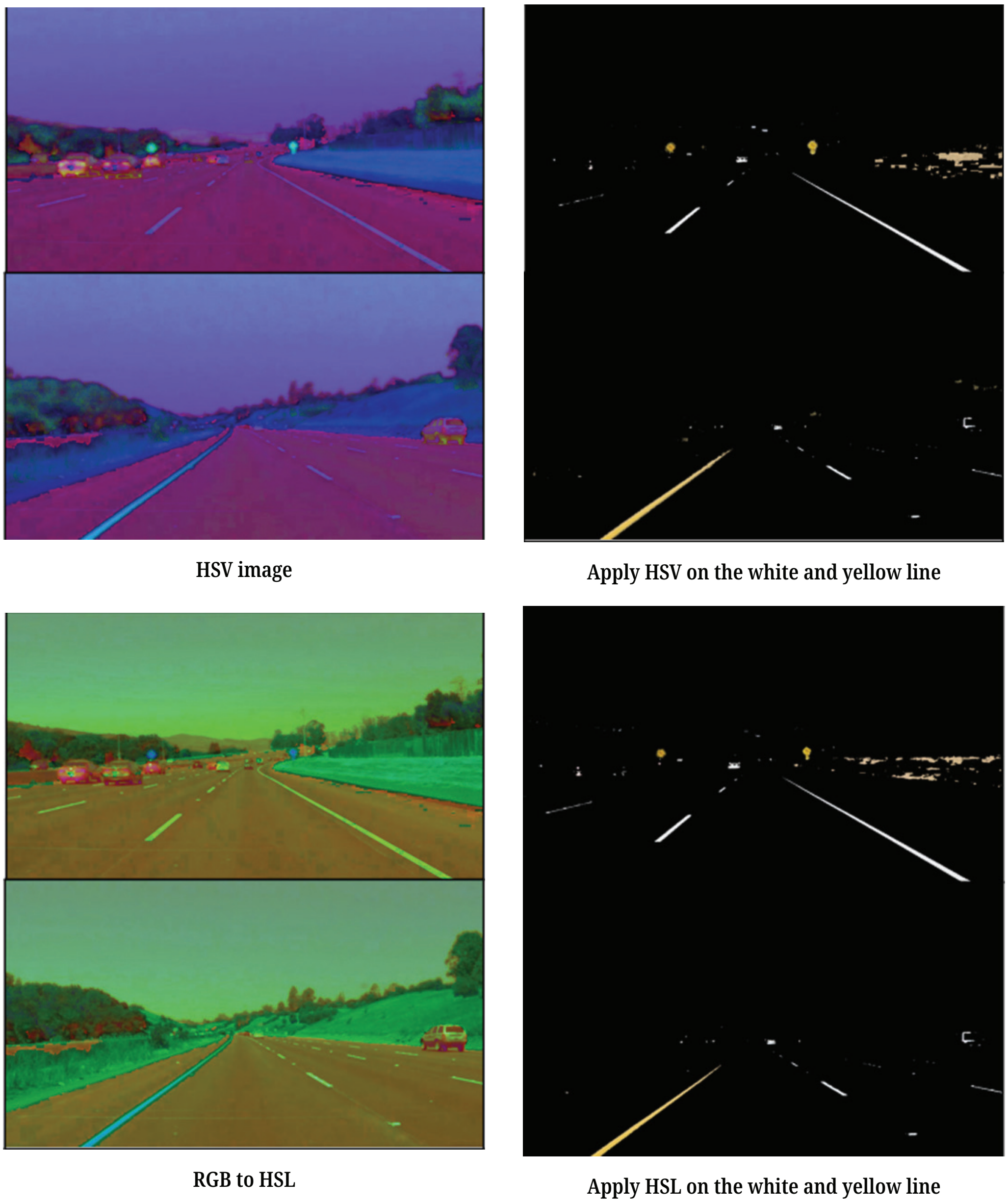

Fig. 2. An example of implementing a color selection technique on RGB images

2.5 Region of interest

It is usual practice to refer to this area of interest as a triangle, and the image proportions are chosen to include the roadway lanes and mark them as the region of interest. Subsequently, a mask is generated, possessing identical dimensions as the image's, effectively constituting an array comprising exclusively of zeroes. The triangle dimensions in the mask are filled with an intensity value of 255 to render the region of interest dimensions as white. Subsequently, a bitwise AND operation will be performed between the Canny image and the mask, yielding the ultimate region of interest. Figure 3 shows an example of a region of interest identification, and its vertices are demonstrated in Table 1.

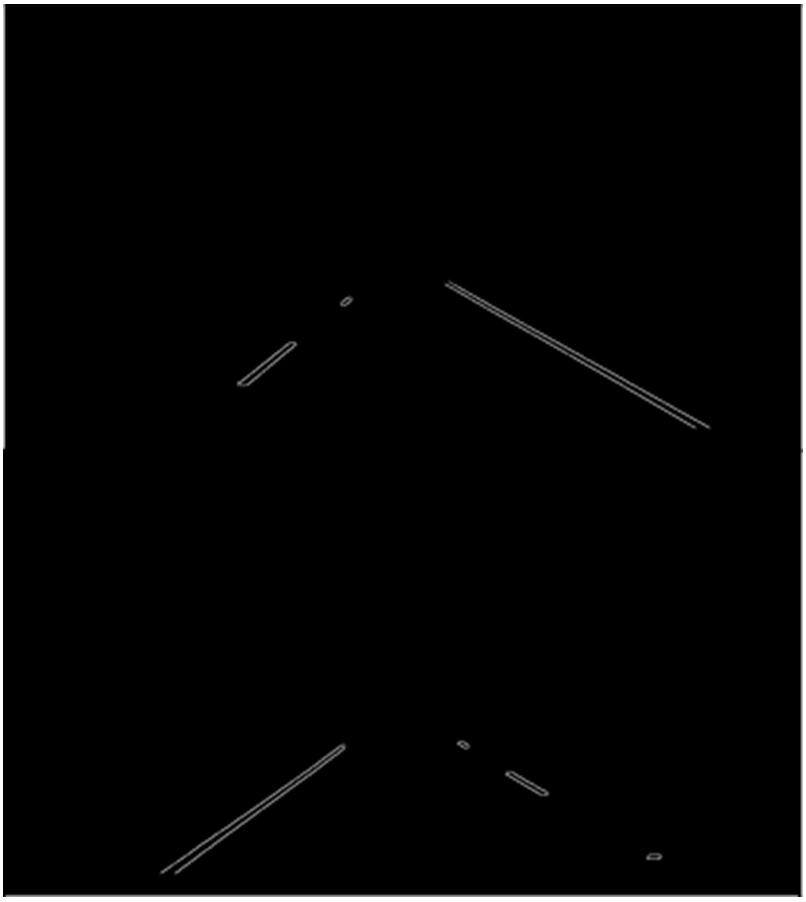

Fig. 3. Region of interest identification

Table 1. Area of interest vertices

Vertex	X	Y
Bottom Left	96	513
Top Left	384	324
Bottom Right	864	513
Top Right	576	324

2.6 Hough transform

Executing Hough transform will extract edges and convert them into lines using the cv2. HoughLinesP() function in OpenCV. It is important to note that the Hough transform requires specific parameters for its definition. For the Hough grid, the distance resolution in pixels was set to 1, and the angular resolution in radians was set to π/180. A minimum of 10 intersections in a Hough grid cell was required, and the maximum gap in pixels between connectable line segments was limited to 30. A blank image is required to apply the Hough transform and generate lines. These lines can be drawn on the image using a for loop and the cv2.line() function, where the initialized parameters are demonstrated in Table 2. Figure 4 shows how the Hough transform is implemented on the image.

Table 2. Hough transform parameters initialization

Parameter	Value
Theta(θ)	1 o = π/180
rho(p)d	1
Threshold	20
minLineLength	20
maxLineGap	300

Fig. 4. Hough transform

Averaging and extrapolating the lane lines. It is recommended to detect multiple lines with all lane lines. It is necessary to compute the mean of the various lines and subsequently generate a singular line for each respective lane line. It is imperative to extrapolate the lane lines to encompass the complete length of the lane line.

3 EXPERIMENTAL PROCEDURE

The lane-lines algorithm has been improved and tested using various images depicting scenarios. The results have been presented in Figure 5. In addition, this demonstrates that the algorithm performs exceptionally well in different conditions, such as cloudy, foggy and sunny environments, as show in Figure 6.

Fig. 5. Create full-length lines from pixel points

Fig. 6. The good performance of algorithm in different conditions: a) sunny environment, b) cloudy environment and c) foggy environment

The algorithm has been validated through real-time video samples of different driving conditions, ensuring its robustness. Lane-lines algorithm proves to be very robust in all previously mentioned conditions. However, the areas of scattered shadows impact the accuracy of lane boundary generation, as shown in Figure 7. Therefore, it is imperative that one should prioritize this matter in the upcoming tasks. The pipeline has proven acceptably fast to implement and use in real time. The setup was implemented using an Intel Core (TM) i7-8550U CPU with 1.80GHz and 16GB of RAM, a moderate computing platform. Table 3 shows measurements that are collected from three video tests.

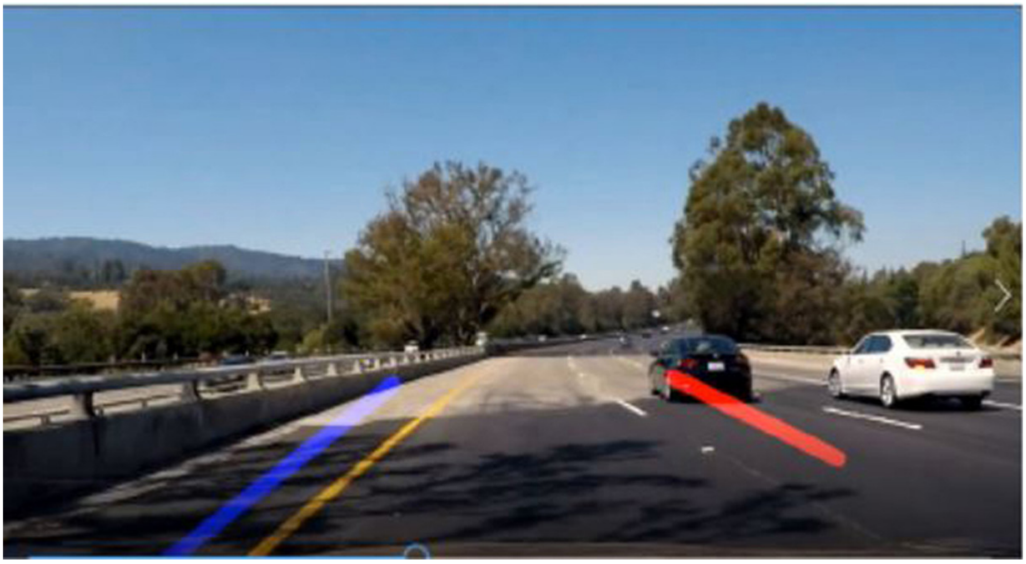

Fig. 7. The identification of lane lines can be rendered inaccurate due to shadow patterns

Table 3. Computation speed for the lane-line algorithm

Sample Name	No. of Frames	Total Time (Sec.)	Frame/Sec
Challenge Video	251	23.0	23.65
SolidWhiteRight Video	222	8.0	49.81
SolidYellowLeft Video	682	48.0	14.38

Based on the last test, the processing speed has stayed below 14.38 frames per second, sufficient for ensuring smooth operation and precise identification of lane lines. A higher frame rate typically results in smoother motion, while a lower frame rate may produce a choppier or less fluid appearance. The successful implementation of the lane-line detection functionality has effectively demonstrated its ability to detect straight lanes. The outcomes of the image processing procedure were presented in conjunction with the works of Farag [30] and Farag and Saleh [31]. The LaneRTD algorithm is subjected to additional testing using images depicting various scenarios. The results presented in this study demonstrate that the algorithm exhibits high performance across various conditions.

In addition, the algorithm was tested on multiple real-time video samples that depicted various driving scenarios to ensure its robustness. The LaneRTD was highly reliable, except for one situation where scattered shadows caused the algorithm to produce incorrect lane line detections. This is illustrated in Figure 7. This point is solved using the HSL property, as shown in Figure 8. Applying appropriate thresholding, filtering, or segmentation techniques in the HSL color space can help isolate lane lines from the background and other objects, making them more prominent. A distinctive feature of the HSL color space is that it separates color information from brightness information, allowing for more accurate analysis and manipulation of specific color components.

Fig. 8. Final lane detected image

The performance of the tested algorithm was shown regarding the accuracy, precision, recall, and processing time as shown in Figure 9. And the results of the training phase of the proposed algorithm regarding the accuracy and loss are demonstrated in Figure 10.

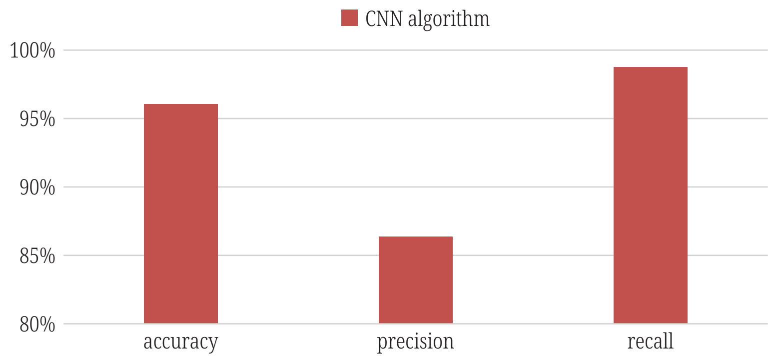

Fig. 9. Demonstrating the performance of the convolutional neural network in our algorithm

For comparison, the performance of our algorithm with the currently available systems regarding accuracy, recall, and processing time is demonstrated in Table 4. We found the high performance of lane line detection based on the CNN algorithm, with an accuracy of 96.06% compared to a slight decrease in accuracy, ranging from 93.5% to 95.4%, observed in [25, 32–34] while the recall in our algorithm was shown at 98.76%, representing higher performance than [33]. The needed processing time based on the CNN algorithm was 285 ms, which means a lower processing time in [34], while Marzougui, et al. [25] and Xiao, et al. [33] showed the most down processing time, 21.54, 113.9 (ms), respectively

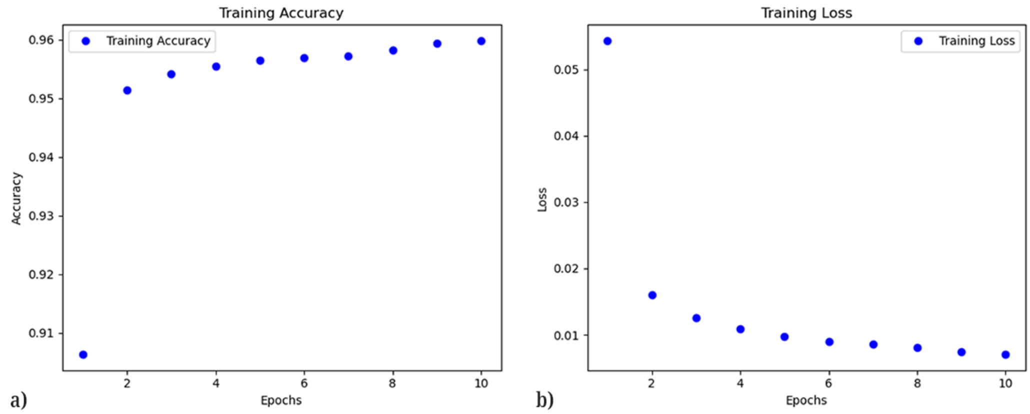

Fig. 10. Evaluation metrics of lane road prediction using lane line algorithm (a) Accuracy (b) Loss

Table 4. Comparison of our algorithm with the currently available systems regarding accuracy (Acc), recall, and processing time

Ref.	Architecture	Acc	Recall	Processing Time (ms)
Yoo and Kim [32]	Graph model	93.89	–	–
Xiao, et al. [33]	SCNN	93.5	94.0	113.9
Chen, et al. [34]	LMD-11 network	95.4	–	2470
Marzougui, et al. [25]	AROI+PPHT+Kalman filter	93.82	–	21.54
Proposed System	CNN	96.06	98.78%	285

Vision approaches have been found to have a shorter execution time compared to deep scanning techniques. However, it is essential to note that vision techniques have lower detection accuracy and are limited in their applicability to specific scenarios [25]. Concerning temporal complexity, our system exhibits a processing time of 285 milliseconds for the tasks of lane detection and the utilization of the chosen lane line algorithm. Regarding temporal intricacy, our system necessitates a processing duration of 285 milliseconds for lane detection and the preferred technique for lane line identification.

The limitation of our study is that our algorithms didn't applicate at night and in dusty weather. Therefore, we recommend future research for applying this algorithm at night to improve the self-driving car at any time of the day and in dusty weather.

4 CONCLUSION

The current methodology used the OpenCV library to detect lane lines in video clips, which achieved an accuracy of 96.06. This has been achieved through the use of HSV and HSL properties. To identify lane lines in photos, the goal is often to focus on specific tones, such as white and yellow. Because HSL allows separate adjustment of Hue, Saturation, and Lightness thresholds, it can provide more precise control over the color selection process. The flexibility inherent in this approach facilitates more accurate isolation of the desired lane line colors. HSL images are processed using Canny edge detection to further improve lane detection. This includes converting images to grayscale and applying Gaussian smoothing to reduce overlapping noise. By doing this, Canny becomes more efficient at detecting the edges of lane lines. The Hough Transform technique is used to identify straight features in an image and determine the boundaries of the selected lanes. This step helps to accurately determine the positions and directions of the lane lines based on the extracted edge information. By combining these methods, the present methodology provides a comprehensive approach for lane line detection in videos, using HSL color representation, sharp edge detection, and Hough Transform analysis.

5 REFERENCES

[1] A. G. Saber *et al.*, "Self-driving car – design and implementation," *The International Undergraduate Research Conference,* vol. 5, no. 5, pp. 660–665, 2021. https://doi.org/10.21608/IUGRC.2021.246735

[2] T. Litman, *Autonomous Vehicle Implementation Predictions.* BC, Canada: Victoria Transport Policy Institute Victoria, 2017.

[3] A. Millard-Ball, "The autonomous vehicle parking problem," *Transport Policy,* vol. 75, pp. 99–108, 2019. https://doi.org/10.1016/j.tranpol.2019.01.003

[4] M. Nourinejad and M. J. Roorda, "Cruising for parking with autonomous and conventional vehicles," *Journal of Advanced Transportation,* vol. 2021, p. 6269995, 2021. https://doi.org/10.1155/2021/6269995

[5] M. N. Ahangar, Q. Z. Ahmed, F. A. Khan, and M. Hafeez, "A survey of autonomous vehicles: Enabling communication technologies and challenges," *Sensors,* vol. 21, no. 3, p. 706, 2021. https://doi.org/10.3390/s21030706

[6] R. T. Kreutzer and M. Sirrenberg, *Understanding Artificial Intelligence*. Springer, 2020. https://doi.org/10.1007/978-3-030-25271-7

[7] E. Stayton and J. Stilgoe, "It's time to rethink levels of automation for self-driving vehicles [Opinion]," *IEEE Technology and Society Magazine,* vol. 39, no. 3, pp. 13–19, 2020. https://doi.org/10.1109/MTS.2020.3012315

[8] D. Watzenig and M. Horn, "Introduction to automated driving," in *Automated Driving: Safer and More Efficient Future Driving*, D. Watzenig and M. Horn, Eds., Cham: Springer International Publishing, 2017, pp. 3–16. https://doi.org/10.1007/978-3-319-31895-0_1

[9] M. Kyriakidis *et al.*, "A human factors perspective on automated driving," *Theoretical Issues in Ergonomics Science,* vol. 20, no. 3, pp. 223–249, 2019. https://doi.org/10.1080/1463922X.2017.1293187

[10] R. Fiedler, C. Bosse, D. Gehlken, K. Brümmerstedt, and H. Burmeister, *Autonomous Vehicles' Impact on Port Infrastructure Requirements.* Hamburg, Germany: Fraunhofer Center for Maritime Logistics and Services CML, 2019.

[11] S. Zang, M. Ding, D. Smith, P. Tyler, T. Rakotoarivelo, and M. A. Kaafar, "The impact of adverse weather conditions on autonomous vehicles: How rain, snow, fog, and hail affect the performance of a self-driving car," *IEEE Vehicular Technology Magazine,* vol. 14, no. 2, pp. 103–111, 2019. https://doi.org/10.1109/MVT.2019.2892497

[12] S. Liu, *Engineering Autonomous Vehicles and Robots: The DragonFly Modular-based Approach.* John Wiley & Sons, 2020. https://doi.org/10.1002/9781119570516

[13] H. A. J. Sadiq Sha and P. P. Patil, "Study on self-driving cars," *Seybold Report,* vol. 15, pp. 789–801, 2020.

[14] S. Campbell *et al.*, "Sensor technology in autonomous vehicles: A review," in *2018 29th Irish Signals and Systems Conference (ISSC)*, IEEE, 2018, pp. 1–4. https://doi.org/10.1109/ISSC.2018.8585340

[15] T. Bräunl, *Embedded Robotics: From Mobile Robots to Autonomous Vehicles with Raspberry Pi and Arduino*. Springer Nature, 2022. https://doi.org/10.1007/978-981-16-0804-9

[16] A. K. Aggarwal, "GPS-based localization of autonomous vehicles," in *Autonomous Driving and Advanced Driver-Assistance Systems (ADAS)*, CRC Press, 2021, pp. 437–448. https://doi.org/10.1201/9781003048381-24

[17] S. N. Alsaad and N. M. Hussien, "Landmark based shortest path detection in alarm system," *Al-Mustansiriyah Journal of Science,* vol. 29, no. 2, pp. 135–140, 2018. https://doi.org/10.23851/mjs.v29i2.276

[18] A. M. Hasan, F. Meziane, R. Aspin, and H. A. Jalab, "MRI brain scan classification using novel 3-D statistical features," in *Proceedings of the Second International Conference on Internet of things, Data and Cloud Computing*, ACM, 2017, pp. 1–5. https://doi.org/10.1145/3018896.3036381

[19] A. M. Hasan, A. F. Qasim, H. A. Jalab, and R. W. Ibrahim, "Breast cancer MRI classification based on fractional entropy image enhancement and deep feature extraction," *Baghdad Science Journal,* vol. 20, no. 1, pp. 221–221, 2022. https://doi.org/10.21123/bsj.2022.6782

[20] N. Kanagaraj, D. Hicks, A. Goyal, S. Tiwari, and G. Singh, "Deep learning using computer vision in self driving cars for lane and traffic sign detection," *International Journal of System Assurance Engineering and Management,* vol. 12, no. 6, pp. 1011–1025, 2021. https://doi.org/10.1007/s13198-021-01127-6

[21] L. A. Tran and M. H. Le, "Robust U-Net-based road lane markings detection for autonomous driving," in *2019 International Conference on System Science and Engineering (ICSSE)*, July 20–21, 2019, pp. 62–66. https://doi.org/10.1109/ICSSE.2019.8823532

[22] S. Rudregowda *et al.*, "Computer vision and the IoT-based intelligent road lane detection system," *Mathematical Problems in Engineering,* vol. 2022, pp. 1–8, 2022. https://doi.org/10.1155/2022/4755113

[23] M. A. Noman, M. Rahaman, Z. Li, S. Ray, and C. Wang, "A computer vision-based lane detection approach for an autonomous vehicle using the image Hough transformation and the edge features," in *Advances in Information Communication Technology and Computing. Lecture Notes in Networks and Systems,* vol. 628. Springer, Singapore, 2023. https://doi.org/10.1007/978-981-19-9888-1_5

[24] H. A. Jalab, R. W. Ibrahim, D. Jalab, A. Jalab, and A. Hasan, "Medical image enhancement based on statistical distributions in fractional calculus," in *Computing Conference*, 2017.

[25] M. Marzougui, A. Alasiry, Y. Kortli, and J. Baili, "A lane tracking method based on progressive probabilistic Hough transform," *IEEE Access,* vol. 8, pp. 84893–84905, 2020. https://doi.org/10.1109/ACCESS.2020.2991930

[26] Z. A. Ramadhan and D. Alzubaydi, "Text detection in natural image by connected component labeling," *Al-Mustansiriyah Journal of Science,* vol. 30, no. 1, pp. 111–118, 2019. https://doi.org/10.23851/mjs.v30i1.531

[27] N. M. Khassaf and S. H. Shaker, "Image retrieval based convolutional neural network," *Al-Mustansiriyah Journal of Science,* vol. 31, no. 4, pp. 43–54, 2020. https://doi.org/10.23851/mjs.v31i4.897

[28] Z. Chen, L. Li, and X. Huang, "Building an autonomous lane keeping simulator using real-world data and end-to-end learning," *IEEE Intelligent Transportation Systems Magazine,* vol. 12, no. 1, pp. 47–59, 2020. https://doi.org/10.1109/MITS.2018.2879224

[29] A. A. A. Al-abayechi, H. A. Jalab, R. W. Ibrahim, and A. M. Hasan, "Image enhancement based on fractional poisson for segmentation of skin lesions using the watershed transform," in *Advances in Visual Informatics: 5th International Visual Informatics Conference,* IVIC 2017, Bangi, Malaysia, November 28–30, 2017, Springer, pp. 249–259. https://doi.org/10.1007/978-3-319-70010-6_23

[30] W. Farag, "Real-time detection of road lane-lines for autonomous driving," *Recent Patents on Computer Science,* vol. 12, 2019. https://doi.org/10.2174/2213275912666190126095547

[31] W. Farag and Z. Saleh, "Road lane-lines detection in real-time for advanced driving assistance systems," in *2018 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT),* Sakhier, Bahrain, 2018, pp. 1–8. https://doi.org/10.1109/3ICT.2018.8855797

[32] J. Yoo and D. Kim, "Graph model-based lane-marking feature extraction for lane detection," *Sensors,* vol. 21, no. 13, p. 4428, 2021. https://doi.org/10.3390/s21134428

[33] D. Xiao, X. Yang, J. Li, and I. Merabtene, "Attention deep neural network for lane marking detection," *Knowledge-Based Systems,* vol. 194, p. 105584, 2020. https://doi.org/10.1016/j.knosys.2020.105584

[34] P.-R. Chen, S.-Y. Lo, H.-M. Hang, S.-W. Chan, and J.-J. Lin, "Efficient road lane marking detection with deep learning," *arXiv pre-print server,* 2018. https://doi.org/10.1109/ICDSP.2018.8631673

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