Lane detection using computer vision

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***Abstract-** Lane detection is essential for autonomous driving and ADAS, ensuring vehicle safety by identifying road boundaries and lane markings. This paper presents a vision-based approach combining image processing and machine learning. The method preprocesses images with Gaussian blur, applies Canny edge detection to identify lane boundaries, and uses the Hough Transform to detect and classify lane lines. To enhance accuracy under varying conditions, color space transformations (HSV/LAB) help distinguish lane markings from the road surface. The system effectively addresses challenges like shadows and glare, with future work focusing on further improving robustness and adaptability.*

***Index Terms** - CNN, SVM, Image processing, Canny edge detection, ADAS, Lane Detection.*

I. INTRODUCTION

Lane detection is a critical task in the development of autonomous driving and advanced driver-assistance systems (ADAS). As the demand for intelligent transportation systems grows, the ability of vehicles to detect and stay within lanes on the road is becoming increasingly essential. Lane detection enables a vehicle to understand its environment and perform crucial functions such as lane-keeping, lane departure warnings, and autonomous lane changes. For both fully autonomous vehicles and ADAS, reliable lane detection contributes significantly to road safety by helping to prevent accidents caused by lane departure or improper lane usage.

The complexity of the lane detection task stems from the wide variety of conditions under which vehicles operate. Real-world driving environments present numerous challenges, including varying road types, lighting conditions, weather phenomena, and road surface quality. For instance, lane markings may be obscured by shadows, other vehicles, or debris. They may also fade due to wear and tear, or be difficult to distinguish under certain weather conditions such as rain or fog. Additionally, urban environments introduce further complications with multiple lanes, intersections, and complex road layouts, all of which require advanced detection capabilities.

Traditional lane detection systems have primarily relied on manual tuning of image processing algorithms such as edge detection, thresholding, and Hough transforms to identify lane boundaries. These methods, while effective in controlled environments, struggle in dynamic, real-world settings where noise, obstructions, and environmental variability degrade performance. Recent advancements in computer vision, coupled with machine learning techniques, offer more robust and adaptable solutions to these challenges.

II. LITERATURE REVIEW

The paper "Vision-Based Lane Detection for Self-Driving Car" by Ziqiang Sun introduces a novel lane detection method using machine vision to enhance accuracy, particularly in detecting yellow and white lane lines under complex conditions. The approach processes yellow lanes in HSV color space and white lanes in grayscale, improving detection efficiency. The method integrates Canny edge detection, inverse perspective transformation, and a sliding window polynomial fitting technique, which overcomes limitations of traditional Hough transforms that work primarily for straight lines. The experimental results demonstrate robustness against lighting variations and curved lanes while also enabling vehicle deviation detection for lane departure warnings. The algorithm proves effective in multiple scenarios, offering a reliable solution for intelligent transportation systems.

The paper "Real-Time Lane Detection for Autonomous Vehicles" by Assidiq et al. presents a vision-based lane detection approach designed for real-time operation with robustness to lighting changes and shadows. The method employs a CCD camera mounted on a vehicle to capture road images, which are then processed using grayscale conversion, noise reduction, and Canny edge detection. The system detects lane boundaries by fitting hyperbola pairs to lane edges using Hough Transform, making it applicable to both painted and unpainted roads under varying weather conditions. The approach is capable of handling slight curvatures and different lighting conditions while maintaining real-time performance. Experimental results demonstrate that the proposed system is fast and reliable, though challenges remain in detecting sharp curves and handling severe weather conditions.

The paper "Lane Detection Image Processing Algorithm Based on FPGA for Intelligent Vehicle" by Zhan and Chen presents an FPGA-based lane detection approach designed for real-time performance in autonomous driving systems. The method integrates digital image processing and deep learning, utilizing an FPGA platform (Xilinx ZYNQ7035) to enhance efficiency and reduce power consumption compared to traditional CPU-GPU implementations. The algorithm incorporates threshold segmentation, inverse perspective transformation, and quadratic curve fitting for lane detection, achieving speeds exceeding 104 FPS. Additionally, a convolutional neural network (CNN) is employed for lane type recognition, improving accuracy under varying road conditions such as shadows.

The paper "New Lane Detection Algorithm for Autonomous Vehicles Using Computer Vision" by Truong and Lee proposes a robust lane detection method utilizing a monocular camera for autonomous vehicle navigation. The approach integrates the Vector-Lane-Concept and Non-Uniform B-Spline (NUBS) interpolation to construct road lane boundaries and estimate lane curvature. The algorithm enhances captured road images using Gaussian and median filtering, applies Canny edge detection, and refines lane markings through a parallel thinning algorithm. Control points for lane boundary estimation are extracted and corrected using the vector-lane concept to reduce noise. The system estimates left and right lane curvatures, ensuring accurate lane tracking. Experimental results validate the algorithm's robustness and efficiency in handling real-world road conditions, making it suitable for autonomous guided vehicle applications.

III. METHODOLOGY

The proposed lane detection system leverages a combination of classical image processing techniques and modern machine learning approaches to accurately detect lane markings under diverse road conditions. This section describes the pipeline of the lane detection process, including image preprocessing, edge detection, line detection, color space transformations, and machine learning-based enhancement.

1. Image Acquisition

The first step in the lane detection process is the acquisition of images from road scenes. These images are typically captured using an onboard camera mounted on the vehicle's front. The camera captures video or still frames of the road, which are subsequently processed in real-time to identify lane boundaries. In our experiments, we use datasets containing images taken from various driving environments, including highways, urban roads, and rural settings, to ensure that our system can handle a wide range of conditions.

Fig 1. Image of the road for processing

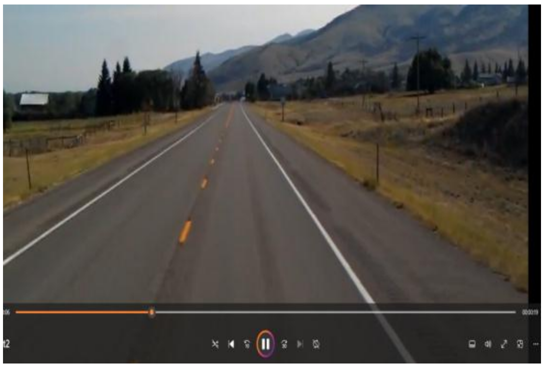

Fig 2. Video Dataset for the processing

2. Image Preprocessing

Raw images from road scenes often contain noise due to factors like lighting variability, weather conditions, or the presence of other vehicles. Preprocessing the images is essential to reduce noise and enhance relevant features, such as lane markings.

- Gaussian Blur : A Gaussian blur filter is applied to smooth the image and reduce high-frequency noise. This helps in mitigating the effect of small-scale variations or noise, ensuring that only significant lane boundaries are emphasized in later steps.
- Region of Interest (ROI) Masking : Since lane lines generally appear in specific regions of the image, a region of interest (ROI) mask is applied to focus processing on the relevant portion of the image (typically the lower half). This reduces computational complexity and minimizes the influence of irrelevant objects such as buildings or sky.

Fig 3. After applying canny edge detection

Fig 4. After applying lane detection on video dataset

3. Edge Detection:

To identify potential lane boundaries, the system employs edge detection, which highlights areas of sharp intensity changes in the image. The Canny edge detection algorithm is chosen for this purpose due to its effectiveness in detecting edges while minimizing false positives.

- Canny Edge Detection: The Canny algorithm is applied to detect edges in the preprocessed image. It uses a multi-stage process that involves computing intensity gradients, applying non-maximum suppression, and then using double thresholding to filter out weak edges. This results in a binary image where strong edges, potentially corresponding to lane markings, are preserved.

4. Line Detection:

Once edges are detected, the next step is to identify lines in the image that correspond to lane markings.
Hough Transform: The Hough Transform is used to detect straight lines by transforming the points on edges into a parameter space where lines can be easily identified. This method is particularly useful for identifying straight lane markings, but it can also be adapted to detect curved lanes by using a probabilistic or modified version of the Hough Transform. Detected lines are then filtered based on their orientation and position relative to the camera's perspective, ensuring that only lines that match the expected geometry of road lanes are retained.

5. Color Space Transformation and Filtering Lane markings often have specific color characteristics (e.g., white or yellow), which can be used to improve detection accuracy. However, lighting conditions and road surfaces may vary significantly, making it challenging to detect lanes based purely on color in the RGB space. Therefore, color space transformation is applied.

Color Space Conversion: The image is converted from the RGB color space to an alternative color space such as HSV (Hue, Saturation, Value) or LAB (Luminance, A and B channels). This conversion allows for easier separation of lane markings from the road surface based on color, especially under varying lighting conditions such as shadows or glare.

Color Thresholding: Thresholds are applied to isolate lane colors (e.g., yellow for dividing lines, white for lane boundaries). This step helps in enhancing the contrast between the lanes and the surrounding road surface, further improving detection reliability.

6. Lane Tracking and Smoothing: Given that the system is designed for real-time applications in autonomous vehicles, lane detection must be consistent across consecutive frames. A lane tracking and smoothing process is applied to ensure continuity in lane detection.

- Exponential Smoothing: To avoid sudden changes in lane positions between frames, an exponential smoothing algorithm is applied to the detected lane positions. This reduces jitter and ensures that lane boundaries are detected smoothly and consistently, even in cases of temporary occlusions or lane markings that are partially fade.

IV. RESULT

The proposed method involves several key steps:

1. Image Preprocessing: Applying filters like Gaussian blur to reduce noise and enhance lane feature visibility.
2. Edge Detection: Performing edge detection using the Canny edge detection algorithm to identify significant lane boundaries.
3. Line Detection: Applying the Hough Transform to detect and categorize lines corresponding to lane markings, distinguishing between straight and curved lanes.
4. Color Space Transformations: Converting images from RGB space to alternative color spaces like HSV or LAB to improve detection accuracy under varying conditions.

The system aims to address challenges such as varying road types, lighting conditions, weather phenomena, and road surface quality.

V. CONCLUSION

Computer vision-based lane detection is a vital component of autonomous driving and ADAS. While traditional methods provide a foundational approach, deep learning models offer higher accuracy and adaptability. Future research should focus on improving real-time efficiency and robustness against environmental challenges.

VI. REFERENCES

[1]. Sun, Ziqiang. "Vision Based Lane Detection for Self-Driving Car." *2020 IEEE International Conference on Advances in Electrical Engineering and Computer Applications (AEECA)*, 2020.

[2]. ssidiq, Abdulhakam AM, Othman O Khalifa, Md Rafiqul Islam, and Sheroz Khan. "Real Time Lane Detection for Autonomous Vehicles." *2008 International Conference on Computer and Communication Engineering*, 2008.

[3]. Zhan, Huiqin, and Lin Chen. "Lane detection image processing algorithm based on FPGA for intelligent vehicle." *2019 IEEE International Conference on Control, Automation and Systems (ICCAS)*, 2019