PROJECT REPORT

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BONAFIDE

This is to certify that **18CSE390T – COMPUTER VISION project report** titled "Road Lane Line Detection" is the bonafide work of Laksmi Priya(RA2011026010121),Jyothsna Sree(RA2011026010126), Rithika V(RA2011026010130) who undertook the task of completing the project within the allotted time.

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ABSTRACT

Road lane detection systems play a crucial role in the context of Advanced Driver Assistance Systems (ADASs) and autonomous driving. Such systems can lessen road accidents and increase driving safety by alerting the driver in risky traffic situations. Additionally, the detection of ego lanes with their left and right boundaries along with the recognition of their types is of great importance as they provide contextual information. Lane detection is a challenging problem since road conditions and illumination vary while driving.

Nowadays, almost every new vehicle features some type of Advanced Driving Assistance System (ADAS), ranging from adaptive cruise control, blind spot detection, collision avoidance, traffic sign detection, overtaking assistance, to parking assistance. ADASs generally increase safety and reduce driver workload. Lane detection constitutes one of the fundamental functions found in autonomous driving systems and ADASs. Lane boundaries provide the information required for estimating the lateral position of a vehicle on the road, enabling systems such as lane departure warning, overtaking assistance, intelligent cruise control, and trajectory planning.

MODULE DESCRIPTION

Most traditional methods extract a combination of visual highly-specialized features using various elements such as colour, edges, ridge features, and template matching. These primitive features can also be combined by way of Hough transforms, Kalman filters , and particle filters. Most of these methods are sensitive to illumination changes and road conditions and thus prone to fail.

Deep Learning-based Approaches :

There are mainly two groups of segmentation methods for lane marker detection:

1) Semantic Segmentation and

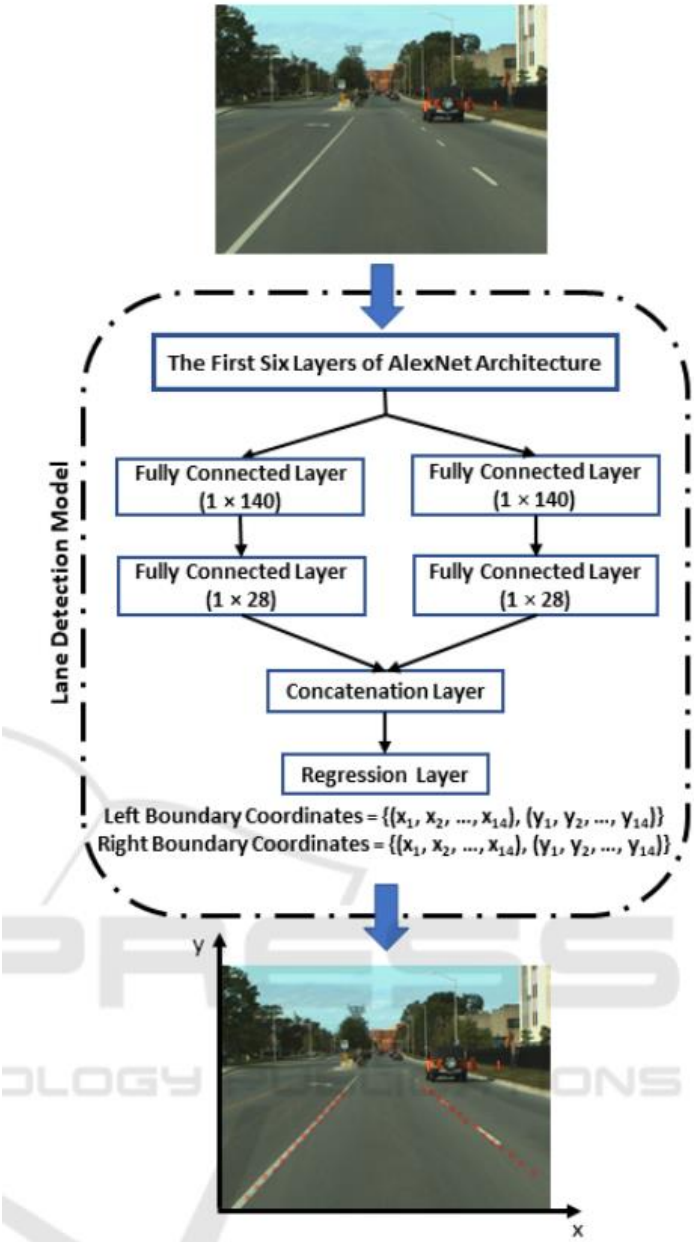
2) Instance Segmentation

In the first group, each pixel is classified by a binary label indicating whether it belongs to a lane or not. For instance, the authors presented a CNN-based framework that utilizes front-view and top-view image regions to detect lanes. Following this, they used a global optimization step to reach a combination of accurate lane lines. proposed a Vanishing Point Guided Net model that simultaneously performs lane detection and road marking recognition under different weather conditions. Their data was captured in a downtown area of Seoul, South Korea. Conversely, Instance Segmentation approaches differentiate individual instances of each class in an image and identify separate parts of a line as one unit. proposed the Spatial CNN (SCNN) to achieve effective information propagation in the spatial domain. This CNN-analogous scheme effectively retains the continuity of long and thin shapes such as road lanes, while its diffusion effects enable it to segment large objects. LaneNet is a branched, instance segmentation architecture that produces a binary lane segmentation mask and pixel embeddings. These are used to cluster lane points. Subsequently, another neural network called H-net with a custom loss function is employed to parameterize lane instances before the lane fitting.

System Architecture with Explanation

Regression-based Lane Detection Model

To identify the ego lane boundaries in the road image, a regression-based network is utilized that outputs two vectors representing the coordinate points of the left and right boundaries from the ego lane. Each coordinate vector consists of 14 coordinates (x, y) on the image plane indicating sampled positions for the ego lane boundary. To construct this model, a pretrained AlexNet architecture is utilized. First, the last two fully connected layers are removed from the network and then four-level cascaded layers are added to the first six layers of AlexNet to complete the lane detection model. These four-level cascaded layers contain two branches of two back-to-back fully connected layers, a concatenation layer and a regression layer. This branched architecture minimizes misclassifications of the detected lane points. Moreover, this architecture is capable of detecting the road boundary as an assumptive ego lane left/right boundary when there is no actual lane marking.



Dataset Description

In this Section, we introduce our lane detection dataset extracted from the driving sequences, captured with the RoadLAB instrumented vehicle (Beauchemin et al., 2012), (see Figure 2). Our experimental vehicle was used to collect driving sequences from 16 drivers on a pre-determined 28.5km route within the city of London Ontario, Canada. (see Figure 3). Data frames were collected at a rate of 30Hz with a resolution of 320 × 240. We used 12 driving sequences, as described in Table 1, to derive our dataset containing 5782 images along with their corresponding lane annotations. Figure 4 illustrates examples from our derived dataset. An essential element of any deep learning-based system is the availability of large numbers of sample images. Data augmentation is a commonly used strategy to significantly expand an existing dataset by generating unique samples through transformations of images in the dataset. The exploitation of data augmentation strategy reduces overfitting from the network. We employed data augmentation techniques.

INPUT/OUTPUT

Results and Discussion

Table 1: Summary of driving conditions of our data (Each row belongs to one driver).

Seq. #	Capture Date	Time	Temperature	Weather
2	2012-08-24	15:30	31°C	Sunny
4	2012-08-31	11:00	24°C	Sunny
5	2012-09-05	12:05	27°C	Partially Cloudy
8	2012-09-12	14:45	27°C	Sunny
9	2012-09-17	13:00	24°C	Partially Cloudy
10	2012-09-19	09:30	8°C	Sunny
11	2012-09-19	14:45	12°C	Sunny
12	2012-09-21	11:45	18°C	Partially Sunny
13	2012-09-21	14:45	19°C	Partially Sunny
14	2012-09-24	11:00	7°C	Sunny
15	2012-09-24	14:00	13°C	Partially Sunny
16	2012-09-28	10:00	14°C	Partially Sunny

Conclusion

Hence ,implementation of Road lane detection is successfully implemented using hough transform and data augumentation techniques. We have piece together a pipeline to detect the line segments in the image, then average/extrapolate them and draw them onto the image for display. Once we have a working pipeline, we will try it out on the video stream

References

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