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Towards Precision Navigation: Curved lane Detection System in Vehicles

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Abstract: Curved lane detection is a critical componentof advanced driver assistance systems (ADAS) and autonomous vehicles, playing a pivotal role in ensuring safeand efficient navigation on complex roadways. In the pursuitof enhancing accuracy and expediting processing speed in road lane detection, researchers have proposed numerous methodologies. Despite these efforts, several challenges persist, including variations in lane markings, fluctuations in lighting conditions, and the emergence of shadows. Addressing these obstacles is crucial for establishing dependable lane detection systems. The curve lane detection algorithm exhibits a robust performance, as evidenced by the experimental results, which consistently reveal a notably high success rate in accurately identifying and delineating curved lanes.

Keywords: Lane Detection, Warped images, Autonomous vehicles, Distortion Correction, Thresholding, Noise reduction, Sobel Detection.

I. INTRODUCTION

Curved lane detection, a pivotal component of autonomous driving perception technology, holds significant sway over the vehicle's trajectory on curved paths and is instrumental in ensuring safe autonomous driving experiences. The development of autonomous vehicles is crucial for ensuring the safety of both drivers and passengers. Traffic accidents can occur due to various factors, with a significant number stemming from improper speeds, sudden lane changes to avoid obstacles, or unexpected turns [4]. Instances of accidents during test drives underscore the imperative need for enhanced safety measures before widespread adoption can be achieved. The domain of autonomous driving research continues to grapple with safety during curve sections, which are notorious for being accident-prone [2].

Beyond safety considerations, the improved ability to detect and navigate curved lanes contributes to enhanced traffic flow, potentially mitigating congestion and reducing commute times. The significance of curved lane detection extends further as autonomous vehicles increasingly rely on detailed road geometry and lane position information to make informed decisions, especially in negotiating turns, curves, and intersections. This technology proves particularly valuable on curved roads, such as those found in complex urban and mountainous terrains, where accurate detection of lane boundaries ensures vehicles stay within designated lanes, minimizing the risk of accidents resulting from lane departures [1]. Traditional lane detection methods predominantly rely on image processing techniques, often leveraging Hough transform for lane feature extraction, which yields satisfactory results for long, solid lanes. However, the emergence of deep learning technologies presents a promising avenue for addressing curve lane detection challenges. In particular, the YOLOv5 algorithm has shown promise in detecting curves and shorter lanes efficiently [8]. Considering that a moving car, depending on its speed, requires a certain amount of time to stop or reduce speed while maintaining stability, it becomes necessary to detect road lanes not only in the near field but also in the far-field of view.

II. LITERATURE SURVEY

As autonomous driving technologies become more prevalent, standards organizations are emphasizing the importance of robust perception systems, including curved lane detection, to ensure the safety and reliability of vehicles on public roads.

Many studies have been conducted to assess its potential applications and effectiveness. Some examples of relevant literature are given below:

1) Wang et al. introduced an algorithm for detecting curves using a linear model [7]. Their research demonstrated that this approach is effective for detecting most curved road conditions. However, the algorithm is primarily designed for small curvature curves found on highways or urban roads.
2) Tamal Datta et al. presented a lane detection technique that involves several image pre-processing steps, including grayscale conversion, Canny edge detection, and bitwise logical operations applied to the input image. Additionally, the technique includes masking the image based on the region of interest (ROI) within the image [3]. The final step employs the Hough transformation method to detect lines, yielding parameters for straight lines.

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3) Shun Yang et al. introduced an alternative approach to enhance lane detection accuracy by replacing traditional image pre-processing methods [5]. Their technique leverages deep learning-based lane detection, shifting away from feature-based detection. However, the implementation of their method, which utilizes a UNet-based encoder-decoder, necessitates a high-performance GPU such as the Nvidia GeForce GTX 1060 for both training and testing phase.

III. PROPOSED METHODOLOGY

The detection of curved lanes in images or video frames is a multifaceted process that typically involves the integration of computer vision and image processing techniques. This complex task requires a cohesive approach to identify and track the curved road markings that guide vehicles along winding roads. In order to extract meaningful information from visual data, a series of image preprocessing steps are employed. The proposed approach for designing a framework to illustrate the functionality can be summarized as follows:

1) *Image pre-processing:* It contains Grayscale Conversion, Image Thresholding, Noise Reduction, Perspective Transformation, Sobel Edge Detection.
2) *Curve Lane Detection:* It mainly includes sliding window search and curve fitting for detection of lane.

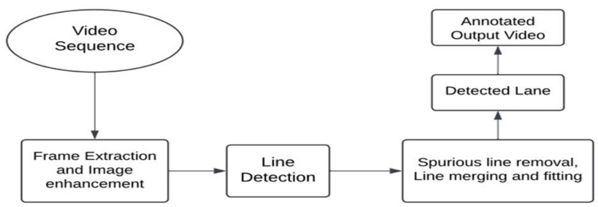

Fig1: Block Diagram of the system

These algorithms collectively form a comprehensive framework for detecting and tracking curved lanes, integrating various techniques to enhance the accuracy and robustness of the overall process.

IV. MODULE DESCRIPTION

Curved lane detection is a crucial component of computer vision systems used in autonomous vehicles and advanced driver assistance systems (ADAS). It involves the detection and tracking of lanes on the road, even when the lanes are curved or have complex geometries. The proposed system needs a set of images and videos that will help to represent various road scenarios along with the curved lanes. These images should be captured under various lighting conditions, weather conditions, and road types to ensure the model's robustness.

A. *Camera Calibration and Distortion Correction*

1) Camera calibration and distortion correction are essential pre-processing steps in computer vision applications, particularly in the context of image processing for autonomous driving, lane detection, and related tasks.
2) Camera calibration involves determining the intrinsic parameters of the camera, such as focal length, principal point, and lens distortion coefficients. This process requires the use of known geometric patterns, such as chessboards or calibration grids, placed at different orientations and positions within the camera's field of view.
3) Distortion correction, utilizes the calibrated parameters to rectify the distortions present in captured images. This correction is crucial for achieving accurate and reliable results in subsequent computer vision tasks. Through the application of geometric transformations, such as the removal of barrel or pincushion distortion, images can be undistorted, providing a more faithful representation of the real-world scene.

Fig 2: Distortion correction

B. Thresholding

1) To enhance the effectiveness of lane line detection in each video frame or image, a crucial preprocessing step involves the application of thresholding. Thresholding, in this context, refers to the technique of setting a specific threshold value to segregate pixels based on their intensity or color.
2) By applying thresholding, we aim to mitigate the impact of factors such as glare from the sun, shadows, car headlights, and variations in the road surface. These elements can pose challenges to the accurate identification of lane lines within a video frame or image.
3) Thresholding process entails the substitution of each pixel in a video frame with a black pixel if its intensity falls below a specified constant or with a white pixel if its intensity surpasses a certain threshold. The outcome of this operation is the generation of a binary image, characterized by pixels exclusively taking on values of 1 for white or 0 for black.

C. Perspective Transformation

1) In the perspective transformation, we implement a critical step by generating a top-view image of the road. This resulting image, often referred to as a bird's-eye view, ensures that lanes appear parallel or nearly parallel post-transformation.

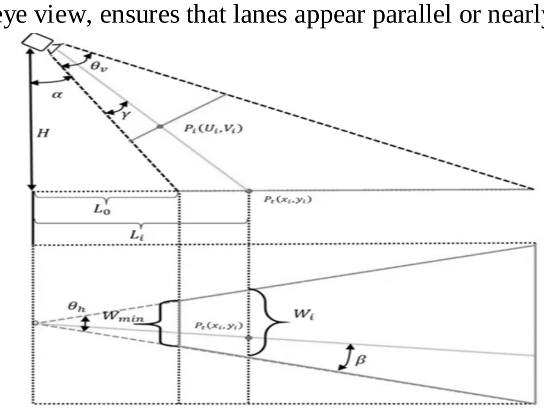

Fig 3: Perspective Projections

2) To execute the transformation process, several key parameters come into play. These include □*h*, representing the horizontal view angle of the camera, and □□, denoting the vertical view angle of the camera. The height of the camera, designated as □, provides information about the camera's position. The tilt angle of the camera, denoted by α, is another essential parameter influencing the transformation.
3) The height of the vehicle-mounted camera is measured in the metric system. Two types of top-view images can be created: one measured in metrics using the H parameter and another measured in pixels using the H_{pixel} parameter.

$$\left.\begin{array}{l} L_{min}=H * \tan(\alpha) \\ W_{min}=2 * L_{min} * \tan(\theta_h/2), \\ K=V/W_{min} \end{array}\right\} \quad (1)$$

4) The coefficient K is employed to convert the metric into pixel data.

$$\left.\begin{array}{l} H_{pixel}=H \cdot K \\ \gamma=\theta_v \cdot \left(\frac{U-Ui}{U}\right) \\ x_i=L_i-L_0=H_{pixel} * \tan(\alpha+\gamma)-H_{pixel} * \tan(\alpha) \end{array}\right\} \quad (2)$$

5) The algorithm establishes a systematic process for determining the corresponding sampling point, P_t (U_i, V_i), on the top-view image for each point P_i(U_i, V_i) present in the front view image. This calculation is carried out utilizing the previously defined equations (1)-(3).

$$\left.\begin{array}{l} \beta=\theta_h \cdot \left(\frac{V-Vi}{V}\right) \\ y_i=L_i \cdot \tan(\theta_h-\beta) \end{array}\right\} \quad (3)$$

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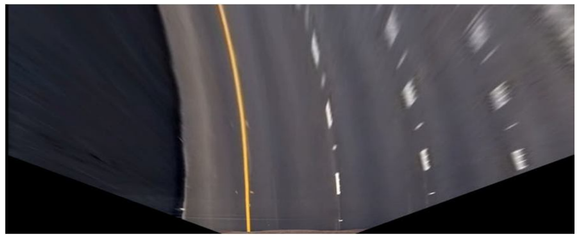

Fig 4: Perspective Warped Image

D. *Sobel Edge Detection*

1) To identify sharp discontinuities in pixel intensities and effectively detect edges within a video frame, a Sobel edge detection technique is applied specifically to the L (lightness) channel of the image. This method is employed to highlight significant changes in intensity along both the x and y axes of the frame.
2) The Sobel operator conducts a 2-D spatial gradient measurement on an image, highlighting areas with high spatial frequency indicative of edges. Its primary function is to approximate the absolute gradient magnitude at each pixel in a grayscale image, making it a commonly employed tool for edge detection in image processing.
3) Furthermore, to identify the yellow lane, a specific combination of saturation and lightness values is defined. This tailored combination enables the method to effectively discern and isolate the pixels associated with the yellow lane markings.

E. *Sliding Window Search*

1) The sliding window algorithm plays a pivotal role in distinguishing between the left and right lane boundaries, facilitating the fitting of distinct curves that accurately represent each lane.
2) To initiate the creation of multiple sliding windows, it is imperative to determine their starting positions. This is achieved by computing a histogram for the bottom portion of the image. By identifying the peak value in this histogram, the initial window location is established, and the mean of the non-zero points within that window is calculated.
3) For the first half of the image, the peak on the left side corresponds to the left lane, while the peak on the right side pertains to the right lane. Consequently, separate starting sliding windows are formed for both the left and right lanes. Subsequently, the centers of these lanes are computed based on these initial selections.
4) The curve model is represented by the quadratic equation:

$$Ax^2+Bx+C=0 \qquad \text{-----------------}(4)$$

Where A, B and C are the constants of the quadratic curve.

The radius of curvature (R) is a crucial parameter calculated using the y-axis point at the bottom of the image.

$$R = (1+ (d^2y/dx^2))^{3/2} \ . \ (dy/ dx)^2$$

Where dx and dy are the positions of the lane.

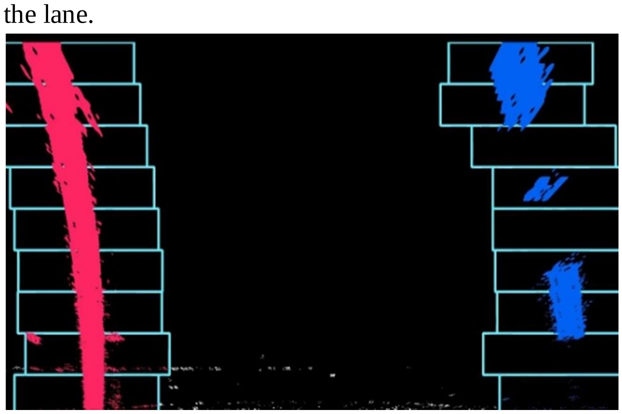

Fig 5: Sliding Window Search

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V. RESULT

The research demonstrates the efficacy of a curved lane detection system with guidance capabilities for drivers. Ther system achieved high accuracy in detecting curved lanes, with a low rate of false positives and negatives. The guidance provided to drivers, determining whether to move left, right, or continue straight, was effective in various driving scenarios. Drivers using the system exhibited improved lane-keeping performance, with reduced lane deviations and fewer instances of lane departures compared to manual driving.

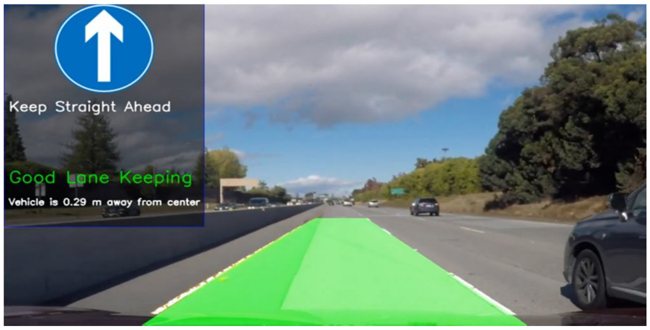


Fig 6: Curved Lane Detection System Showcase

The evaluation focused on the effectiveness of preprocessing techniques in improving lane markings' visibility and reducing noise. Results showed enhanced lane detection accuracy post-preprocessing, with clearer markings and reduced interference.

VI. CONCLUSION

The framework for curved lane detection comprises image preprocessing steps and curve lane detection algorithms. Image preprocessing involves Grayscale Conversion, Image Thresholding, Noise Reduction, Perspective Transformation, and Sobel Edge Detection, enhancing data quality for analysis.
Curve lane detection using sliding window search and curve fitting algorithms demonstrated robustness in identifying curved road markings accurately. Performance across varied scenarios, including different curvatures and lighting, showcased reliability and adaptability.
Quantitative metrics like detection rate, false positives, and false negatives assessed accuracy. High detection rates with minimal false results indicated the system's efficacy in detecting and tracking curved lanes accurately.
The framework seamlessly integrates image preprocessing and curve lane detection, resulting in a reliable system for detecting and tracking curved lanes in images or video frames.

VII. FUTURE SCOPE

1) The future scope of the lane detection includes complex environment taking into account the different environments such as the Weather conditions: fog, mist, cloudy, sunny, bright day light, darker, shadow or when there occurs obstacles and humps, speed Breakers in the road.
2) Future vehicles may communicate with each other (V2V communication) to share lane information, providing a collective awareness of the road, which can improve overall safety and traffic management.
3) Curved lane detection can contribute to the creation of high-definition maps with detailed information about curved roads. These maps are essential for autonomous vehicles and can improve navigation accuracy.
4) Curved lane detection can also be extended to detect pedestrian lanes and crosswalks in curved or complex road scenarios. This would improve pedestrian safety, especially in urban environments.

REFERENCES

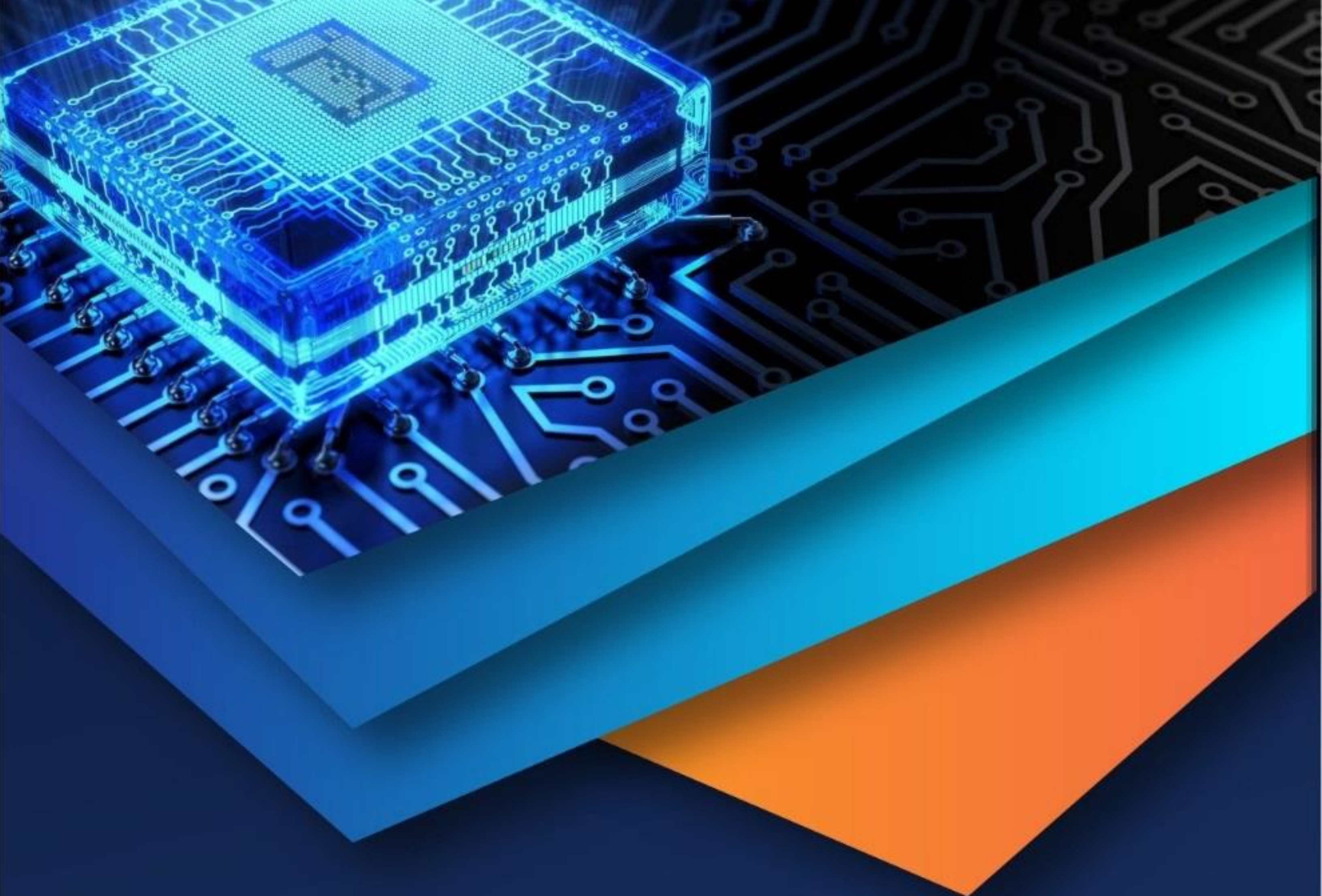
[1] Fleetwood, J. Public health, ethics, and autonomous vehicles. Am. J. Public Health 2017, 107, 532–537
[2] Chen, C.; Tang, L.; Wang, Y.; Qian, Q. Study of the Lane Recognition in Haze Based on Kalman Filter. In Proceedings of the 2019 International Conference on Artificial Intelligence and Advanced Manufacturing (AIAM), Dublin, Ireland, 16–18 October 2019; pp. 479–483.
[3] Datta, T.; Mishra, S.K.; Swain, S.K. Real-Time Tracking and Lane Line Detection Technique for an Autonomous Ground Vehicle System. In Proceedings of the International Conference on Intelligent Computing and Smart Communication 2019; Springer: Singapore, 2020; pp. 1609–1625.
[4] Deng.J, and Han .Y. A real-time system of lane detection and tracking based on optimized RANSAC B-spline fitting. Research in Adaptive and Convergent System, 2013, pp. 157-164.

[5] Yang, S.; Wu, J.; Shan, Y.; Yu, Y.; Zhang, S. A Novel Vision-Based Framework for Real-Time Lane Detection and Tracking; S.A.E. Technical Paper; S.A.E.: Warrendale, PA, USA, 2019; Volume 2019.

[6] Jiang, L.; Li, J.; Ai, W. Lane Line Detection Optimization Algorithm based on Improved Hough Transform and R-least Squares with Dual Removal. In Proceedings of the 2019 IEEE 4th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), Chengdu, China, 20–22 December 2019; Volume 1, pp. 186–190.

[7] Wang, H.; Wang, Y.; Zhao, X. Lane Detection of Curving Road for Structural Highway with Straight-Curve Model on Vision. IEEE Trans. Veh. Technol. 2019, 68, 5321–5330.

[8] Cheung yuk-wing, Wong keung-keung. Research on wheat imperfect grain recognition based on Python-OpenCV image processing technology[J]. Journal of the Henan University of Technology, 2021, 42(06):105-112.



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