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SmartDrive: Enhancing Road Safety with AI & ML

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ABSTRACT

This paper introduces a novel lane detection and tracking technique tailored for integration into Advanced Driver Assistance Systems (ADAS) or autonomous vehicles. The primary objective of this technique is to provide a solution that is both efficient and reliable, ensuring its feasibility for implementation on affordable central processing units (CPUs) commonly utilized in ADAS systems. The proposed approach is characterized by a pipeline of computer vision algorithms, each contributing to the process of extracting lane lines from raw RGB images captured by the vehicle's front-mounted camera. The emphasis is placed on the simplicity and rapid computational capability of the technique, enabling real-time lane detection and tracking. The pipeline encompasses a series of well-defined steps, each aimed at enhancing the accuracy and robustness of the lane detection process. Each algorithm within the pipeline is meticulously described, implemented, and evaluated using real-world road images and videos. The performance of the individual algorithms, as well as the overall pipeline, is rigorously assessed to ensure effectiveness under various conditions and scenarios. The evaluation of the proposed technique demonstrates its ability to reliably detect and track road boundaries across diverse environments and lighting conditions. Real-world testing using actual road images and videos highlights the technique's capability to operate effectively in real-time scenarios, crucial for its integration into ADAS systems or autonomous vehicles. Moreover, the comprehensive evaluation of the technique provides insights into its strengths and weaknesses, allowing for a deeper understanding of its performance characteristics.

Keywords - computer vision, lane detection, self-driving cars, autonomous driving, and ADAS

I. Introduction

Enhancing road safety, reducing the occurrence of accidents, and improving the overall driving experience serve as primary incentives for the integration of Advanced Driving Assistance Systems (ADAS) into modern vehicles [1-4]. Over the past few decades, leading automobile manufacturers have introduced a plethora of sophisticated ADAS functionalities, including Lane Departure Warning (LDW), Lane Keep Assist (LKA), Electronic Stability Control (ESC), and Anti-lock Brake System (ABS), among others. Notably, LDW and LKA functionalities underscore the criticality of accurately and promptly detecting and tracking road lane lines or boundaries. As advancements in ADAS technology continue, forthcoming functionalities such as Collision Avoidance, Automated Highway Driving (Autopilot), Automated Parking, and Cooperative Maneuvering necessitate increasingly rapid and reliable detection of road boundaries, posing complex and challenging tasks.

The functionality of road boundary detection involves several key aspects, including road localization, determination of the vehicle's relative position to the road, and analysis of the vehicle's heading direction. Computer vision techniques play a pivotal role in enabling vehicles to sense their surrounding environment for detecting, identifying, and tracking road lane lines. Lane detection primarily entails identifying specific patterns or features, such as lane markings (colored segments) on painted road surfaces, which facilitate the lane detection process. However, certain scenarios can impede lane detection, such as the presence of other vehicles on the same lane obscuring lane markings or scattered shadow regions caused by highway infrastructure.

In this study, a vision-based approach capable of achieving real-time performance in detecting and tracking structured road boundaries, including painted or unpainted lane markings with slight curvature, is proposed. The proposed approach demonstrates robustness in shadowy conditions, addressing common challenges encountered in road boundary detection.

Several vision-based road lane detection algorithms have been proposed in the literature to mitigate fatal driving accidents [5-14]. Early endeavors, such as the GOLD system developed by Brogg [4], utilize edge detection for lane detection, transforming captured images into a bird's eye view of the road to isolate vertical line segments representing lane boundaries. Similarly, the LOIS algorithm proposed by Kreucher et al. [6] employs a deformable template approach to detect lane markings by evaluating the match between parametrized lane shapes and image features. Additionally, systems like AURORA developed by Carnegie Mellon University [7] track lane markings using a color camera mounted on the vehicle and apply image processing techniques to detect lanes. Ran et al. [8] proposed an algorithm capable of handling both painted and unpainted roads by utilizing color cues for image segmentation and shadow removal.

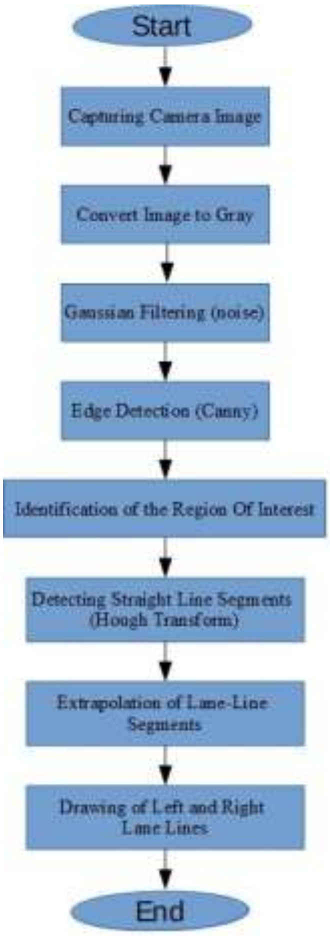
Specifically, the LaneRTD (Lane Real-Time Detection) algorithm is introduced in this study as an innovative approach to lane detection, tailored to meet the demands of autonomous driving and Advanced Driver Assistance Systems (ADAS). The primary focus of LaneRTD lies in achieving real-time performance, maintaining a low computational footprint, and ensuring robustness and reliability suitable for ADAS applications.

I. The LaneRTD algorithm

begins by converting the RGB color image from the camera to grayscale, effectively reducing processing time. Subsequently, Gaussian Blur is applied to the grayscale image to mitigate noise and enhance edge detection accuracy. Edge detection is then performed using the Canny algorithm, producing an "edged image" that simplifies subsequent processing. A Region of Interest (ROI) is extracted from the edged image to focus on the relevant areas for lane detection.

The edged image with the ROI is then passed to the line detector function, responsible for identifying the left and right lane boundary segments. By finding the intersection of these segments, LaneRTD determines the horizon. Hough transformation is employed to detect potential straight line segments within the ROI, which could constitute

parts of the lane boundary. These segments are grouped together to construct both the left and right lanes, with two straight lines fitted to represent the lane boundaries. The LaneRTD algorithm's workflow is visually depicted in a flowchart for clarity, and the resultant straight lane lines are overlaid onto the original color image for visualization purposes.



II. CANNY EDGE DETECTOR

The Canny edge detection algorithm involves a sequence of five steps to accurately identify edges in an image [17]. Firstly, a Gaussian filter is applied to the image to remove noise and smoothen it. Next, intensity gradients are computed for all pixels, followed by a process called non-maximum suppression to enhance edge detection. Double-threshold categorization is then applied to evaluate edges and identify potential ones. Finally, edges are evaluated by categorization, retaining strong edges while filtering out weak ones.

The Gaussian filter, implemented through convolution with a carefully designed kernel, smooths the image and reduces the impact of noise on edge detection. The choice of Gaussian kernel size is critical, with larger sizes offering lower sensitivity to noise but potentially increasing localization error. A 5x5 kernel size is often suitable, although adjustments may be necessary based on specific application requirements.

To detect edges in various directions, the Canny algorithm employs four filters for horizontal, vertical, and diagonal edges. Edge detection produces intensity gradients in both horizontal (Gx) and vertical (Gy) directions, allowing calculation of edge gradient and direction.

Non-maximum suppression thins the detected edges by retaining only pixels with locally maximum gradient values. Weak edges that are not associated with strong ones are eliminated, enhancing edge accuracy.

After non-maximum suppression, thresholding is applied using high and low threshold values to preserve strong edges and remove weak ones. Strong edges contribute to the final edged image, while weak ones are retained only if they are closely connected to strong edges.

Hough transform, another important technique, detects straight lines, circles, and other shapes in images by quantizing the parameter space and implementing a voting process. Local maxima in the parameter space are identified, and a threshold is applied to extract likely lines.

2. THE IMPLEMENTED LINE-DRAWING FUNCTION

The line drawing function "Draw_Lines()" serves to connect line segments generated by the Hough transform into solid lines representing the actual lane lines in images. These line segments are classified as belonging to the left or right lane lines based on their slopes. Segments with positive slopes between 0.4 and 1.0 are categorized as left lines, while those with negative slopes between -0.4 and -1.0 are classified as right lines.

Once classified, the lengths, intercepts (intersections with the x-axis), and slopes of the left and right line segments are calculated and stored. A line fitting technique is then applied to each class, taking into account the slope of each line segment to determine its quality.

To reduce jitter and ensure smoothness, information from previous frames is incorporated using an Nth order finite impulse response (FIR) filter, where N ranges up to the 30th order. The FIR filter equation used in this implementation is:

The specific FIR filter parameters and coefficients employed in this implementation are tailored to optimize the line drawing process, ensuring accurate representation of the lane lines while minimizing noise and fluctuations in the output. These parameters and coefficients are carefully chosen and adjusted to achieve the desired level of performance and stability in lane line tracking.

3. TESTING AND VALIDATION

The LaneRTD algorithm underwent extensive testing using numerous images depicting diverse scenarios, with samples of the results displayed in these results showcase the algorithm's robust performance across various conditions. To further validate the pipeline's robustness, real-time video samples capturing different driving conditions were also utilized for testing. Overall, LaneRTD demonstrated commendable robustness, except in cases where scattered shadows obscured accurate lane line detection, as illustrated in Fig. 15. Addressing this issue is a priority for future enhancements.

In terms of computational efficiency, LaneRTD exhibited satisfactory execution speed suitable for real-time applications. Utilizing a moderate computational platform equipped with an Intel Core i5 processor operating at 1.6 GHz and 8 GB of RAM, the following performance metrics were recorded for three sample testing video streams:

Even the slowest processing speed measured at 11 frames per second remains ample for accurate lane-line detection. A frame rate of 10 frames per second is deemed sufficient for the intended application, highlighting LaneRTD's suitability for real-world deployment.

4. Conclusion

This paper introduces LaneRTD, a novel lane-lines detection and tracking method designed for robust and efficient performance. LaneRTD employs a sophisticated pipeline comprising established algorithms such as Canny edge detection and Hough transform, supplemented by a comprehensive lane line detection and drawing technique. Unlike complex systems, LaneRTD requires only raw RGB images captured by a single CCD camera mounted on the vehicle's front windshield. Extensive testing and evaluation of LaneRTD's performance were conducted using numerous stationary images and real-time videos. The results demonstrate its impressive accuracy and robustness across various scenarios, with notable exceptions in cases involving intricate shadow patterns. Despite these challenges, LaneRTD exhibits commendable performance, particularly in terms of throughput, as demonstrated by its efficient execution on affordable CPUs. This capability makes LaneRTD highly suitable for real-time lane detection applications in Advanced Driving Assistance Systems (ADAS) and autonomous vehicles. The paper offers a thorough analysis of LaneRTD's strengths and limitations, accompanied by insightful suggestions for further improvements and future research directions. By addressing the identified shortcomings, such as handling complex shadow patterns, LaneRTD can be enhanced to achieve even higher levels of accuracy and reliability. Additionally, the paper highlights the importance of ongoing research and development efforts to continually advance lane detection technologies, ultimately contributing to safer and more efficient transportation systems. In summary, LaneRTD represents a significant advancement in lane detection technology, offering a compelling combination of speed, accuracy, and robustness. With its potential to enhance the capabilities of ADAS and self-driving cars, LaneRTD stands poised to play a pivotal role in shaping the future of automotive safety and automation.

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