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Lane Line Detection Based on Deep Learning

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1. Introduction:

With the development of autonomous driving technology, lane detection has become an essential component of autonomous driving systems [1]. Firstly, for autonomous driving, lane detection can assist vehicles in navigating automatically under different road conditions, improving driving accuracy and safety. Secondly, in intelligent transportation systems, lane detection can help monitor and manage road traffic flow, reducing the probability of traffic congestion and accidents. Finally, in driving assistance systems, lane detection can provide useful auxiliary information to drivers, such as reminding them whether the vehicle is deviating from the center line of the road. Therefore, research on lane detection is of great significance for improving the safety and efficiency of road travel. The purpose of lane detection is to use image data obtained from sensors such as cameras to identify the lane markings on the road and convert them into vehicle control commands so that the vehicle can follow the lane markings. In the past, traditional computer vision techniques were the main means of lane detection, such as methods based on edge detection, color segmentation, Hough transform, and so on [2]. However, these methods have many problems, such as being sensitive to factors such as lighting and weather, and are easily affected. At the same time, traditional methods often have difficulty effectively dealing with complex road situations, such as vehicle occlusion and multiple intersecting lanes. With the rise of deep learning technology, lane detection based on deep learning has gradually become mainstream. Deep learning technology has powerful non-linear fitting ability and adaptability, can automatically learn feature representations from a large amount of data, thereby improving the accuracy and stability of lane detection [3]. At the same time, deep learning technology can also cope with complex road situations and has strong robustness. Therefore, lane detection based on deep learning has become a hot research direction in the current field of autonomous driving, attracting the attention and research of a large number of scholars and engineers.

Lane line detection faces many difficulties [4], such as the slender shape of lane lines, complex changes in lane lines in real-world scenarios, occlusion, lighting effects, and semantic ambiguity. Moreover, lane line detection algorithms applied to onboard systems require processing of real-time data, placing very high demands on algorithmic responsiveness. How to improve algorithm performance while reducing hardware requirements is another challenge facing lane line detection tasks. Therefore, it is crucial to develop reasonable lane detection methods.

2. Literature Review

The detection of lane lines is an important prerequisite for many advanced driver assistance systems, which requires identifying the lane lines in complex scenarios and obtaining the vehicle's relative position and expected trajectory. After years of development, lane line detection technology has made some progress in terms of speed and accuracy. However, in actual traffic environments, the complex and ever-changing road conditions present significant challenges for detecting lane lines. In the field of computer vision, lane line detection is an important research direction, and currently, lane line detection methods can mainly be classified into three categories: methods based on road features, methods based on road models, and recently developed methods based on deep learning [5].

2.1 methods based on road features

This method mainly extracts some common low-level features such as color, gray scale, edge gradient, etc. [6], and sets appropriate thresholds to segment the image to extract the lane lines. Generally, this method requires preprocessing of the image to remove unwanted noise, using many types of filters, including mean, median [7], Gaussian [8], and FIR [9] filters. To deal with the influence of illumination changes, threshold segmentation [10], including Otsu [11] and PLSF [12] methods, is usually adopted. Region Of Interest (ROI) is usually used to reduce redundant information, and fixed-size ROI [13], ROI based on vanishing point [14], and adaptive ROI [8] have been widely discussed. Color is another information that needs preprocessing, and color space conversion between RGB, YCbCr, or HLS is commonly used to improve the quality of lane lines.

Kang D et al. [15] used the Sobel operator [16] for edge detection, divided the input image frame into sub-regions along the vertical direction, extracted local information candidate lines of the lane in the sub-regions, selected the most prominent lane lines through the DP-based method, and finally demonstrated the feasibility of the method with experimental results of real road scenes. Sehestedt S et al. [17] used a weak model tracking particle filter combined with inverse perspective transformation to detect lane lines. Gao Ruiqin [18] combined SVM and machine learning algorithms, extracted curve lane line features with tower gradient histogram, and tested them with their self-built dataset. The detection rate was greatly improved in foggy weather conditions. In the lane line detection task, since the lane lines have different colors such as yellow, white, etc., methods for detecting lane lines in different color spaces have been proposed. Chiu K et al. [19] detected lane lines based on lane color information. They first selected the region of interest and then used statistical methods to find a threshold that can distinguish the lane lines from the road in the color image. This method is also stable in the presence of noise, shadows, and obstacles on the road surface. Hao C et al. [20] established a Gaussian statistical color model (G-SCM) and used an

improved Hough transform to detect lane lines. Liu Yanbin [21] merged the gradient threshold filtering in the gray scale image and the yellow-white color information filtering in the HSL color space and used the Hough transform algorithm to detect straight lane lines.

The method based on road features has a relatively small computational load and high efficiency, but it can only accurately detect lane lines in relatively simple road conditions, and is easily affected by actual road scenes such as trees, weather changes, etc. The robustness of this method is relatively poor.

2.2 Methods based on road model

The road model-based approach simplifies the problem of lane detection by describing the lane lines using specific mathematical models. Many algorithms model the lane as a straight line, while others use curve models such as parabolic [22], Catmull-Rom [23], and clothoid [24] curves.

Wang et al. [25] proposed a B-Snake lane detection algorithm based on the characteristics of B-Splines, which can detect wide lanes with high robustness. Chen et al. [26] used the RANSAC algorithm to estimate the parameters of a hyperbolic lane model. Wu et al. [27] proposed an image-based edge feature method that switches between straight and curve models based on the lane line's state. Wang et al. [28] reduced the computation load by first selecting the best ROI, then converting the image to grayscale and using the Sobel operator to extract lane line feature points. Finally, the feature points are perspective-transformed to a bird's-eye view and fitted using the least squares method. Li et al. [29] extracted white and yellow lane lines using image color information, used a sliding window method to find the center points of the lane lines, and then fitted them using a parabolic model. Gao [30] proposed an adaptive method that establishes a dynamic ROI based on the lane line's direction and starting point position and determines the lane line model type based on the slope of the lane line's starting point pixel. Then, the approach decides whether to use a straight or quadratic curve to fit the final lane line. Hu [31] improved the segmental fitting method by classifying the lane line's valid points, selecting the segmentation based on the number of valid points, and then deciding whether to fit the lane line using a cubic curve or straight line. This approach is an adaptive segmented curve fitting method.

The road model-based approach considers the geometric characteristics of the road, and selecting a suitable road model can determine the model's coefficients to fit the lane lines. This approach has better robustness than the road feature-based approach. However, selecting the model and parameters is crucial, and the computation cost is also high.

2.3 Methods based on deep learning

With the development of deep neural networks and the improvement of computing power, despite many years of research on traditional methods for detecting lane lines, many researchers have used deep learning methods to detect lane lines. Kim J et al. [32] first used Gaussian smoothing function for image preprocessing, combined with RANSAC algorithm and neural network, and successfully eliminated the interference lines under complex road conditions. Compared with traditional RANSAC algorithm and Hough transform, their performance was greatly improved. Some researchers also treat lane line detection as an image segmentation task. Zhang W et al. [33] used a Global Convolutional Neural Network (GCNN) model to solve the classification and positioning problems of lane line semantic segmentation and evaluated the feasibility of the model with color-based segmentation. Pan X et al. [34] proposed a Spatial Convolutional Neural Network (SCNN) to enhance the ability of convolutional neural networks to capture spatial relationships. They transformed the traditional deep layer-by-layer convolution into a layer-by-layer convolution in the feature map, so that the information between the pixels in the image can be processed between the rows and columns of a layer. This is particularly suitable for detecting continuous and long lane line structures and improves performance, which is more accurate than other networks at the same time. Ghafoorian M et al. [35] proposed the EL-GAN network based on the Generative Adversarial Networks (GANs) framework to better preserve the structure of the output of the semantic segmentation network and reduce the dependence on complex post-processing. They used embedded loss to greatly improve the stability of the adversarial network. This method achieved an accuracy of 96% on the TuSimple dataset. Hou Y et al. [36] proposed a new knowledge refinement method called Self-Attention Distillation (SAD) to solve lane line detection problems in some special scenarios such as severe occlusion, lane blur, and poor lighting conditions. It allows the model to learn from itself and achieve substantial improvements without any additional supervision or labeling. ENet-SAD has fewer parameters and runs faster with good detection performance. Leung L. [37] designed a lane line detection method based on the R-FCN (Region-based Fully Convolutional Networks) object detection network and proposed a method for lane line fitting based on angle estimation. Kuang H. [38] proposed a novel fast spatial attention module and used semantic segmentation method based on convolutional neural networks for lane line detection, improving the situation where the lane line is not obvious or visible. Yuan F. [39] proposed a lane line regression network based on the global grid and verified the accuracy of the detection algorithm on a domestic urban dataset, and designed a lane line fitting algorithm based on K-means and least squares. Wang Shuqi [40] proposed a deep high-level semantic extraction network for lane detection by combining Convolutional Long Short-Term Memory Network (CONV-LSTM) with CNN and DenseNet, to address the problem of missing advanced semantic information in convolutional neural networks. Experimental results showed good performance in both detection accuracy and recognition rate. As most 2D lane detection methods are not robust and effective in various operating conditions, many

3D lane detection methods have emerged. Mátyus G et al. [41] improved the fine-grained segmentation results of ground view by using aerial images, which can identify and simulate all lanes and establish models. Bai M et al. [42] combined LIDAR and camera data for lane detection, where 3D LIDAR points are used to predict ground height and angle.

Since the introduction of deep learning in the field of image segmentation, improving segmentation accuracy has been a popular research direction as an important indicator for measuring semantic segmentation performance. The FCN [43] model first achieved pixel-level segmentation of images, leading to a significant improvement in segmentation accuracy in this field. Most deep learning-based lane detection algorithms proposed to date have been developed based on improvements to the FCN [43] model. In 2018, Davy Neven [44] et al. implemented lane segmentation by establishing a dual-branch network, where the segmentation branch outputs pixels with lane features at pixel-level accuracy and the embedding branch classifies the segmented pixels into different lanes to achieve end-to-end training, solving the problem of incorrect lane number sequencing when changing lanes. Xingang Pan [45] et al. transformed the information propagation direction in the CNN from inward propagation to sequential propagation, allowing better detection of thin lane targets, which improves both detection accuracy and speed. In 2019, Qin Zou et al. [46] considered inter-frame correlations and used the CNN+RNN approach, inserting an LSTM module between the Encoder and Decoder to predict binary segmentation maps of lane images across consecutive frames, achieving better precision, recall, and accuracy. Yuenan Hou [47] et al. designed a self-distillation module that allows simple features to learn complex features to enhance the overall feature representation capability of the network. In 2020, Yuenan Hou [48] et al. decomposed the given road scene image into different regions based on the self-distillation module, representing each region as a node in the graph. Then, a pairwise affinity graph was established between regions based on the similarity of the nodes in the feature distribution to obtain better performance. Liu Bin et al. [49] pruned and optimized the original ENet network, performed semantic segmentation of lanes to segment them from the image, and finally used the DBSCAN algorithm to cluster the segmented results and distinguish adjacent lanes. Zhou Su et al. [50] proposed a three-view adaptive clustering method for imbalanced image data obtained by in-vehicle cameras and designed a new loss function, Tversky Loss, to train the convolutional neural network. Zhao Zhendong et al. [51] designed an end-to-end multi-task network, LDNet-SFE, based on prior knowledge that thin lane lines have strong spatial information. By treating each row of the feature map as a new convolutional layer and applying the principle of layer-by-layer convolution operation to row-by-row convolution, rich spatial information is extracted.

Compared with the other two methods, deep learning-based methods have higher accuracy and better generalization ability, while fully utilizing the feature extraction ability of convolutional neural networks to extract useful features from images. Although this method requires a large

amount of annotated data and higher computational cost, it is more prominent in accuracy and robustness than traditional methods. With the development of computer science, many low-cost, efficient, and robust lane detection methods based on deep learning have emerged.

3. Methods

First, to be clear, I will not use the traditional computer vision techniques. I will use the deep learning-based approach. I will draw inspiration from existing deep learning models proposed by others and make some improvements based on their work. Compare and analyze the results between different networks.

There are some widely-used lane line data sets, and I will choose one or more between them to train and test the model.

(1) TuSimple: A dataset of 72k images located on highways with clear lane markings and sunny weather. The lane markings are annotated using points, and the image size is 1280x720.

(2) CULane: A dataset of 98k images containing eight challenging scenarios, including congestion, nighttime, wireless, and shadow. Up to four lane markings are annotated, and the image size is 1640x590.

(3) Caltech: A dataset of approximately 1.2k images with simple scenes and good viewpoints. The image size is 640x480.

(4) VPGNet: A dataset of 20k images containing various lane types, other lane markings (left turn arrow, straight arrow, zebra crossing, etc.), and daytime and nighttime data, including rainy and heavy rainy days.

(5) BDD100k: A dataset of 120M images containing eight categories of two-dimensional lane markings under different weather conditions during the day and night in four regions in the United States. The image size is 1280x720.

(6) ApolloScape: A dataset of 140k images with lane markings annotated as masks and containing 28 categories of 2D or 3D lane markings. The image size is 3384x2710.

(7) CurveLanes: A dataset of 135k images for curved lane detection developed by Huawei. All lane markings are manually annotated using cubic spline curves, including complex scenarios such as S-shaped and Y-shaped lanes, nighttime, and multi-lane situations. The dataset includes 100k training images, 20k validation images, and 30k testing images with an image size of 2650x144.

TuSimple and CULane are the most commonly used datasets for lane detection research. TuSimple has lower difficulty, with scenes mainly located on highways, while CULane has complex

scenarios, with many scenes located in the city center of Beijing, making it more challenging. I think the choice of which dataset to use depends on the compatibility between the dataset and the algorithm. By far I am still considering which algorithm and dataset to use, or use self-made dataset instead of open-source dataset.

Here are some deep learning algorithms for lane detection. I plan to make improvements based on some mature algorithms.

3.1 Lanenet^[52]

Lanenet is a deep learning-based algorithm for lane detection, whose main idea is to divide the image into two parts: lane region and non-lane region. The main steps of Lanenet include feature extraction, semantic segmentation, clustering, curve fitting, and binarization. Firstly, Lanenet uses an encoder-decoder network to extract features from the input image, generating a feature map. Then, the semantic segmentation network is used to classify each pixel in the feature map into different categories, where the lane region is classified as the foreground and the non-lane region is classified as the background. This step effectively distinguishes the lane region from other areas. Next, Lanenet clusters the pixels in the foreground region to identify different lane instances. For each lane instance, Lanenet uses a curve fitting algorithm to fit a curve model of the lane line, determining its position and direction. Finally, the model is applied to test images, and pixel-level binarization is performed to output the position information of the lane lines. The binarization process marks the position of the lane lines as a binary value, achieving lane detection.

Compared with other lane detection algorithms, Lanenet has multiple advantages. For example, Lanenet can detect not only single-instance lane lines but also multiple-instance ones, and it has high accuracy and real-time performance. Additionally, Lanenet is adaptable to different weather and lighting conditions, exhibiting strong robustness and adaptability. Finally, Lanenet has been validated on multiple datasets, demonstrating its outstanding performance in lane detection.

3.2 SCNN^[53]

SCNN (Spatial CNN) is a convolutional neural network-based algorithm for lane detection. It uses a convolutional neural network to extract image features and pixel-level classification to achieve lane detection. The main idea is to divide the image into different pixel levels and classify each pixel to recognize the lane lines. Firstly, SCNN uses a convolutional neural network to extract image features and generate a feature map. Then, the feature map is passed through a spatial convolution layer, where each pixel in the feature map is convolved with surrounding pixels to generate a new feature map. Through multiple convolution operations, each pixel in the feature map can obtain more comprehensive contextual information. Next, SCNN uses a softmax classifier to

classify each pixel in the feature map. The loss function used in the classification is cross-entropy loss function, which optimizes the classification results and improves the accuracy of the model. By classifying each pixel, SCNN can detect lane lines and classify different types of lane lines, including solid lines, dashed lines, and road edges. Finally, SCNN outputs the position information of the lane lines through pixel-level binary segmentation to achieve lane detection.

3.3 LaneCNN^[54]

LaneCNN is a convolutional neural network-based algorithm for lane detection, which mainly utilizes CNN to extract features and classify images for detecting lane markings. The main steps of LaneCNN include feature extraction, segmentation, and post-processing. LaneCNN uses a CNN to extract features from input images. To extract features with more semantic information, LaneCNN uses depthwise separable convolution to reduce the number of parameters and uses dilated convolution to enlarge the receptive field. In the feature extraction stage, LaneCNN can effectively extract the lane features from the image. LaneCNN uses the CNN to segment the feature map and separate the lane pixels from the non-lane pixels. This step can separate the lane from other regions for further processing. LaneCNN uses a fully convolutional network to achieve pixel-level segmentation, which can maintain accuracy while achieving faster inference speed. Finally, LaneCNN performs post-processing on the segmented lane to remove noise and fill gaps. LaneCNN uses polynomial fitting to fit the curve model of the lane markings and sliding window methods to smooth the shape of the lane markings. Through these methods, LaneCNN can effectively reduce false detection and missed detection rates, and improve the accuracy and robustness of lane detection.

3.4 LaneATT

LaneATT is a lane detection algorithm based on attention mechanism, which aims to improve the focus on the lane region for more accurate detection. The main steps of LaneATT include feature extraction, attention mechanism, segmentation, and post-processing. LaneATT uses a convolutional neural network to extract features from the input image. To extract more discriminative features, LaneATT utilizes multiple layers of convolution and pooling operations. During the feature extraction phase, LaneATT can effectively extract the lane features from the image. LaneATT uses an attention mechanism to enhance the focus on the lane region. Specifically, LaneATT introduces an attention module to learn the dependencies between pixels, thereby enhancing the expression of the lane features in the feature map. This step allows the model to focus more on the lane region, thereby improving the accuracy and robustness of lane detection. Then, LaneATT uses a convolutional neural network to perform pixel-level segmentation on the feature map, separating the lane pixels from the non-lane pixels. This step separates the lane region from other regions for

subsequent processing. LaneATT uses a fully convolutional network to achieve accurate and fast inference. LaneATT performs post-processing on the segmented lane lines to remove noise and fill gaps. LaneATT uses a sliding window method to smooth the shape of the lane lines and a quadratic curve fitting method to fit the curve model of the lane lines. Through these methods, LaneATT can effectively reduce error detection and missed detection rates, thereby improving the accuracy and robustness of lane detection. Compared with other lane detection algorithms, LaneATT has better robustness and accuracy. It can adapt to different lighting and weather conditions and detect lane lines in complex scenes. Additionally, LaneATT has high real-time performance and low computational complexity.

3.5 FOLOLane

FOLOLane is a lane detection algorithm based on the fusion of global and local features. The main idea is to combine global and local information to improve the accuracy and robustness of lane detection. The main steps of FOLOLane include image pre-processing, global feature extraction, local feature extraction, feature fusion, and lane fitting. FOLOLane pre-processes the input image, including denoising, grayscale conversion, and binarization. This step can remove noise and interference from the image, and extract useful image features. It uses a convolutional neural network to extract global features. To extract more discriminative features, FOLOLane uses multiple convolution and pooling operations. In the global feature extraction stage, FOLOLane can effectively extract the overall feature information from the image. Then, it uses a convolutional neural network to extract local features., and a sliding window to divide the image into blocks and extracts local features of each block. This step can capture the local features of the lane, thereby improving the accuracy and robustness of lane detection. Next, FOLOLane fuses the global and local features. Specifically, it inputs the global and local features into two different classifiers, and then fuses their output results. This step can combine global and local information to improve the accuracy and robustness of lane detection. FOLOLane uses curve fitting methods to fit the curve model of the lane. It uses a quadratic curve model to fit the shape of the lane, and calculates the curvature of the lane using the least squares method. Through these methods, FOLOLane can accurately detect and fit the shape of the lane.

4. Results

1. Confusion matrix: Presenting the algorithm's accuracy and error metrics on both the training and test sets, such as acc, FP, FN, etc., and analyzing the performance differences of different parameters or models.

2. Image Examples: Using sample images to illustrate the differences between the algorithm's detected lane lines and the ground truth labels. These examples can be used to demonstrate the algorithm's performance and quality.

3. Visualization Results: Visualizing the algorithm's detected lane lines and labels on input images using tools such as OpenCV, and conducting comparison and analysis.

4. Video Demonstration: Using video demonstrations to display the algorithm's performance in real-time scenarios.

5. Evaluation

Firstly, I will describe how the experiment is designed, including the dataset used, evaluation metrics, evaluation methods, and experimental environment. I will then perform accuracy and error analysis, providing accuracy and error metrics on the test set and analyzing performance differences based on different parameters or models. I will compare my algorithm with existing ones and analyze its performance on various evaluation metrics. I will conduct a detailed analysis of the experimental results, including the strengths and weaknesses of the algorithm, false detection and omission rates, and performance bottlenecks. Finally, I will draw conclusions summarizing the performance and limitations of the algorithm, propose possible future directions for improvement and research.

6.Ethical consideration

The use of deep learning for lane detection in autonomous driving has the potential to improve road safety and reduce traffic accidents. However, as with any new technology, there are ethical considerations that need to be taken into account.

One ethical concern is the potential loss of jobs for drivers as autonomous vehicles become more prevalent. Although the implementation of autonomous driving is still far away, this could have a significant impact on employment and the economy, particularly in industries such as transportation and logistics. Additionally, the use of autonomous vehicles raises questions about liability and responsibility in the event of accidents. Who is responsible if an autonomous vehicle causes an accident? How will insurance policies be affected? These are important questions that need to be addressed as the technology continues to develop.

There is the issue of privacy and data security. The data used for training the lane detection model should be open source or obtained with the authorization of others, and should not violate personal privacy.

7.Timetable

Currently, I have several coursework assignments to complete, and I will focus on research work related to my paper after May 4th. In May, my main task is to run open-source code and reproduce existing models on some open-source datasets.

In June, I plan to make improvements to the network model and test the performance on some self-made datasets.

In July, I will further optimize the algorithm models and may conduct comparative experiments to compare the strengths and weaknesses of different algorithms under different scenarios. Starting in late July, I will begin to organize the data and start writing the dissertation.

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