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Highly Curved Path Prediction and Vehicle Detection in Lane Roads

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Abstract: *Lane detection and curve identification pose significant challenges in the advancement of autonomous vehicles. This paper explores diverse algorithms and their integration to accurately detect lanes and identify curvature within them. Our objective is to develop a real-time program capable of identifying lanes and curves in video footage. By leveraging Computer Vision algorithms and OpenCV libraries, we successfully detect lanes and determine lane curvature within dynamic video sequences. However, it is important to note that the program may not produce accurate results in scenarios where lane markings are absent or distorted.*

Keywords: CNNs, Unstructured Lane, Lane Detection, Haar Cascade, Deep Learning

I. INTRODUCTION

The advancement of autonomous driving technology necessitates robust solutions for highly curved path prediction and vehicle detection on lane roads. Negotiating highly curved roads poses specific challenges for autonomous vehicles, requiring them to navigate these roads safely and efficiently while identifying other vehicles and obstacles. Highly curved path prediction involves anticipating the vehicle's trajectory as it traverses curved road sections, while vehicle detection entails recognizing other vehicles present on the road. The precise and dependable performance of these tasks is essential for ensuring the safe and efficient operation of autonomous vehicles. In this paper, we provide an overview of recent research on highly curved path prediction and vehicle detection in lane roads, encompassing both traditional and deep learning-based approaches. We also address the challenges and opportunities in these areas and highlight promising avenues for future research. The development of accurate and reliable highly curved path prediction and vehicle detection systems is of paramount importance for widespread adoption of autonomous driving technologies and the realization of a transportation system that is both safer and more efficient.

Also one of the added feature in this project is detection of eye blinking and yawning basically drowsiness detection. This if helpful in monitoring driver while driving a vehicle and giving alert to stay awake and if sleepy can give reminder to take sleep by parking a vehicle on a side. This becomes very important as 9.5% of the total accidents happening are due to drowsy driving of driver.

II. PROPOSED ALGORITHM

A. For Lane Detection using OpenCV

Algorithm: Lane Detection

- STEP 1: Conversion Of video to frames.
- STEP 2: Smoothing of video frames using Gaussian Blur function.
- STEP 3: Conversion to Gray Scale using BGR2GRAY function.
- STEP 4: Extracting Edges using canny edge detection algorithm.
- STEP 5: Extracting the area of interest using geometricalcoordinates on a particular frame.
- STEP 6: Applying Hough Transform method for to find best fitting line for lane.
- STEP 7: Averaging those lines using mathematical line equation (Y = m*X + C).
- STEP 8: Finally display line on frames of video.

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Video Dataset Link :[VIDEO]

B. For Vehicle Detection (Implemented Through CNN)

Algorithm: Vehicle Detection

- STEP 1: Data Normalization (Batch Normalization with lambda function).
- STEP 2: Training of Model using 6 convolutional layers.
- STEP 3: Then the input video is fed to sliding window technique (uses trained classifier).
- STEP 4: Creation of heat map to reject outliers.
- STEP 5: Finally Displaying result with bounding box fordetected vehicles.

Dataset Used :[Stanford Car Dataset]

C. For Eye Blinking and Yawn Detection

Algorithm: Eye Blinking and Yawn Detection

- STEP 1: Data Normalization
  - Apply any necessary pre-processing steps, such as resizing or normalization, to prepare the input data.
- STEP 2: Model Training
  - Train a model using computer vision techniques to detect eye blinking and yawn events.
  - This may involve using pre-trained models or designing a custom architecture with suitable layers.
- STEP 3: Capture and Pre-process Frames
  - Capture video frames from the input source, such as a webcam.
  - Pre-process each frame by converting it to grayscale or applying any other necessary transformations.
- STEP 4: Eye Blink Detection
  - Apply an eye detection algorithm to locate the eyes within the face region.
  - Calculate the eye aspect ratio (EAR) using the detected landmarks or other relevant features.
  - Determine if the calculated EAR falls below a predefined threshold, indicating an eye blink event.
- STEP 5: Yawn Detection
  - Apply a mouth or lip region detection algorithm to locate and track the mouth region within the face.
  - Calculate the mouth aspect ratio (MAR) using the detected landmarks or other relevant features.
  - Check if the calculated MAR exceeds a predefined threshold, indicating a yawn event.
- STEP 6: Blink and Yawn Tracking
  - Keep track of consecutive frames where the eyes remain closed to identify a complete blink.
  - Keep track of consecutive frames where the mouth remains open to identify a complete yawn.
- STEP 7: Display Results
  - Finally, display the results by indicating the occurrence of eye blinks and yawns on the video frames.
  - This can be done by overlaying visual cues, such as bounding boxes or text, to highlight the detected events.

III. Implementation

Lane Detection:

The lane detection process consists of three main steps: Pre-processing, Edge detection, and Line detection. However, the challenge in developing a lane detection system lies in accurately predicting the road traffic environment. In complex traffic scenarios with high vehicle density and fast-moving vehicles, the risk of accidents is higher than usual.

Pre-processing:

The input for the lane detection system is an image or video of the road obtained from NYC traffic data. We propose a two-step pre-processing method to eliminate noise and enhance data detection. The input video is converted into frames, and these frames are then converted to grayscale images to reduce processing time. The frames are further segmented into binary images. To improve accuracy, we apply both HSV Saturation and RGB to grayscale conversions.

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Noise in the image can interfere with accurate edge detection, so we employ filters such as bilateral filter, Gaussian filter, and Gabor filter to remove noise.

Edge Detection:

The edge detector takes the pre-processed image and filters it to identify edges. The resulting image is then passed on for line detection, which determines the boundaries of the right and left lanes. The lane boundary detection utilizes the information obtained from the edge detection, producing a series of points on both sides of the lane.

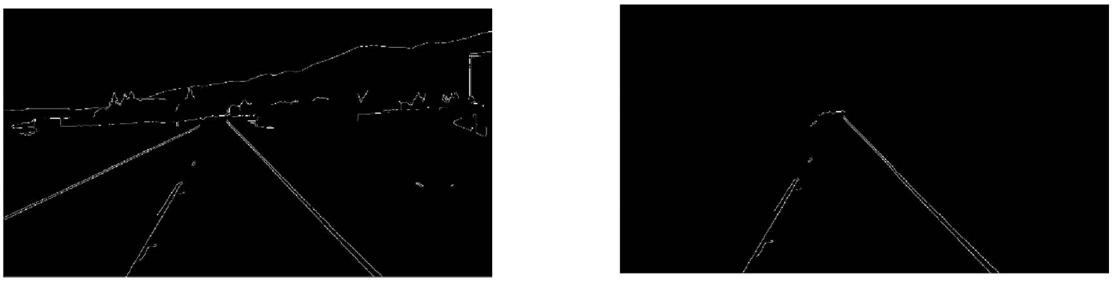

Fig. 1: Detected Edges (Canny Edge Detection).

Fig. 2: Obtained Lane After Detection.

Detecting the vehicle in the detected lane roads

Training Data:

The vehicle detection is implemented through the CNN (Convolutional Neural Network). The training input images are fed into our network. The model first does the normalization while normalizing the data to the same scale approximately. We do Batch normalization here to our dataset. We add a lambda function to the model defining our function. The model is built with 6 Convolutional layers. We have an input layer, hidden layers (Convolution2D, MaxPooling2D and Dense) layers. We add a flattening layer to feature into 1D feature vector. The feature extraction is done using the DNN Classifier and the results are observed.

Detecting Vehicles:

Then the input video is fed into a sliding-window technique that uses the trained classifier to search for vehicles in the input video frames. We have created a heat map of detection frame by frame to reject outliers. Finally we result having a bounding box for vehicles detected.

Predicting the curvature of the lane:

After filtering the lane lines with the morphological operations and detecting the lane with the edge detection algorithm we have got the resultant lane line. In the resultant lane we will find the left lane and right lane using the centre point of the lane and fit the lane line using the triangle region. Then we determine the curvature of lane from centre of the lane. From the previous detection, if any vehicle exists in the lane a warning will be given to the system to change the lane.

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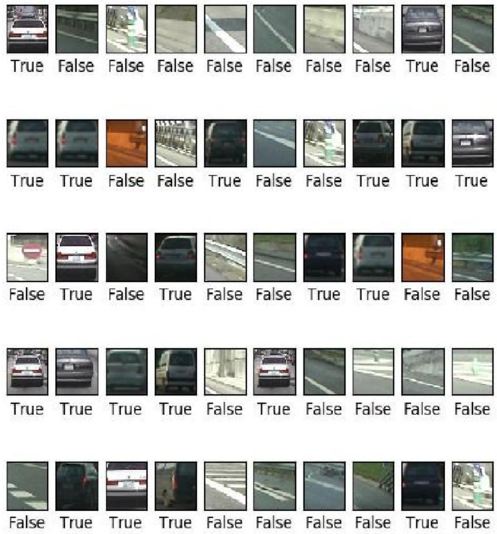

Fig. 3: Labelled Dataset Containing Vehicle and No-Vehicle.

IV. CONCLUSION

In this study, we have conducted an investigation into the lane detection technique, exploring the various approaches employed and suggested for accurate lane detection. We have also highlighted the challenges, potential applications, and performance measures associated with lane detection. While many innovative methodologies have been utilized in lane detection, it is important to acknowledge that challenges still persist. Specifically, these challenges tend to arise in scenarios involving curved roads or poor environmental conditions, making detection difficult or even impossible.

Furthermore, this study has delved into the topic of vehicle detection algorithms. We have discussed the extraction of the road surface area of the highway as a means to obtain a more effective Region of Interest (ROI). Additionally, we have implemented the YOLOv3 object detection algorithm, which has yielded an end-to-end vehicle detection model based on the Stanford Cars Dataset.

It is crucial to recognize that both lane detection and vehicle detection are complex tasks, and ongoing research and development are necessary to address the remaining challenges and improve overall system performance.

Ultimately, the successful implementation of accurate and reliable lane detection and vehicle detection systems plays a vital role in advancing autonomous driving technologies and creating a safer and more efficient transportation system.

Integrating eye blinking and yawn detection into the existing system enhances the overall awareness and monitoring capabilities. By incorporating appropriate computer vision techniques and machine learning algorithms, it becomes possible to accurately detect and track eye blinking and yawn events in real-time.

It is important to note that eye blinking and yawn detection are still active areas of research, and there are challenges in accurately detecting and interpreting these signals in various driving conditions and environments. Further research and development are needed to refine the algorithms and improve the robustness and accuracy of eye blinking and yawn detection systems.

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