**Robust Lane Detection from Continuous Driving Scenes Using Deep Neural Networks**

**Abstract:**

Lane detection in driving scenes is an important module for autonomous vehicles and advanced driver assistance systems. In recent years, many sophisticated lane detection methods have been proposed. However, most methods focus on detecting the lane from one single image, and often lead to unsatisfactory performance in handling some extremely-bad situations such as heavy shadow, severe mark degradation, serious vehicle occlusion, and so on. In fact, lanes are continuous line structures on the road. Consequently, the lane that cannot be accurately detected in one current frame may potentially be inferred out by incorporating information of previous frames. To this end, we investigate lane detection by using multiple frames of a continuous driving scene, and propose a hybrid deep architecture by combining the convolutional neural network (CNN) and the recurrent neural network (RNN). Specifically, information of each frame is abstracted by a CNN block, and the CNN features of multiple continuous frames, holding the property of time-series, are then fed into the RNN block for feature learning and lane prediction. Extensive experiments on two large-scale datasets demonstrate that, the proposed method outperforms the competing methods in lane detection, especially in handling difficult situations.

**Existing system:**

In recent years, a number of lane-detection methods have been proposed with sophisticated performance as reported in the literatures. Among these methods, some represent the lane structure with geometry models, some formulate lane detection as energy minimization problems, and some segment the lane by using supervised learning strategies, and so on. However, most of these methods limit their solutions by detecting road lanes in one current frame of the driving scene, which would lead to low performance in handling challenging driving scenarios such as heavy shadows, severe road mark degradation, serious vehicle occlusion, as shown in the top three images. In these situations, the lane may be predicted with false direction, or may be detected in partial, or even cannot be detected at all. One main reason is that, the information provided by the current frame is not enough for accurate lane detection or prediction.

**Proposed system:**

Based on the discussion above, a hybrid deep neural network is proposed for lane detection by using multiple continuous driving scene images. The proposed hybrid deep neural network combines the DCNN and the DRNN. In a global perspective, the proposed network is a DCNN, which takes multiple frames as an input, and predict the lane of the current frame in a semantic-segmentation manner. A fully convolution DCNN architecture is presented to achieve the segmentation goal. It contains an encoder network and a decoder network, which guarantees that the final output map has the same size as the input image. In a local perspective, features abstracted by the encoder network of DCNN are further processed by a DRNN. A long short-term memory (LSTM) network is employed to handle the time-series of encoded features. The output of DRNN is supposed to have fused the information of the continuous input frames, and is fed into the decoder network of the DCNN to help predict the lanes.

**Advantages:**

* The advantage of this model is that, the predicted lanes are thin and accurate, avoiding marking large soft boundaries as usually brought by CNNs.
* UNet- ConvLSTM outperforms other methods in terms of precision for all scenes with a large margin of improvement, and achieves highest F1 values in most scenes, which indicates the advantage of the proposed models.
* Meanwhile, the experimental results demonstrated the advantages of ConvLSTM over FcLSTM in sequential feature learning and target-information prediction in the context of lane detection. Compared with other models, the proposed models showed higher performance with relatively higher precision, recall, and accuracy values.

**Disadvantages:**

* Among these methods, some represent the lane structure with geometry models, some formulate lane detection as energy minimization problems, and some segment the lane by using supervised learning strategies, and so on.
* Meanwhile, we notice that deep learning as an emerging technology has demonstrated the state-of-the-art, human-competitive, and sometimes better-than-human performance in solving many computer vision problems such as object detection image classification/retrieval and semantic segmentation.

**Modules:**

**Advanced driver assistance system:**

WITH the rapid development of high-precision optic sensors and electronic sensors, high-efficient and high effective computer vision and machine learning algorithms, real-time driving scene understanding has become more and more realistic to us. Many research groups from both academia and industry have invested large amount of resources to develop advanced algorithms for driving scene understanding, targeting at either an autonomous vehicle or an advanced driver assistance system (ADAS). Among various research topics of driving scene understanding, lane detection is a most basic one. Once lane positions are obtained, the vehicle will know where to go, and avoid the risk of running into other lanes.

**Lane detection:**

In recent years, a number of lane-detection methods have been proposed with sophisticated performance as reported in the literatures. Among these methods, some represent the lane structure with geometry models, some formulate lane detection as energy minimization problems, and some segment the lane by using supervised learning strategies, and so on. However, most of these methods limit their solutions by detecting road lanes in one current frame of the driving scene, which would lead to low performance in handling challenging driving scenarios such as heavy shadows, severe road mark degradation, serious vehicle occlusion, as shown in the top three images. In these situations, the lane may be predicted with false direction, or may be detected in partial, or even cannot be detected at all. One main reason is that, the information provided by the current frame is not enough for accurate lane detection or prediction.

**Encoder-decoder CNN:**

The encoder-decoder CNN is typically used for semantic segmentation. In, lane detection was investigated in a transfer learning framework. The end-to-end encoder-decoder network is built on the basis of road scene object segmentation task, trained on Image Net. In, a network called LaneNet was proposed. LaneNet is built on SegNet, but has two decoders. One decoder is a segmentation branch, detecting lanes in a binary mask. The other is an embedding branch, segmenting the road. As the output of the network is generally a feature map, clustering and curve-fitting algorithms were then required to produce the final results In , real-time road marking segmentation was exploited in a condition of lack of large amount of labeled data for training.

**Parameter analysis:**

There are mainly two parameters that may influence the performance of the proposed methods. One is the number of frames used as the input of the networks; the other is the stride for sampling. These two parameters determine the total range between the first and the last frame together. While given more frames as the input for the proposed networks, the models can generate the prediction maps with more additional information, which may be helpful to the final results. However, in other hand, if too many previous frames are used, the outcome may be not good as lane situations in far former frames are sometimes significantly different from the current frame. Thus, we firstly analyze the influence caused by the number of images in the input sequence. We set the number of images in the sequence from to and compare the results at these five different values with the sampling strides .