Collaborative Learning Lane Detection Model

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Abstract— **Lane detection is one of the most important tasks for autonomous vehicles and advanced driver assistance systems (ADAS). From image processing algorithms to deep learning approaches, many lane detection methods have been proposed for different purposes. To achieve highly accurate lane detection results with real-time efficiency for different lane types, this research trains a deep learning lane detection model through collaborative learning. The trained model achieves over 95% accuracy under real-time efficiency on TuSimple Dataset and has been shown to be able to detect different lane types in Taiwan traffic scenarios.**

I. Introduction

As the computing power of edge computing platforms increases, many computer vision techniques have been ported to them to become Advanced Driver Assistance Systems (ADAS) or even autonomous vehicles. Lane detection is one of the most important tasks and plays an important role in the Lane Keeping Assistance (LKA) system and Lane Departure Warning (LDW) system.

From image processing algorithms to deep learning approaches, many lane detection methods have been proposed for different purposes[1]. UFLDv2[2] is one of the well-known lane detection models that treat the lane detection task as an anchor-driven ordinal classification problem, completing the inference under really high speed; RCLane[3] proposes its model structure with two auxiliary modules that provide additional information and achieve highly accurate lane detection results. In this study, a deep learning lane detection model trained by collaborative learning[4] based on the concept of UFLDv2 and RCLane was proposed to achieve highly accurate lane detection results with real-time efficiency for different lane types.

To prove the effectiveness of the model design and the whole collaborative learning framework, the improvements related to the auxiliary modules were first evaluated. Then, the lane detection accuracy was calculated on the TuSimple dataset[5]. Finally, we prove that the trained model can deal with different types of lanes through data collected from Taiwan traffic scenarios. The experimental results showed that the trained model achieved over 95% accuracy in real-time efficiency on the TuSimple dataset, and was shown to be able to detect lanes in Taiwan traffic scenarios, including dotted lane lines, solid lane lines, channelizing lines, etc.

II. Procedure for Paper Submission

In order to develop a highly accurate real-time lane detection model for detecting different lane types, collaborative learning was employed in this research. As there are different patterns to complete collaborative learning, a simple intermediate-level representation (ILR) sharing pattern had been adopted, shown as Figure 1. ResNet-34[6] has been selected as the backbone in the proposed network, shown in the blue background in Figure 1. , and its output plays the role of shared ILR for the prediction heads. The grey and yellow blocks shown in Figure 1. are the prediction heads, the grey ones are implemented based on the concept of RCLane and the yellow ones are implemented based on the concept of UFLDv2.

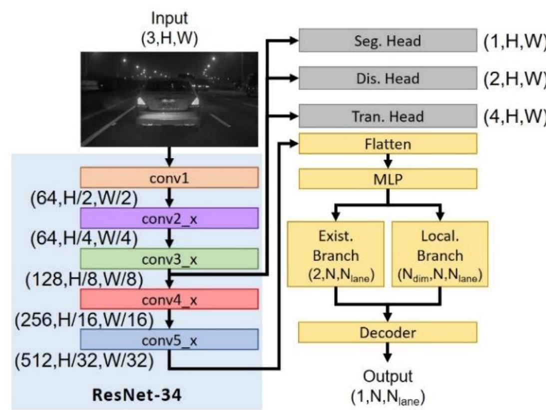

Figure 1. The overview of the collaborative learning framework.

General lane detection methods, solved by segmentation views, predict the probability of each point in the images, which indicates how likely it is to belong to a lane. RCLane deals with the lane detection task based on such output, a segmentation head will predict the probabilities for each position in the images, in addition, two scalars (D_f, D_b) and two vectors (T_f, T_b) representing the absolute distances to the edges and the relative distances between the neighbor lane points for each position in the images are simultaneously predicted. Based on the predicted probabilities, the most likely points can be selected, and based on the absolute distances and relative distances, the lane can be decoded. The lanes detected more accurately with the help of more information provided, which had been proved in RCLane's paper, as a result, we build one of our prediction head based on such concept, for helping to improve the detection accuracy of the whole framework.

To achieve real-time inference, we design our result prediction head based on the concept of UFLDv2, as it's anchor-driven ordinal classification approach achieve high efficiency inference. The output of ResNet-34 is flattened first, then the dimension is reduced by a multilayer perceptron (MLP). There are two branches in the head of the UFLDv2 structure, one is the existence branch and the other is the localization branch. For the existence branch, it provides the probabilities of the existence of each coordinate on the hybrid anchors; for the localization branch, it provides the coordinate

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information related to the hybrid anchors. Based on the output of the two branches, the detected lanes can be decoded.

Since the two prediction heads are designed based on the concept of RCLane and UFLDv2, the loss functions are calculated in the same way, and the loss value for the whole collaborative learning framework is determined by summing the results of the two loss functions with equal weights.

III. Experimental Results

In this section, we will first introduce the datasets we used for the experiment, then the effectiveness of the auxiliary modules will be proved by the datasets. Finally, the lane detection performance and visualization results will be shown.

A. Dataset

We use two datasets in our experiment, one is a public dataset - TuSimple, and the other is a private dataset collected under Taiwan traffic scenarios. The images in TuSimple are collected from US highways, including 6,408 images; the images in the private dataset are collected from Taiwan general roads, including 10,118 images. Both images in the dataset have a resolution of 1280x720.

B. Effectiveness of the auxiliary modules

We prove the effectiveness of the auxiliary modules, including the distance head and transfer head, implemented based on the concept of RCLane by TuSimple dataset, the results shown as TABLE I. . Taking the prediction results from the seg.-head-only model as a baseline, the F1 score and recall are improved no matter whether we apply transfer head and distance head for forward prediction or backward prediction. The detection performance improves even more when we apply both transfer head and distance head, therefore we can observe that the detection performance can be improved under the supervision by applying the auxiliary modules.

TABLE I. Auxiliary Modules Improvement Results

Seg. Head	**Tran. Head**		**Dis. Head**		**F1 (%)**	**P (%)**	**R (%)**
	T_f	T_b	D_f	D_b			
V					52.9	91.19	37.56
V	V		V		54.38 (+1.48)	84.81 (-6.38)	40.6 (+3.04)
V		V		V	61.3 (+8.4)	88.26 (-2.93)	47.65 (+10.09)
V	V	V	V	V	76.3 (+23.4)	84.39 (-6.8)	70.28 (+32.72)

C. Lane Detection Results

Regarding the effectiveness of adopting auxiliary modules for supervision, we trained the whole collaborative learning framework on TuSimple dataset and private dataset. TABLE II. shows the comparison results between the collaborative learning model and UFLDv2, obviously collaborative learning achieves better lane detection performance, which that the lane points are detected more easily and the false detection rate has decreased.

TABLE II. Comparison Results On TuSimple

	Acc. (%)	**F1 (%)**	**FN (%)**	**FP (%)**
UFLDv2[2]	94.85	93.63	6.85	5.88
Proposed	95.06 (+0.21)	94.01 (+0.38)	6.45 (-0.4)	5.53 (-0.35)

We randomly select sample data from the TuSimple dataset and the private dataset, and visualize the prediction result of the proposed learning method and its ground truth, the visualization results are shown in Figure 2. and Figure 3. . The ground truth is shown as red lines and the prediction results are shown as green dots. The visualization results show the ability of the trained model to detect general lane types, including dotted lane lines and solid lane lines, and even special lane types, such as channelizing lines. From the results, we can conclude that the collaborative learning framework has its functionality to improve the model for dealing with different types of lane types.

Figure 2. Fig. 1. Visualization result of TuSimple[5] dataset.

Figure 3. Visulization result of private Taiwan scenario dataset.

IV. Conclusion

This research trains a lane detection model through collaborative learning framework. Based on the experiment results on TuSimple dataset and private dataset, it's effectiveness has been proved. More studies will be done in the future to design more effective auxiliary modules to train a better lane detection model.

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