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Lane Line Detection based on Mask R-CNN

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Abstract. Lane detection plays an important role in driverless system. However, the complexity of the actual road environment makes lane detection more challenging. In recent years, the rapid development of deep learning has pointed out the direction to solve this problem. Deep learning does not care about the change of environment, but only about the diversity of samples. As long as enough samples are trained, the target can be detected and identified. Based on this, a lane detection algorithm based on Mask R-CNN is proposed, which can not only detect lane quickly, but also reach to a total 97.9% of accuracy on our TSD-Max datasets.

Keywords: lane detection; deep learning; the diversity of samples; Mask R-CNN.

1. Introduction

With the rapid rise of artificial intelligence technology, many problems that could not be solved in the past or solved badly have a new problem-solving idea. Especially complex classification detection tasks. Such as lane line detection problems. In the past, traditional methods have focused on the characteristics of lane lines themselves, such as the color, brightness, texture, and line type of lane lines. However, this type of method is powerless when it encounters that the lane line is unclear, occluded, traffic jams, rain, snow, fog and bad weather conditions. In recent years, the rapid development of deep learning has brought about a turning point in the research of this problem. Especially for the problem of classification of processing targets, deep learning has special advantages. When dealing with target detection classification problems, the deep learning method does not need to consider how to deal with the impact of various complex road conditions on lane line detection and identification. These problems are directly handed over to the computer for processing. Only need to collect enough samples to accurately mark the computer to learn the characteristics of the lane line. When the computer sample is rich enough, the number of learning is appropriate, and the computer can accurately detect and identify the lane line accurately. This is why we use deep learning methods.

2. Related Work

In recent years, deep learning methods have achieved great success in computer vision, including Lane detection. [1,2] A lane detection algorithm based on Convolutional Neural Network (CNN) is proposed. Jun Li et al. [3] used CNN and a Recurrent Neutral Network (RNN) to detect lane boundary. In this method, CNN provides geometric information of lane structure, and this information is used by RNN to detect lane. Bei He et al. [4] proposed using Dual-View Convolutional Neutral Network (DVCNN) framework for lane detection. A large number of studies have shown that the neural network as a feature extractor and classifier can improve the performance of lane detection and recognition. Bailo et al. [5] proposed a method of extracting multiple regions of interest, merging regions that might belong to the same class. Finally, the candidate regions were classified by Principal Component Analysis Network (PCANet) [6] and neural network. Kim et al. [1] proposed a lane detection method based on convolution neural network and RANSAC algorithm, which can detect lane information steadily even in complex road scenes. Lee et al. [7] proposed a Vanishing Point Guided Network (VPGNet) based on vanishing point guidance to solve the recognition and classification of lanes and road signs under complex weather conditions. Although the above method

uses deep learning method for lane detection and achieves good results, it still needs further improvement in real-time performance and lane fitting.

Traditional vision-based methods detect lane lines according to the characteristics of camera images, such as color gradient, histogram or edge. Visual-based solutions can be divided into two main categories. One is feature-based method [8-11], which can distinguish feature points of lane lines according to road characteristics such as color, gradient or edge. Chang ChinYu et al. [8] applied a Canny edge detection operator to extract the boundary, and proposed an edge scanning method and Hough transform to verify whether the edge belongs to the lane line. In previous studies [9], they introduced an adaptive region of interest (ROI) and lane location method. Benligiray et al. [10] proposed a fast vanishing point estimation algorithm for lane detection. In previous studies [11], they used Canny edge detection algorithm based on vanishing points and Hough transform for lane detection. Feature-based methods are simple, but they require clear road conditions and strong color contrast.

Another kind of model-based method [12-15] establishes the mathematical model of road structure. They use the geometric coordinates of cameras and lanes as input parameters and depend on their accuracy. In order to determine the parameters, the initial configuration information is merged with the feature points of lane lines extracted from road images. For example, Li Wenhui et al. [12] used extended Kalman filter and B-spline curve model to ensure the continuity of lane detection. Tan Huachun et al. [13] used improved River Flow (IRF) and Random Sample Consensus (RANSAC) to detect curved lanes based on hyperbolic hyperbolic and hyperbolic hyperbolic model. Li Hua et al. [14] used Inverse Perspective Mapping (IPM) model to detect lines in images. Mu Chunyang et al. [15] determined the candidate area of lane line by target segmentation, extracted redundant edges by Sober operator, and detected lane line by piecewise fitting linear or parabolic model. For the model-based method, the difficulty of lane detection lies in solving the mathematical model, so as to accurately fit the lane. The accuracy of detection depends not only on the initial input parameters of the camera or the shape of the road, but also on the feature points extracted from the captured road image.

In order to solve the above problem, we combine the Mask-RCNN [16] network to instantiate the lane line. There are three main advantages: (1) Mask-RCNN network can solve lane line detection in complex situations in road scenes. The training process only needs to be rich enough and accurate to mark, without considering other factors, avoiding the influence of artificial subjective factors; (2) Mask-RCNN's regional suggestion network can be used to roughly locate the lane line, greatly reducing the amount of calculation and improving efficiency; (3) Mask-RCNN can perform instantiation segmentation, improve the detection accuracy of lane line boundaries, and meet the requirements of lane line detection applications.

3. Methods

This section contains three parts, Mask-RCNN network structure, TSD-Max Datasets introduction, and experimental results.

3.1 Mask-RCNN Network

The Mask-RCNN network is a small and flexible general object instance segmentation framework that can achieve the best experimental results. Mask-RCNN is an extension on the Faster-RCNN [17]. A mask layer for segmentation is added to the region of interest to achieve the purpose of instantiating the target. The essence is multi-task learning, adding a mask layer, just adding a small amount of computation to the system, does not affect the overall efficiency of the system, but at the same time get the target detection and instantiation segmentation results. At the same time, in order to ensure efficiency and accuracy, we use a 50-layer deep residual network (ResNet) and a feature pyramid network (FPN). The deep ResNet not only reduces the network training burden, but also has deeper depth than the previous network. The FPN extracts regions of interest from features of different levels according to the size of the feature. In addition, we only label the lane line sample here, that is, this

training is a single task learning, which also greatly reduces the amount of calculation. The Mask-RCNN network structure is shown in Figure 1.

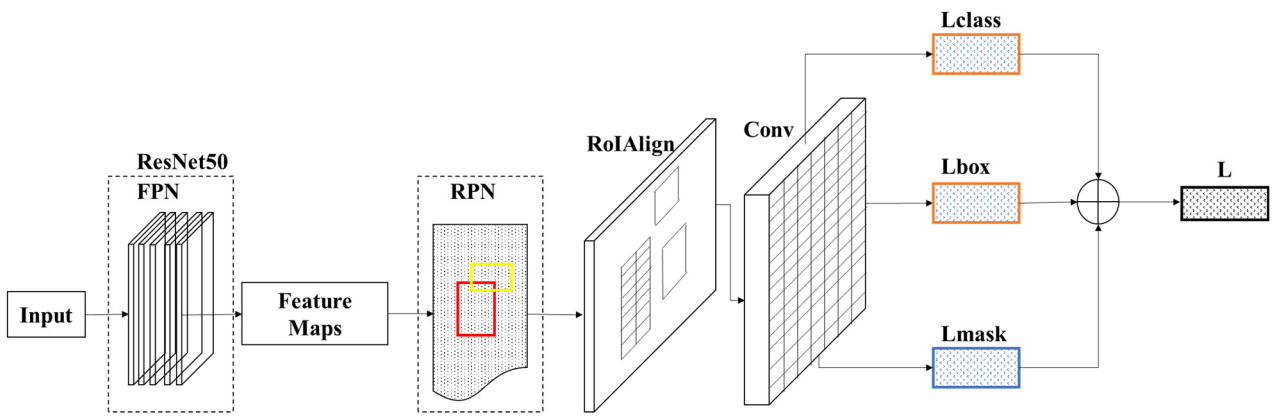

Fig. 1 Mask-RCNN Structure

3.2 TSD-Max Datasets

Our TSD-Max Datasets contains a total of 100,383 sample images, including 9,925 shadows, 11,343 damage, 6,243 less exposures, 15,343 over exposures, 9,561 fogs, 13,290 rains, 8,424 snow stains, 7,789 nights and 18,356 regular road conditions. Which covers the complexities of the actual road scene, ensuring the richness of the sample.

3.3 Experimental Results

We use 4/5 of each category as a training sample and 1/5 as a test sample. After 100,000 iterations, the accuracy rate reached 97.9%, and the different road conditions were tested separately. The detection accuracy is shown in Table 1.

Table 1. All road condition comparing

Road condition	Total	Shadows	Damage	Less exposures	Over exposures	Fogs	Rains	Snow	Nights	Regular
Accuracy(%)	97.9	97.5	98.2	98.6	98.5	96.9	96.4	95.7	97.8	99.9

It can be seen from Table 1 that there is a slight gap in the effect of deep learning in different road conditions. This is mainly due to the difficulty of learning the complicated road conditions. It is also due to the fact that machine learning itself still has certain limitations, whose learning ability can't achieve perfection. However, the overall experimental results, which has far exceeded the height that traditional methods can achieve.

4. Summary

In this paper, we apply the multi-task learning Mask-RCNN network to single-task lane detection to solve the problem of poor adaptability of traditional lane detection methods for complex road conditions. The experimental results show that deep learning can achieve good results in the case of lane detection in complex road conditions, and the detection can achieve 97.9% accuracy.

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