Lane Detection Based on Deep Learning

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Abstract

Lane detection is a crucial task in autonomous driving. It is a challenging task due to the complex road conditions and the diversity of lane markings. Recent advances in deep learning have shown promising results in lane detection. In this project, we will review the state-of-the-art deep learning methods for lane detection and propose a new method to improve the performance of lane detection. We will evaluate the proposed method on various datasets and compare it with existing methods. The goal of this project is to develop an accurate and robust lane detection system for autonomous driving.

1 Introduction

Lane detection is a computer vision task that involves identifying the boundaries of driving lanes on the road. The goal is to accurately detect and track the lane markings in real-time, even under challenging conditions such as poor lighting, occlusions, and varying road surfaces. Lane detection is a crucial component of autonomous driving systems, as it provides information for vehicle control, path planning, and decision-making, which are essential for safe and efficient driving.

Recent advances in deep learning have shown promising results in lane detection. Convolutional neural networks (CNNs) have achieved state-of-the-art performance on various lane detection datasets. These models can learn complex features from raw images and generalize well to unseen road conditions.

In this project, we will review the state-of-the-art deep learning methods for lane detection and propose a new method to improve the performance of lane detection. We plan to evaluate the proposed method on CULane [1], TuSimple [2] and our own dataset collected in SUSTech campus. We will compare the proposed method with existing methods and analyze the results to identify the strengths and weaknesses of different approaches.

2 Related Work

2.1 Lane Detection with CNNs

Recent studies of lane detection with CNNs can be divided into three categories: segmentation-based methods, anchor-based methods, and parameter-based methods. And we will cover them in the following sections.

2.1.1 Segmentation-based Methods

Segmentation-based methods treat lane detection as a semantic segmentation task, where the goal is to classify each pixel in the image to belong to a lane or background. SCNN [3] proposes a message-passing mechanism to address the no visual evidence problem, thereby improving the performance of lane detection. However, it is slow for real-time application. RESA [4] proposes a real-time feature aggregation mechanism to improve the efficiency of lane detection. CurveLane-Nas [5] uses neural architecture search to automatically design a network for lane detection, but it requires a large amount of computational resources. These methods are generally time-consuming, since they need to process each pixel in the image.

2.1.2 Anchor-based Methods

In anchor-based methods, lanes are represented by x-coordinates at each row of the image. LaneATT [6] uses an anchor-based attention mechanism that aggregates global information. UFLD [7] first proposes a row anchor-based lane detection method and adopts lightweight backbones to achieve high inference speed. CondLaneNet [8] introduces a conditional lane detection strategy based on conditional convolution and row anchor-based formulation. CLRNet [9] uses learnable anchor parameters (x, y-coordinates, angle, and width) to represent lanes. CLRerNet [10] develops a novel row detector based on CLRNet and achieves state-of-the-art performance. LaneFormer [11] employs a transformer with row and column attention to detect lane instances in an end-to-end manner. These method are more adopted as they leverages speed and accuracy.

2.1.3 Parameter-based Methods

Parameter-based methods represent lanes as parametric curves or polynomials. PolyLaneNet [12] uses a polynomial regression model to predict lane parameters. LSTR [13] uses transformer-based models to predict the parameter set of lanes. These methods generally have faster inference speed. However, they have difficulty handling complex lane shapes, especially when the lane shape is not well represented by the chosen parametric model.

2.2 Datasets

2.2.1 CULane

CULane [1] is a large scale challenging dataset for academic research on traffic lane detection. It is collected by cameras mounted on six different vehicles driven by different drivers in Beijing. More than 55 hours of videos were collected and 133,235 frames were extracted. The dataset is divided into 88880 for training set, 9675 for validation set, and 34680 for test set. An example of annotated images and categories in CULane dataset is shown in Figure 1.

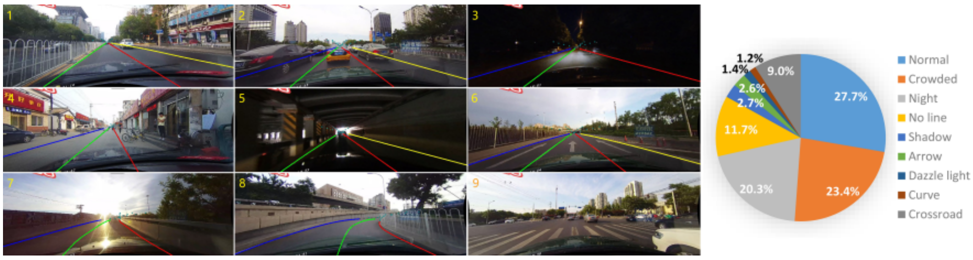

Figure 1: Example annotated images and categories in CULane dataset.

2.2.2 TuSimple

The TuSimple [2] dataset consists of 6,408 road images on US highways. The resolution of image is 1280*720. The dataset is composed of 3,626 for training, 358 for validation, and 2,782 for testing. It is first used in CVPR 2017 Workshop on Autonomous Driving Challenge. An example of annotated images in TuSimple dataset is shown in Figure 2.

Figure 2: Example annotated images in TuSimple dataset.

2.2.3 3D Lane Dataset

In addition to traditional lane detection tasks that requires predicting the lane markings in 2D images, recently, 3D lane detection has attracted increasing attention. In 3D lane detection, the goal is to predict the 3D coordinates of the lane markings in the world coordinate system. The two most popular 3D lane detection datasets are the OpenLane [14] dataset and the Apollo [15] dataset. However, due to the lack of corresponding tools for 3D data collection and annotation, we will focus on 2D lane detection in this project.

3 Completed Work

Currently, we have reviewed the state-of-the-art deep learning methods for lane detection and collected the CULane and TuSimple datasets. The two methods we want to implement are CLRNet and CLRerNet. The former, CLRNet, achieves state-of-the-art performance on the LLAMAS dataset and ranked 4-th on the TuSimple dataset. The latter, CLRerNet, achieves state-of-the-art performance on the CULane dataset.

3.1 Model Architecture

In CLRNet, it first performs detection in high semantic features to coarsely localize lanes. Then, it performs refinement based on fine-detail features to get more precise locations. Progressively refining the location of lane and feature extraction leads to high accuracy detection results. To solve the problem of non-visual evidence of lane, it introduces ROIGather to capture more global contextual information by building the relation between the ROI lane feature and the whole feature map. Moreover, it defines the IoU of lane lines and proposes the Line IoU (LIoU) loss to regress the lane as a whole unit and considerably improves the performance compared with standard loss. The architecture of CLRNet is shown in Figure 3.

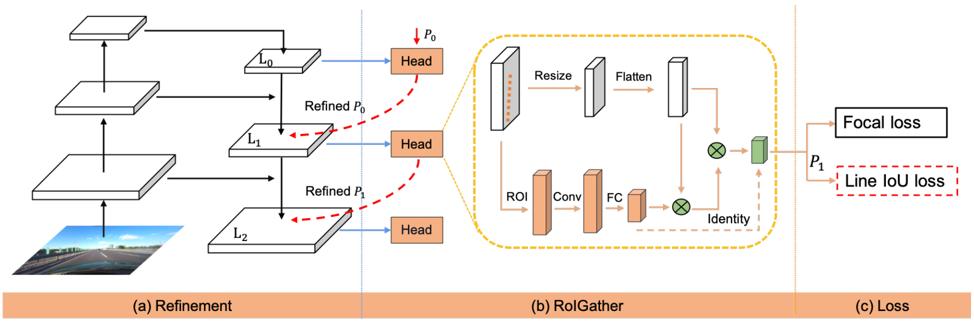

Figure 3: CLRNet architecture.

3.2 Model Inference Outcome

We already trained the CLRNet model on the CULane dataset and achieved a F1 score of 0.79. We are currently training the CLRerNet model on the CULane dataset and expect to achieve a higher F1 score. The results are shown in Figure 4.

Figure 4: Results of CLRNet on the CULane dataset. The blue dots represent the predicted lanes.

4 Research Plan

1. Week 13: Finish training CLRerNet on the CULane dataset and evaluate the performance.
2. Week 14: Implement the proposed method for lane detection and evaluate the performance on the CULane and TuSimple datasets.
3. Week 15: Compare the proposed method with existing methods and analyze the results.
4. Week 16: Write the final report and prepare the presentation.

5 Potential Challenges and Solutions

5.1 Data Augmentation

One of the challenges in lane detection is the lack of annotated data for training. To address this issue, we plan to use data augmentation techniques such as rotation, translation, scaling, and flipping to generate more training samples. We will also explore domain adaptation techniques to improve the generalization of the model to unseen road conditions.

5.2 Inference Speed

Another challenge in lane detection is the inference speed, especially for real-time applications. To address this issue, we plan to optimize the model architecture and use efficient backbones to reduce the computational cost. We will also explore hardware acceleration techniques to speed up the inference process.

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