Lane Detection for Driverless Vehicle: A Survey

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Abstract

Under the intelligent transportation system, the driving of unmanned vehicles depends on lane keeping. Lane keeping technology, as one of the core technologies of smart cars and an important guarantee of driving safety, has gradually attracted public attention. In actual driving, the detection of lane is the core of its control thought, and there are many methods. Lane detection is regarded as the core requirement for the development of each intelligent transportation system. The extracted lane information can be used in a variety of intelligent applications to avoid collisions with other vehicles. In our work, we mainly study the lane detection from the two mainstream methods of traditional image processing and deep learning, summarize the main functions and existing problems of the two methods, and look forward to the direction worth studying in the future.

Keywords

Driverless Vehicle, Intelligent Traffic, Lane Detection, Traditional Image Processing, Deep Learning.

1. Introduction

With the gradual improvement of living standards and the rapid development of science and technology, people's demand for intelligent transportation system is becoming stronger and stronger. Intelligent Transportation System (ITS) is the effective comprehensive application of advanced scientific technology(information technology, computer technology, data communication technology, sensor technology, electronic control technology, automatic control theory, artificial intelligence, etc.) to transportation, service control, vehicle manufacturing and strengthen the connection between vehicles, roads, and users to form an integrated transportation system that guarantees safety, improves efficiency, improves the environment, and saves energy. Therefore, it can manage noise, pollution, congestion, etc. while improving the comfort and safety of goods and personnel, and optimizing the management of infrastructure and public policies related to the entire transportation system [1]. These facts have led many researchers and car manufacturers to focus on the development process of the automotive industry. With this, the development of Advanced Driver Assistance Systems (ADAS) has matured the technology and accelerated the development of autonomous vehicles. Technology related to lane detection is not only the first step towards semi-autonomous driving, but will also open the way for fully automated and advanced autonomous vehicles.

Lane detection is to detect the white or yellow marking line on the painted road surface, and draw it to limit the boundary of the lane, as shown in Figure 1.For our research project, it is difficult and challenging to define a consistent and robust lane detection system, and the important factors of lane detection are the diversity of lane appearance, lane marking and lane width are existing indistinguishable variants and are not standardized. In addition, vehicles near the lane will also cause

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serious blocking to the detection lane, and bad weather conditions such as excessive light, haze weather, tunnel environment, night conditions and so on will limit the performance of the system.

We are using multiple modules to construct reliable results for lane line detection. Light Detection and Ranging (LIDAR) are usually also possible solutions for lane detection, and Geographic Information Systems (GIS) are also used as important supplementary global positioning information for vehicles. The vision-based method using cameras is the most important research area of lane detection, because marking is carried out for human vision, and lane marking only appears in the visual domain, which is usually correct. Therefore, the lane detection system cannot be realized without referring to the visual mode.

This paper makes some investigations on lane detection methods, which are mainly vision-based systems, while vision-based systems are mainly divided into two categories: traditional image processing and deep learning methods. At present, many companies are still using traditional image processing methods to solve the problem. In the actual scene, the traditional methods have low robustness and are vulnerable to environmental interference. In recent years, with the rapid development of deep learning, the recognition rate of lane detection has been significantly improved [2], and the method based on deep learning has good robustness. Deep learning has the ability to deal with complex recognition tasks quickly and accurately, so it is widely used in various fields [3], including intelligent transportation [4]. We will introduce the overview of traditional lane detection methods in section 2 of this paper, introduce the overview of lane detection based on deep learning method in section 3, summarize it in section 4, and put forward some suggestions in the future.

Fiqure 1: Lane Detection

2. Traditional Method

Lane detection is mainly used in autonomous navigation system, lane maintenance auxiliary system, lane departure warning system and so on. Only when the driverless vehicle accurately knows the location of the lane, can the autonomous navigation system plan the appropriate driving route, and the driverless vehicle can correctly make driving behaviors such as lane change, acceleration and so on. At present, there are many ways to detect the lanes of driverless vehicles. In traditional methods, using a relatively simple algorithm based on Hough transform, without any tracking or post-processing, can solve about 90% of the problems in highway cases [5]. This section mainly introduces the traditional methods of lane detection.

2.1 Generic Model

We analyze the existing vision-based literature [6], [7] and come up with a general method to process the images collected from the road environment for lane detection. Figure 2 shows the general system: that is the general function decomposition of the lane detection system. Generally speaking, lane detection based on visual perception algorithm includes widely used modules, although these modules are implemented differently in different systems. Based on the commonness between algorithms, the system is universal, almost all the algorithms we encounter can be mapped to the subsystem of the

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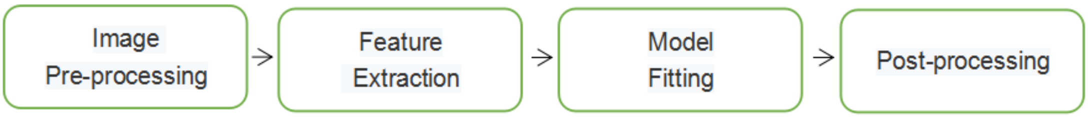
system, and the most mature system has almost all modules. The main module we identified is shown in figure 2.

(1) Image Preprocessing: Effectively preprocessing the collected road images is an important link to achieve accurate detection of lane. Preprocessing can remove the redundant information that is useless in lane detection, reduce the interference caused by the external environment, and thus improve the accuracy of lane detection.

(2) Feature Extraction: Low-level features are extracted from the image for lane detection. For lane detection, lane marks are collected for feature extraction, and completely different features are found for each estimation task in the feature extraction module. According to the different methods, the method of lane feature extraction can be divided into the method based on color feature and the method based on edge feature.

(3) Model Fitting: The hypothesis of road and lane is formed by fitting the lane model. The purpose of lane model fitting is to extract a more compact high-order representation path and use it for path decision-making. a lane is usually uniquely determined by its boundary point or the road width of its centerline and transverse range. The commonly used geometric models of road shape are linear model, curve model and piecewise function model.

(4) Post-processing: The extracted lane model is post-processed to correct some errors to improve the accuracy of lane recognition. Commonly used are a variety of clustering methods and lane tracking and so on. Because in the picture sequence or video sequence, the lane has a considerable time correlation between the adjacent frames, the lane position information obtained from the previous image can guide the detection of the next frame. The image information of the current frame is modified to realize the real-time tracking of the lane.



Fiqure 2: Generic Model for Lane Detection

2.2 State of Art

In the process of vision-based lane detection, it is easy to be disturbed by external environment, such as the shadow of trees, the text of the road, the driving vehicles and so on. In addition, the shape of the lane in the real road scene is also different, which can not be described by a fixed geometric model. The main purpose of the preprocessing stage is to eliminate the influence of noise on the image, which helps to reduce the false positives. Each reliable lane detection system should be able to adapt to a variety of lighting environments such as sunlight, shadows, tunnels and so on. Dealing with such situations and taking these factors into account is a decisive step in correctly extracting features from collected images.

Reviewing the development of lane detection algorithm [12], traditional lane detection methods rely on highly specialized and handmade features to detect lane [8]. These feature selections include color-based features [9, 13], ridge features [10], texture features [11], edges [14], gradients [15] and so on. According to these features, the lanes are separated from the road region, and the lanes can be clearly identified, thus the position of the vehicle relative to the lane and other information can be obtained. This method is called feature-based method. Another method of lane detection is to abstract the lane into an appropriate geometric model, and then obtain the parameters of the geometric model to fit the corresponding lane. The commonly used geometric models include linear model [16], linear parabolic model, hyperbolic model and spline model [17].

Yu Zhaowei [18] proposed a lane detection algorithm based on dynamic region of interest and overcoming illumination change, which converts lane detection to YCbCr color space, looks for white

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line region in Y space, yellow line region in Cb space, combined with image binarization, detects lane by Hough transform. Guo Keyou et al. [19] combine the LDA (Linear Discriminant Analysis) algorithm with the LSD (Line Segment Detector) algorithm, first use the LDA algorithm to preprocess the road image, and then use the LSD algorithm to detect the lane. Cai Yingfeng et al. [20] proposed an improved lane detection method based on Hough transform. After preprocessing the image, the algorithm uses the sobel operator to enhance the edge preprocessing, and then uses the local optimal threshold method to binarize the behavior unit, which can better screen the lane feature points. Lee et al. [21] proposed a lane detection algorithm which combines lane gradient information and color information, and combined with scan line technology to realize lane detection in bad night environment. Yoo et al. [22] convert the urban road image from RGB space to grayscale image based on LDA technology, and can adaptively adjust the gray value according to the illumination change, so that it can adapt to different lighting scenes. The feature-based lane detection method is analyzed from the bottom features of the image, in order to strengthen the lane features, we strengthen the underlying features such as color, edge, gradient and so on. In order to overcome the interference of light, shadow and so on, the corresponding feature design is targeted, these feature design methods need a lot of expert knowledge in some cases, and the skill is very strong. Therefore, the feature-based lane detection algorithm can achieve good results in some specific scenes, but it is often not effective in other scenes.

The model-based lane detection algorithm generally establishes the lane into an appropriate geometric model. Then the geometric model parameters of the lane are obtained by post-processing methods such as random sampling uniform algorithm (RANSAC), least square method and Hough transform, and finally the corresponding lane is fitted according to the model parameters. Li et al. [23] first divides the lane detection area into upper and lower parts, and then uses the B-spline model to determine the lane parameters in the lower part of the lane area, and then carries on the further detection combined with the vanishing point. Peng He et al. [24] successfully fitted curved lane lines on semi-structured roads by using Catmull-ROM spline curve combined with Hough transform. Hur et al. [25] generate super-pixel points according to the direction and angle information of lane pixels, establish a conditional random field model, and then optimize the model parameters by energy minimization to realize multi-lane detection on the road scene. Song et al.[26]designed a model based on geometric moment sampling to detect the lane, and successfully overcome the interference of noise in the lane.

Chen et al. [27] carried out night detection and observed the effect of night on the road color space, so they provided conversion on the RGB channel. Do et al. [28] proposed a view-based lane detection method, which uses the ridge image based on its histogram to apply adaptive threshold, and morphological bridge connection to eliminate the noise of the interference intermediate axis, and then carries out the intensity check to complete the operation. Noise reduction is a conventional preprocessing step to improve the results of edge detection. The median filter [29] is a nonlinear filter, which is usually used to reduce noise. Canny edge detection operator is a multi-stage edge detection method. Canny edge filter is often used [30]. This algorithm finds the contour by testing the norm and gradient direction of the image. If the norm of one of its two adjacent points is larger than the norm of the gradient, then the gradient of the non-local maximum will be suppressed. Because the Canny operator only considers the amplitude, [31] proposed to use convolution operators such as Sobel filter to calculate the gradient amplitude and its direction. Some lane feature extraction uses symmetrical local threshold [32].This method uses local image information instead of global image information, and focuses on local phenomena. A scan window range is applied to each input pixel (x, y) to calculate the average intensity. For points to be marked as driveway features, the intensity of each pixel should be greater than that of its adjacent pixels, so that the points will be mapped. Kim et al. [33] proposed a forward collision early warning system with integrated lane detection module. The algorithm of this lane detection module is based on a single camera input to define the Region of Interest (ROI). ROI is part of the image, by the boundary definition, and then through the Inverse Perspective Mapping (IPM) [34] to detect the lane of candidates. The IPM allows the perspective effect to be removed from the collected image, remapping it to a new two-dimensional domain, and finally using a Kalman filter to track the next lane. Bottazzi et al.[35] proposed a lane detection algorithm based on histogram, which makes use of illumination invariance. Duong et al.[36]proposed a method to generate aerial view mapping, which is simpler than IPM's method. Aerial view mapping eliminates noise and perspective of deformed perspective mapping. In the process of edge detection, the image is processed, and each pixel value is compared with the left and right neighborhoods to generate an edge map to remove noise. Morphological open operation is also applied in this process. Then Hough transform is used to detect the lane and finally complete the lane fitting. Tsai et al.[37] used Sobel edge detector and boundary recognition to establish a new lane detection algorithm in gradient direction. The gradient orientation is ensured by the application of the circular mask, and the initial gradient is determined by the directional maximum histogram bin. Finally, the third-order polynomial is used to fit the lane. Y. Yenİaydinetal et al. [38] use the "neighborhood and operator" method, in this method, the feature is extracted by Sobel operator, and the aerial view is obtained by IPM. Finally, the lane detection model with least square error is established.

3. Deep Learning Method

3.1 State of Art

In recent years, thanks to the improvement of computer computing ability, deep learning—a data-driven technology, has been successfully applied in various fields. As deep learning has made breakthroughs in the fields of image classification [39], target detection [40] and semantic segmentation [41], a large number of scholars have begun to try to use deep learning technology to solve the problem of lane measurement. Due to the great success of convolution neural network, many researchers detect lanes based on convolution neural network. Convolution neural network (CNN) classifies lane and background in the form of feature extractor and classifier [42]. [43] an 8-layer CNN is used for lane detection. [44] A 7-layer CNN is used to complete the classification of lanes and background pixels based on the side view.

With the improvement of detection accuracy and efficiency of R-CNN [45], Faster-RCNN [46], YOLO [47] and other network models, researchers introduce target detection network into lane detection system. Huval et al.[48]proposed an algorithm for lane detection using traditional convolution neural network, which is the first time to apply depth learning to lane detection. The author uses laser point cloud information to label the lane, but limited by the convolution neural network structure at that time, the algorithm is complex and time-consuming. Gurghianet et al.[49]proposed the DeepLane network structure for lane detection, adopted a new way to collect lane pictures, captured a large number of videos from transversely installed cameras, and modeled the lane detection problem as a classification problem. Heet et al.[50]designed a dual-view CNN (DVCNN) network structure, which collects the front view and top view pictures of the road scene, and uses the front view information and top view information to eliminate road interference, such as passing vehicles, guardrails, road signs, arrows and so on. The dual-view method improves the accuracy and robustness of detection than the previous method. SeokjuLee et al. [51] designed a multi-task convolution network structure (VPGNet), and used the vanishing point information to further define the location of the lane, so that it can detect the lane in real time more accurately, adopted a new way of grid to label the lane, and modeled the lane detection problem as a regression problem. BailoO et al.[52]use the maximum stable extreme region algorithm to extract multiple regions of interest, merge regions that may belong to the same class, and finally classify the candidate regions by PCANet [53]and neural network. Liang [54] proposed two deep learning lane detection methods: one is to determine the candidate region according to the gray characteristics of the lane, and then use CNN to distinguish between the lane and the non-lane; the other is to use the target detection network R-FCN to detect the lane, so as to complete the location and classification of the lane. VanGansbeke et al.[55]proposed a method of training lane detector for end-to-end direct regression of lane parameters. The biggest highlight is undoubtedly that the Least-Squares Fitting method is added to Network, and using its differentiable properties, arealoss is designed and backpropagation, is designed to prove the

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feasibility of direct regression fitting parameters. [56] A new method of knowledge distillation, self-attention distillation (SAD), is proposed, which allows a model to learn from itself and obtain substantial improvements without any additional supervision or labeling. SAD can be easily integrated into any feedforward convolution neural network (CNN) without increasing reasoning time. Chougule et al. [57] proposed a regression method based on CNN, which puts the problem of lane detection and classification on the CNN regression task, which relaxes the classification requirements of each pixel to several points along the lane boundary, which is used to detect multiple lanes and classify their locations without any post-processing or tracking operations. Chang et al. [58]proposed a new multi-lane detection method: the pre-processing of the input frame is fed back to the lane marking segmentation network, which divides the visible lane marking pixels, and then uses the graph-based method to detect the segmented lane marking example. The perspective transformation (aerial view) is applied to the example setting output, and then the classification method based on attention voting and polynomial curve fitting are used to provide the final output. Garnett et al.[59] proposed a network that can predict the 3D layout of lanes in a road scene directly from a single image. This work marks the first attempt to use on-board sensing to solve this task, rather than relying on a pre-mapped environment.

Because the output of the target detection network can not accurately represent the boundary of the lane, the semantic segmentation network [60] has the ability to classify the image pixel by pixel. The researchers proposed a series of variants based on pixel segmentation and case segmentation [61,62]. FCN network [63] is the first time that deep convolution neural network can realize end-to-end semantic segmentation. LaneNet [61] regards the lane detection in the image as an instance segmentation problem, an end-to-end model, and trains the instance segmentation network to output each lane as an instance, thus dealing with any number of lane. Li Songze [64] of Harbin University of Technology proposed to use convolution neural network instead of manual filter operator, using the symmetrical structure of Convolution and Deconvolution to segment the lane on the highway at the instance level, and get the pixel information of each lane region, and then use the least square method to regression the lane parameters and feedback the lane parameter equation. Zhu et al. [65] proposed a road detection method based on convolutional neural network, which uses the idea of image coding and decoding to extract low-scale image features and realize the pixel-level classification of road regions. Pizzati et al. [66] developed an end-to-end deep learning method based on the connection of multiple neural networks, which is used to perform the segmentation and classification of lane boundary instances. First, CNN is trained to segment the lane boundary instance, then a descriptor is extracted for each detected lane boundary, and the second CNN is used to process it. This method can achieve real-time high precision. Ghafoorian et al. [67] proposed that EL-GAN, is used to overcome the inherent exception of taking it as a semantic segmentation problem. By using the generative countermeasure network structure of a discriminator that trains prediction and tags at the same time, the structure is applied to those problems that are mistakenly proposed as semantic segmentation; compared with the normal adversarial loss criterion, embedded loss has stable training and produces more useful gradient feedback, and does not require additional engineering loss conditions or complex post-processing, resulting in better prediction quality similar to tags. U-Net[68] was originally used as a binary semantic segmentation model for medical images, which is mainly used to obtain the edge of the image. This network uses data enhancement method to achieve better segmentation accuracy by using a small amount of data training, and the speed of the network is very fast. Using this network structure in lane detection can improve real-time performance. Koltun et al. [69] proposed hollow convolution, which is mainly aimed at the convolution strategy that down sampling in image semantic segmentation will reduce the resolution and lose information. It expands the receptive field but does not increase the amount of computation, and retains more image information, which can be used in lane detection to improve the accuracy.

However, the methods of semantic segmentation also have the problems encountered by traditional feature detection methods, that is, missed detection caused by small proportion of targets in the image, misdetection caused by lane occlusion, insufficient use of information caused by obvious structural

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features of lane, etc., which affects the improvement of the accuracy and recall of lane detection technology [70]. Drawing on the achievements of traditional lane detection methods in spatio-temporal image, vanishing point, lane width and shape, and lane trajectory [71,72] the researchers introduced these methods into the depth neural network. [73] two-level semantic segmentation network is used to improve the accuracy of lane boundary detection. [57] the bicycle lane coordinate vector composed of 15 points is used to avoid the problem of inaccurate lane boundary detection. [51] the vanishing point detection task is added to the multi-tasking network to improve the overall accuracy of the network. Pixel blocks are used instead of regression, and pixel blocks are used to represent the lane boundary. [74]The traditional layer-by-layer convolution is replaced by layer-by-layer convolution in the feature graph, this network structure is called SCNN. This architecture increases the information flow between cross-row and cross-column pixels, and increases the weight of lane structure in the network. This spatial structure is especially suitable for the detection of long continuous shape structure objects, such as lane and telephone poles. In the future work, we can consider introducing PSPNet [75] (using pyramid pooling module to aggregate context information from different regions)into SCNN structure, so as to improve the ability to obtain global information and further improve the detection accuracy.[76] RNN is introduced into the feature detection module, RNN can encode the output structure and save the internal state from one instance to another, which accords with the characteristics of many targets and structure correlation in lane detection. The network structure of lane detection combined with CNN and RNN is based on the codec framework, which takes multiple consecutive frames as input and predicts the lane in the current frame by a semantic segmentation method. [77,78] It is verified that RNN can detect lanes successfully without a priori and without lane marking, and a more robust feature detection model is obtained.

3.2 Evaluation Criteria

In order to compare the performance of different methods, it is necessary to establish a common benchmark to measure the performance of each method. Due to the lack of recognized data sets and performance indicators, there is no unified benchmark in the relevant lane detection literature. KITTI dataset [79] is one of the most widely used data sets in self-driving academic circle. Target detection includes vehicle detection, pedestrian detection and bicycle. Target tracking includes vehicle tracking and pedestrian tracking. Road segmentation includes urbanunmarked, urbanmarked, urbanmultiplemarked and the average urbanroad of the first three scenes. TuSimple lane dataset [80] has a total of 72000 pictures, located on the highway, the weather is sunny, the lane is clear, characterized by the lane line marked by dots, but there is a serious data imbalance between classes. The CULane dataset [74] contains 133235 images, including a variety of weather, lane heavy occlusion, lane wear and other scenes, but only bike lanes and adjacent lanes are marked. The BDD100K dataset [81] contains 100000 images, the data set is very comprehensive, and the lanes and driveable areas are marked, adding continuity and direction to the lanes. The Lane Segmentation subset [82] of the Apolloscapes dataset contains more than 110000 stereo images, which are pixel-level semantic segmentation annotations based on a variety of complex weather. The number of images, image acquisition conditions and image acquisition locations in the above datasets are different, the types and corresponding numbers of lane contained in the images are also varied, and the labeling of lane attributes is also inconsistent. it is difficult to form a unified and standard public dataset. We need a large dataset that can be robustly identified in challenging scenarios. On the basis of large datasets, we unify the test protocols and performance indicators of lane detection, and provide a benchmark for different methods. This is also the direction of development in the future.

4. Conclusions

This paper introduces the lane detection method of driverless vehicles, which enables readers to have a clearer and in-depth understanding of the technical development and application in this field, and provides a reference basis for researchers in this direction to a certain extent. The automatic control system technology of self-driving vehicles has gradually become a hot topic in recent years, and some

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practical experiments about self-driving vehicles are also being carried out at the same time. Therefore, it is particularly important to do a good job of lane detection for the research and development of related systems.

Most of the existing lane detection methods are based on vision or lidar, and they are very easy to detect. Most of the traditional lane detection methods need to adjust the parameters manually, which is difficult to get the optimal parameters, and the robustness of the algorithm is poor, while the deep learning detection method has achieved ideal results in many datasets and can be applied to bad driving scenes. Robustness is good, but the detection accuracy is relatively low, lack of common datasets, but the future is unlimited. Therefore, the main research work in the future is mainly devoted to the deep learning method for lane detection, especially in the scene of lane damage and bad, through continuous training and optimization of the network model to improve the detection accuracy.

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