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Lane Detection: A Survey with Evolving Methods

Sangram Nangare[1*], Sohel Shaikh[2], Prashant G. Tandale[3], Ajay Kumar[4]

[1,2] MCA Students, Bharati Vidyapeeth Deemed University Institute of Management, Kolhapur, India.
[3]Assistant Professor, Bharati Vidyapeeth Deemed University Institute of Management, Kolhapur, India.
[4] Assistant Professor, Bharati Vidyapeeth Institute of Management & Research, New Delhi, India.

[*]Corresponding author
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Abstract

One of the main factors that contributed to the large advances in autonomous driving is the advent of deep learning. For safer self-driving vehicles, one of the problems that has yet to be solved completely is lane detection. Since methods for this task have to work in real-time (+30 FPS), they not only have to be effective (i.e., have high accuracy) but they also have to be efficient (i.e., fast). Although lane detection is challenging especially with complex road conditions, considerable progress has been witnessed in this area in the past several years. In this survey, we review recent visual-based lane detection methods, we focus on methods based on deep learning and organize them in terms of their detection targets, a new direction for lane detection that is applicable to autonomous driving in complex road conditions.

Keywords: Advanced driver assistance systems (ADASs), convolutional neural network (CNN), dataset, deep learning, lane departure warning system (LDWS)

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1. Introduction

In the past decade, autonomous driving has gained much attention with the popularity of in-vehicle smart devices and the improvement of vehicle-road collaboration systems. Lane detection is a basic step in many intelligent advanced driver assistance systems (ADASs), such as a lane departure warning system, which warns drivers when vehicles deviate from their lanes. ADASs, together with other traffic information detection technologies [1–3] , are becoming mature and widely integrated into vehicles, especially electric ones, and people are getting used to automatic driving.

However, when tested on real roads, complex road conditions such as occlusion, lighting, among other factors, make it challenging for accurate lane detection. Lane detection is applied in both online and offline scenarios with specific requirements for performance. In the former scenarios, such as lane-based navigation and lane departure detection, the lane detection algorithm has to be fast enough with immediate feedback about the lane the vehicle is on. In the latter scenarios, which is the foundation for safe automatic driving, the accuracy of lane detection results plays a key role in both localization and navigation.

Figure.1. Differences between ego-lane (in red), ego-road (in green and red), andall-roads (in blue, green and red).

Ego-lane detection- detects the current lane and its boundary and is mainly applied online, e.g., so that autonomous driving cars can stay in the current lane with the aid of lane departure detection.

Ego-road lane detection-detects the lane number, lane marking types and the road boundary of the current road. Ego-road lane detection is also mainly applied online, e.g., so that autonomous driving cars can change their lanes and make turns.

All-roads lane detection-detects the lane markings and the road boundaries of all visible roads (including the opposite lane). All-roads lane detection is more challenging and is mainly required by offline applications, such as HD map modeling. With the rapid development of deep neural networks, similar to other computer vision tasks, the methodology to solve the lane detection problem has been taken over by learning-based methods in recent years and the state-of-the-art results have been superior to those of the traditional non-learning methods.

2. Lane Detection with Deep Learning

With the rapid development of deep learning methods, especially the deep CNNs are also applied in the task of lane detection, achieving promising results, ranging from ego-lane detection, ego-road lane detection to all-roads lane detection with an increasing difficulty. In this section, we focus on recent progress of learning-based methods for the lane detection on these three aspects.

2.1 Ego-Lane Detection

The ego-lane detection is often used in scenarios such as lane departure warning system (LDWS) and lane centering, where real-time performance is usually required in order to instantly determine whether a vehicle is driving normally in its lane, thus reducing traffic accidents. To this end, various features ranging from traditional hand-crafted, such as Hough , to learned features [5] have been adopted to detect the egolane. Though the network details may vary a lot across different methods, they still can be roughly divided into two fashions: single task network and multi-task network. In the former case, the networks are specifically designed for the only task, i.e., lane detection; while in the latter case, other than the lane detection, the networks can perform other tasks, such as road classification, vehicle detection, and HD map parameters regression. Although the advantages of using multi-task networks are obvious, other tasks may degrade the performance of lane detection. Single Task designed an encoder decoder network based on VGG for road segmentation proposed dilated feature pyramid network (FPN) with feature aggregation for drivable road detection and achieved the best F1 score on the KITTI ego-lane segmentation task. Lyu et al. proposed to combine CNN and LSTM for road segmentation where the feature extracted by CNN is fed to LSTM in row/column order. In order to refine the segmentation in faraway area, the centre part of the image is cropped and enlarged for prediction and fused back to the full image. Multi-Task. Chen and Chen proposed an end to-end network, RBNet, for road and road boundary detection, which is implemented as a multi-task learning problem. The network exploited Resnet50 as the feature network, followed by three task-specific sub-networks to simultaneously detect roads and road boundaries, achieving better performance than some two-stage methods. Bittel et al. [5] estimated essential HD maps parameters, such as street type, the number of lanes, roadside and angle, using a multi-task CNN. These parameters are generated from separated fully connected layers fed with shared CNN features. However, this method requires intensity map, semantic map and occupancy grid map generated from navigation as inputs.

2.2. Ego-Road Lane Detection

Different from the ego-lane detection, ego- road lane detection needs to find out all the lanes in the road of driving direction . Despite the common challenges met in ego-lane detection, such as light conditions, weather conditions, occlusions, and so on, the number of lanes in ego-road lane detection may change due to the varying width of roads. The ego-road lane detection is thus regarded as an instance segmentation problem. One kind of methods is end-to-end trainable, directly outputting individual lanes, and the other kind of methods for ego-road lane detection first trains a segmentation network to locate the lane markings, and then performs post-processes, e.g., clustering and lane curve fitting, to obtain the lane instances. End-to-End. Lee et al. [14] proposed a multi-task CNN to detect lanes and road marks simultaneously by taking advantage of the vanishing point of lanes. Pan et al. designed a special layer called Spatial CNN (SCNN) to segment out the road lanes. SCNN is a special 3D manipulation that facilitates message passing along rows/columns and enlarges the receptive field to the whole image. This is useful for lane recognition since some lanes may cross over the image. The network also learns to connect the dashed lanes for they were annotated as solid lanes in tuSimple. However, since this method treats the lane detection as a semantic segmentation task, it can only detect a predefined number of lanes in the input image. Fan et al. proposed SpinNet which includes a new spinning convolution layer to gather more information from multiple directions, contributing to the whole lane boundary detection. Unlike previous methods extracting lane instances from lane segmentation, SpinNet introduces a lane boundary parameterization branch to regress lane curves from the feature map and is thus end-to-end trainable. Hou et al. Proposed a new module Self Attention Distillation (SAD), for ENet encoder to learn the self-attention between two neighboring ENet encoders and segments out the fixed number of lanes. De Brabandere et al. proposed a general network for instance segmentation which can be applied to lane detection by clustering features through a fast post- process. The network learned a map from the image space to a feature space with a discriminative loss function, which satisfies that the pixels belonging to the same instance are close in the feature space and far enough from each other otherwise. Neven et al. proposed a complicated network consisting of a lane segmentation subnetwork, a pixel embedding sub-network like in and a perspective transformation network. The lane instances are obtained using iterative clustering based on the predicted lane masks and features. Finally, a 3rd order polynomial is fitted for each lane instance in the learned perspective transformation.

All-Roads Lane Detection All-roads lane detection is required for more intelligent autonomous driving in complicated road conditions, especially the crossroads, where the vehicle may take turns. In this situation, the lanes in other road should be clearly detected for the autonomous driving system to determine which lane to turn to. For HD map modelling, the lanes in all roads should also be detected and stored in the map. To detect lanes in other roads from a front- view image, some methods [14, 20] aimed at ego-lane or egoroad lane detection can also be retrained on the data with all roads annotated to fulfil the task of all-roads lane detection. A large field-of-view (FoV) is important for the all-roads lane detectors to understand global structures. For example, to detect the gaps inside dashed lanes, FOV is required to be large enough to cover the length of the gap. Thus more input modalities are required through other views or specific equipment to enlarge FOV. Front View. There are two types of approaches that can detect all road lanes from a front-view image using ego-lane or ego-road lane detectors. The first one is based on road surface segmentation aimed at ego-lane detection[20] . However, these methods are easily affected by occlusions; besides, the types of lane boundaries are ignored. The second type of approaches exploits the informative lane markings. However, the lane markings would become too narrow and too small to be distinguished towards the vanishing points due to the front-view input image. More Input Modalities. He et al. combined features from the front view and the bird’s eye view for lane detection. These two views were also exploited others to train a two-stream and end-to-end network to predict road plane and 3D lanes. M´attyus et al. used aerial images to improve the fine-grained segmentation result from the ground view, through which all roads can be recognized and modeled.

3. Key Points Estimation and Point Instance Segmentation Approach for Lane Detection

Key points estimation techniques predict from input images certain important points called key points. Human pose estimation is a major research topic in the key points estimation area. Stacked hourglass networks [21] consists of several hourglass modules that are trained simultaneously.

The hourglass module can transfer various scales' information to deeper layers, helping the whole network obtain both global and local features. Because of this property, an hourglass network is frequently utilized to detect centers or corners of objects in the object detection area. Not only network architecture or loss function but also refinement methods adapted to existing networks are developed for key point estimation.

For lane detection The network, Point Instance Network (PINet), generates points on lanes and distinguishes predicted points into individual instance. To achieve these tasks, proposed neural network includes three output branches, a confidence branch, offset branch, and embedding branch. The confidence and offset branches predict exact points of traffic lines, The embedding branch generates the embedding features of each predicted point; the embedding feature is fed to the clustering process to distinguish each instance. The Similarity Group Proposal Network (SPGN) [26], an instance segmentation frameworks for 3D point cloud, introduces a simple technique and a loss function for instance segmentation. Based on the contents proposed by SPGN, we design a loss function fitting to discriminate each instance of the predicted traffic lines.

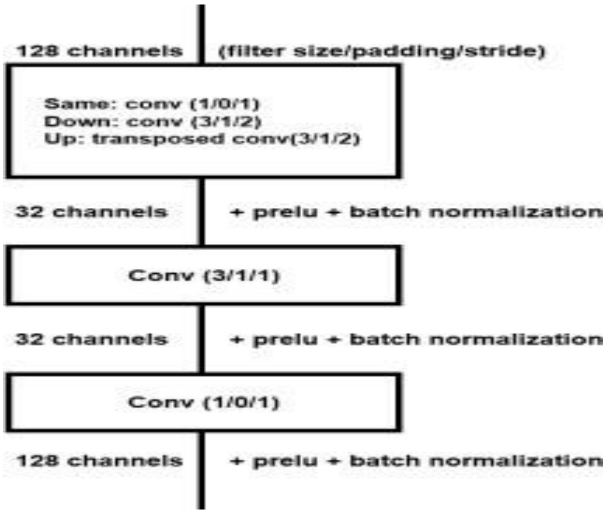

Figure. 2. Details of bottle-neck. The threekinds of bottle-neck have different firstlayers according to their purposes.

4. Ultra Fast Structure-aware DeepLane Detection

Fast speed and the no-visual-clue problemsare important for lane detection. Hence, how to effectively handle these problems is key to good performance. Definition of formulation In order to cope with the problems above, it propose to formulate lane detection to a row-based selecting method based on global image features. In other words, this method is selecting the correct locations of lanes on each predefined row using the global features. In this formulation, lanes are represented as a series of horizontal locations at predefined rows, i.e., row anchors. In orderto represent locations, the first step is gridding. On each row anchor, the locationis divided into many cells. In this way, the detection of lanes can be described as selecting certain cells over predefined row anchors

5. End-to-End Lane Marker Detectionvia Row-wise Classification

In autonomous driving, detecting reliable and accurate lane marker positions is a crucial yet chalprolenging task. The conventional approaches for the lane marker detection problem perform a pixel-level dense prediction task followed by sophisticated post-processing that is inevitable since lane markers are typically represented by a collection of line segments without thickness. In this method performing direct lane marker vertex prediction in an end-to-end manner, i.e., without any post-processing step that is required in the pixel-level dense prediction task. Specifically, it translate the lane marker detection problem into a row-wise classification task, which takes advantage of the innate shape of lane markers but, surprisingly, has not been explored well. In order to compactly extract sufficient information about lane markers which spread from the left to the right in an image,they devise a novel layer,inspired by [8], which is utilized to successively compress horizontal components so enables an end-to-end lane marker detection system where the final lane marker positions are simply obtained via argmax operations in testing time.

Experimental results demonstrate the effectiveness of the proposed method, which is on par or outperforms the state- of-the-art methods on two popular lane marker detection benchmarks, i.e., TuSimple and CULane.the lane marker detection problem has been tackled with various approaches and each of them has its own pros and cons. However, most of them are based on semantic segmentation with complex postprocessing which hinders end-to-end training for extracting lane marker positions. Inspired by recent works [29], we consider the above problem as finding the set of horizontal locations of each lane marker in an image. Specifically, we divide an image into rowsand obtain a row-wise representation for each lane marker using a convolutional neural network. Then lane marker detection can be thought as row-wise classification. In other words, contrasted tothe conventional segmentation-based lane marker detection, the proposed method candirectly provide lane marker positions.

6. Conclusions

In this survey, we reviewed the applications for lane detection, summarized deep learning methods for lane detection, discussed trends for effective and robust lane detection and made improvements by introducing a newdataset with detailed annotations and a novel deep neural network for lane detection that is more robust in complex road conditions.All the proposed method are simple and efficient while maintainingcompetitive accuracy when compared to state-of-the-art methods. Although works with state-of-the-art methods with slightlyhigher accuracy exist, most do not providesource code to replicate their results, therefore deeper investigations on differences between methods are difficult.

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