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An Intelligent Lane and Object Detection using YOLO V7 algorithm

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Abstract : Developing self-driving cars is an important foundation for the development of intelligent transportation systems. It is challenging to detect lanes quickly and accurately due to a variety of complex noise, so the main aim is to develop a collection of image processing techniques that give accurate results quickly. To solve problems such as low detection accuracy of traditional image processing methods and poor real-time performance of methods based on deep learning methods, lane detection algorithm barriers for smart traffic are proposed. This paper includes an intelligent lane and vehicle recognition technique that utilizes a collection of distinct photos and applies the results to a video stream. The Hough transform is chosen as the most effective beeline detection technique, and the Canny algorithm is chosen as the edge detection technique. The ROI is defined to decrease noise for accurate rise and to increase processing speed to satisfy the real-time need. For detecting the vehicle, to provide fast implementation and smooth real-time update of the vehicles nearby we are implementing the YOLOV7 algorithm. We use real time videos and the TuSimple dataset to perform simulations for the proposed algorithm.

***IndexTerms* - Lane detection, Vehicle detection, systematic literature review, geometric modeling, deep learning, machine learning.**

Introduction

ransportation represents the prosperity and progress of a country. However, it also creates several serious problems such as accidents and traffic congestion. Subjective causes related to vehicle drivers are drunkenness, fatigue, and inaccurate vehicle control. To reduce negative impacts and improve the efficiency of transportation, countries are developing smart systems, including infrastructure and vehicles, based on the basis of advanced networks such as 5G and 6G networks. For smart cars, one of the most indispensable tasks is lane recognition and obstacle detection. A driver can effectively steer a smart vehicle that provides its precise position on a road surface based on a lane. Obstacle recognition such as location and distance from other smart vehicles or animals on the road and recognition of objects such as signs or traffic lights significantly improve driving efficiency and safety. •

However, proposed techniques face several difficulties in detecting lanes where they are not fully visible, resulting in changing color values or shadows. Several systems are developed based on an edge detection algorithm [1] to solve the cases that the color threshold is not able to handle. However, it causes a lot of noise. YOLO is popularly used due to many reasons with legitimate neural networks. One of the basic reasons is the speed of recognition in real time. The authors [2] have detected many objects based on a deep learning algorithm (YOLO). The results are ideal for obstacle detection problems. Therefore, we will use YOLO for the proposed algorithm in the paper.

We use a threshold for edge detection for the lane algorithm. Images with a top down perspective are determined through a region of interest (ROI) extraction and inverse perspective transformation.

The Advanced Driver Assistance System (ADAS) is one of the essential systems in autonomous vehicles for making the driving environment safer for drivers and passengers. ADAS aims to reduce driver error by helping to avoid vehicle collisions, increase traffic efficiency, and enhance transportation development. Adaptive Cruise Control [3], Automatic Braking/Steer Away [4], Lane-Keeping System [5], Blind Spot Assist [3], Lane Departure Warning System [6], and Lane Detection [7] are several examples of the ADAS module.

I. Related Work

The purpose of the algorithm is to find the features belonging solely to the lanes. While driving on the road with continuous lane marking, the positions of the lanes are not changing significantly over time from the driver's point of view. This algorithm takes advantage of the smaller region of interest right in front of the moving vehicle. The lane detection algorithm consists of three stages: preprocessing, post-processing, road lane modeling. Details of these steps and related computations are described in this section.

A. Pre-processing Stage

The first step is low-level image processing, which deals with images from the vision sensor and generate useful information for detection parts. In this stage, image of the road is copied for the computational part. The image is reduced to a smaller region of interest to save computational time. The image is also converted into gray scale as Canny edge detection works with monochromatic image. Noise reduction with image processing such as erosion, dilation and image smoothing are also applied for better useful information.

B. Post-processing Stage

Canny edge detection is implemented in the post processing stage. Lines and edges in the smoothen image are detected in the feature recognition stage. Then Hough Transform is implemented to connect discontinuous line and differentiate different lines. In short, postprocessing is one of the most important steps as it ties together feature extraction stage and the road lane modeling stage.

C. Road Lane Modeling

Computation is done to recognize possible left and right lane markers. Parameters of the lines, rho (T) and theta (d) are used for the computation. Grouping similar lines together and then getting an average result. The final result attached on the original image showing the left and right lane marking on the road.

II. METHODOLOGY

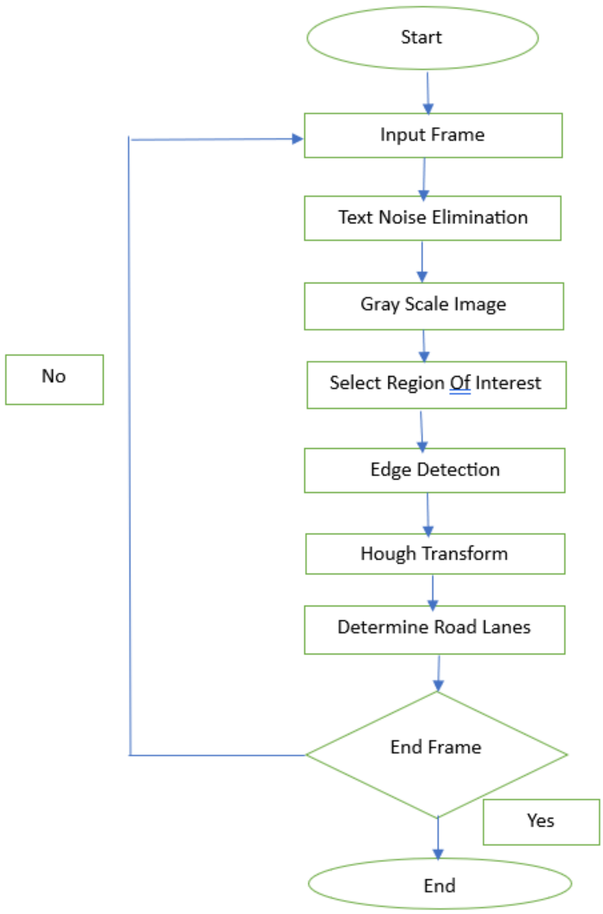

Fig 1. Flowchart for Lane Detection

In the present system we proposed a lane detection system for self driving car.
For an instance, autonomous cars can be trained on this synthetic dataset for detecting lanes in an efficient and timely manner. It will then use Canny edge detection to detect the edges of the lane, along with a masking function that obscures unwanted details in images, such as trees, rocks, and power lines, and will be used to allow the model to concentrate on identifying lanes. The Hough Transform is used to identify and draw the lanes on the frame in python output window.

Capturing and decoding video file: We will capture the video using VideoFileClip object and after the capturing has been initialized every video frame is decoded (i.e. converting into a sequence of images).

Grayscale conversion of image: The video frames are in RGB format, RGB is converted to grayscale because processing a single channel image is faster than processing a three-channel colored image.

Reduce noise: Noise can create false edges, therefore before going further, it's imperative to perform image smoothening. Gaussian blur is used to perform this process. Gaussian blur is a typical image filtering technique for lowering noise and enhancing image characteristics. The weights are selected using a Gaussian distribution, and each pixel is subjected to a weighted average that considers the pixels surrounding it. By reducing high-frequency elements and improving overall image quality, this blurring technique creates softer, more visually pleasant images.

Canny Edge Detector: It computes gradient in all directions of our blurred image and traces the edges with large changes in intensity.

Region of Interest: This step is to take into account only the region covered by the road lane. A mask is created here, which is of the same dimension as our road image. Furthermore, bitwise AND operation is performed between each pixel of our canny image and this mask. It ultimately masks the canny image and shows the region of interest traced by the polygonal contour of the mask.

Hough Line Transform: In image processing, the Hough transformation is a feature extraction method used to find basic geometric objects like lines and circles. By converting the picture space into a parameter space, it makes it possible to identify shapes by accumulating voting points. We'll use the probabilistic Hough Line Transform in our algorithm. The Hough transformation has been extended to address the computational complexity with the probabilistic Hough transformation. In order to speed up processing while preserving accuracy in shape detection, it randomly chooses a selection of picture points and applies the Hough transformation solely to those points.

Draw lines on the Image or Video: After identifying lane lines in our field of interest using Hough Line Transform, we overlay them on our visual input(video stream/image).

III. RESULT AND DISCUSSION

Fig.2 In the above image the lane is detected properly

Fig.3 The model works well in predicting the class and location we can see both the cars are detected correctly

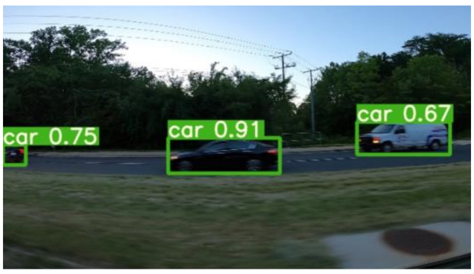

Fig.4 The algorithm works properly even the car on left side is not capture properly still it is detected

IV. CONCLUSION

In this paper, A video-based lane detection and vehicles tracking is presented for autonomous vehicle. Our model was divided into 2 modules: lane detection and vehicles tracking. We have presented a computer vision technique for lane detection and tracking. We used Hough Transform algorithm to detect the lane in low light conditions and different road situation. Since this algorithm was used in lane departure warning system, the use of it is to detect the lane and warn when the danger of departure came. The test result shows that the algorithm shows a strong robustness different light condition as well as smooth curved and straight road. Vehicle detection and tracking essential for autonomous vehicles to collision avoidance. We have presented a deep learning approach Yolov7 for vehicle detection, tracking, and distance estimation. In future, we can implement our model in real time with live streaming camera mounted on autonomous vehicle.

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