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Personal Information

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RA Period:	**From 2019-09 to present**

Biography

I'm a Ph.D. student at New York University and a research assistant in NYU Multimedia and Visual Computing Lab, advised by Professor Yi Fang. I am broadly interested in 3D Computer Vision, Pattern Recognition and Deep Learning.

Research Project: CurveNet: a Novel Approach to Curved Lane Detection

1 Description

Lane detection is a critical part of any autonomous driving system. Although lane detection appears to be a relatively uncomplicated task compared to most other computer vision applications, there are several factors that challenge lane detection in real world scenarios. In particular, the lack of any distinctive features makes lane detection dif- ficult, readily resulting in the network being confused by other objects with similar appearance. Despite current lane detection algorithms performing well on standard lane detection tasks, curved lane detection has not yet been well addressed in the literature. In this paper, we propose a novel multi-stage network CurveNet specifically for curved lane detection. There are 3 main components of CurveNet – Primary Convolutional Neural Network (P-CNN), Far-Near Convolutional Neural Network (FN-CNN) and Bend Network (BendNet). The first stage, P-CNN, encodes foundational visual features from the input image into a latent feature map, which is then fed separately to both FN-CNN and BendNet. FN-CNN then extracts horizontal and vertical feature maps, whereas BendNet generates horizontal and vertical orientation weights to weight the corresponding feature maps, allowing the network to learn the curvature of the lanes. Finally, the combined feature map is used to produce a probability map which in turn yields the desired instance segmentation results. Experiments on the CULane dataset show that CurveNet delivers outstanding performance on curved lane detection and is comparable to other existing methods on regular lane detection.

2 Method

The framework of the pipeline is shown in Figure.1, which consists of three main components: Primary Convolutional Neural Network (P-CNN), Far-Near Convolutional Neural Network (FN-CNN) and Bend Network (BendNet). Firstly, Primary Convolutional Neural Network (P-CNN) encodes foundational visual features from the input image into a latent feature map which is then fed separately to both FN-CNN and BendNet. Far-Near CNN extracts low-level visual

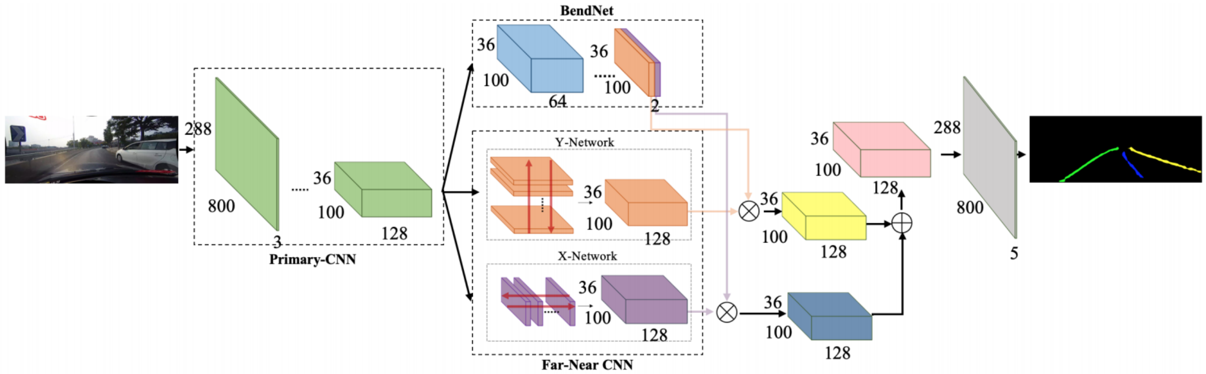

Figure 1: The entire architecture of our multi-stage network CurveNet.

features which are related to both near and far regions of the roadway with respect to the position of the camera (driver), whereas BendNet generates orientation weights to weight the vertical and horizontal feature maps generated by the FN-CNN. These orientation weights generated by BendNet are instrumental in helping the network learn the curvature of the lanes. Finally, the combined feature map (obtained by the weighted sum of the vertical and horizontal feature maps) is used to produce a probability map which in turn yields the desired instance segmentation results. Figure.1 shows the entire architecture of our multi-stage network CurveNet. The architecture consists of 3 main components – 1) Primary Convolutional Neural Network (Primary-CNN), 2) Far-Near Convolutional Neural Network (Far-Near CNN) and 3) Bend Network (BendNet). The Far-Near CNN further consists of Y-network (which produces vertical feature map) and X-network (which produces horizontal feature map). The vertical and horizontal components of the orientation weights produced by BendNet are shown in orange and purple respectively. The Hadamard product of these orientation weights with the corresponding vertical and horizontal feature maps produced by the Y-network and X-network yields the yellow and grey feature maps respectively. These weighted feature maps are then summed to give the fused feature map (shown in pink). Finally, the fused feature map is used to generate the probability map, which in turn yields the desired instance segmentation results.

3 Results

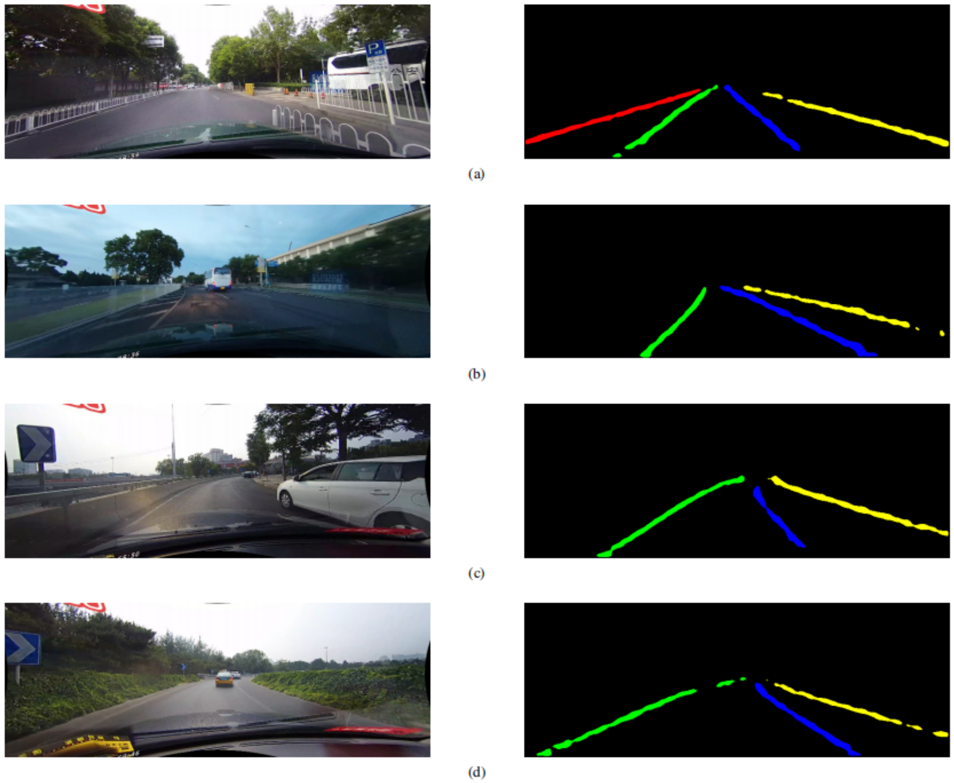

Figure 2: Input images along with the final instance segmentation results are presented.

We test our CurveNet on the CULane dataset, which is a large scale challenging dataset containing 88880 images for training set, 9675 images for validation set, and 34680 images for test set. CULane dataset consists of approximately 55 hours of videos and has 133235 frames. Each image in the dataset has a resolution of 1640x590. Furthermore, the test set is further divided into several challenging categories: curved, crowded, night, no line, shadow, arrow, dazzle light and crossroad. For the ground truth, all the images are annotated with cubic splines. Note that in CULane dataset even if the lane lines are not visible in the images due to occlusion, abrasion or low illumination, the lanes are still annotated. We provide our results for both the normal and the challenging curved lanes in Table 1 below. For evaluation, we follow the widely used evaluation metrics of True Positive Rate (TPR) and False

Approach	**Normal**	**Curved**
SCNN	90.6	64.4
ReNet	83.3	59.9
DenseCRF	81.3	57.8
ResNet-50	87.4	59.8
CurveNet	84.3	61.1

Table 1: Comparison of experimental results of CurveNet with other state-of-the-art methods on normal and curved categories of CULane test set.

Positive Rate (FPR). Table 1 shows the results for both the normal and the curved categories in the CULane test set. Figure.2 shows some instance segmentation results on the curved test set in CU-Lane. We observe that our network CurveNet robustly detects and estimates the curvature of the lanes in the images. Furthermore, it must be noted that our network is also able to adapt to different numbers of lanes in the images (4 lanes in Figure.2a and 3 lanes in Figure.2b – 2d). Closely observing the instance segmentation results yields several interesting insights about the performance of our CurveNet. In Figure.2a, we observe that the network accurately predicts the lane masks with high confidence except in the small region masked by the hood of the car. In Figure.2b, we observe that the network accurately predicts the curvature of the lane masks despite the low illumination conditions. Similarly, in Figure.2c, we observe that CurveNet accurately predicts the sharp curvature of the lanes despite no lane markings on the road. Again in Figure.2d, CurveNet accurately predicts the lane masks for the 3 lanes. It is also interesting to note that the network is less confident about the curvature of the parts of the lane that are occluded by the vegetation (small gaps in the green and yellow lane masks in Figure.2d).