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Lane Detection with Deep Learning: Methods and Datasets

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Lane detection problem has been considered as an important computer vision task in autonomous driving. While it has received massive research attention in the literature, the problem is not yet fully solved. In this paper, a comprehensive literature review for lane detection, especially those with deep learning models, is presented. Furthermore, the latest collection of lane detection datasets is presented. The research gap is further filled by proposing a novel lane detection dataset named MudLane, which focuses on the lane detection task on suburban roads.

KEYWORDS: Lane Detection, Deep Learning, Convolutional Neural Network, Dataset.

1. Introduction

In autonomous driving technology, lane detection is one of the basic modules and is also a long-standing task. In this task, the computer extracts the lanes from the road data collected by sensors such as cameras to determine the position of the vehicle in the current lane and ensure that the vehicle does not rush out of the lane. With the deepening of research, the application fields of lane detection are getting increasingly wider. At present, this task is no longer only for the detection of yellow and white lanes in the early years. People now hope to detect the concept of semantic lanes in as many scenes as possible, even if the lanes are incomplete or fuzzy.

Since the emergence of the task of lane detection, many methods have been proposed to solve this problem. These methods can be divided into two categories, traditional computer vision-based methods and machine learning methods, which have become popular in recent years.

Traditional machine vision methods generally use manually extracted features and some mathematical methods, such as curve fitting. Due to its small computing load and fast computing speed, the research started very early, and there have been some research works in recent years. Traditional machine vision always grayscales the image first [16, 23, 26, 27], then uses an edge detection algorithm to extract image edge features [8, 16, 18, 23, 26, 27], and then uses the Hough transform [8, 16-18, 23, 26, 27, 30] and other methods to obtain the description of the lanes. The researchers use color features to detect lanes [23, 31, 22], and some researchers use an inverse perspective to solve the difficulty of lane detection caused by the perspective phenomenon [5, 9, 19].

However, the effect of using traditional machine vision methods often makes it difficult to achieve better results in more complex environments. In recent years, many works have applied deep learning to lane detection. Among these methods, the most widely used are end-to-end networks with convolutional encoders and decoders [21, 32, 33]. Some studies improve the structure of convolution to obtain better results [6, 25, 32], while different attention mechanisms are introduced in [4, 7, 29, 33] to achieve certain progress. Emerging graph neural networks have also been applied [10], and the processing of continuous images is also under study [4]. While some methods pursue precision, some works try to reduce the computational load [10, 25, 28, 33] or use unsupervised learning [6]. In addition, there are also approaches that combine traditional computer vision methods with machine learning [5].

To the best of my knowledge, this field is still developing rapidly, and a timely summary of the literature is needed. In addition, due to the increasing importance of data to algorithms, many new datasets have been proposed in recent years, but few people use these datasets, and no one has evaluated the effects of existing methods on emerging datasets.

The contributions of this study are summarized as follows:

1 This study presents a comprehensive literature review for lane detection, especially those with deep learning models.

2 This study presents the latest collection of lane detection datasets.

3 This study contributes a new lane detection dataset named MudLane, which focuses on the lane detection task on suburban roads.

The rest of this paper is organized as follows. Section 2 presents the literature review. Section 3 collects relevant datasets. Section 4 describes the new dataset. Section 5 concludes this study.

2. Literature Review

2.1. Traditional Models

Traditional lane detection methods are mainly based on heuristic methods, e.g., the Hough transform and color-based detection methods. The Hough transform is a very common method in traditional lane detection and has been successfully applied in real world systems.

A lane detection algorithm based on the Hough transform with multiple constraints is proposed in [1]. This method comprehensively uses a variety of processing methods to screen the results of the Hough transform, which effectively improves the robustness of the output results. The experimental results on the dataset collected by the author prove that the method can adapt to lane detection requirements under complex working conditions and has high real-time performance.

A lane detection algorithm based on the Hough transform is proposed in [26]. In this method, the image information in the RGB image and the edge image are properly fused, and then the Hough transform is performed, which reduces the false detection rate compared to directly using the edge image to perform the Hough transform.

A method that can detect lanes at night is proposed in [16]. This method uses the adaptive Canny edge detection algorithm and the improved Hough transform algorithm and uses the slope constraint method to constrain the Hough change results. After testing, this method can stably adapt to the road illuminated only by car lights at night.

The authors in [27] add polar angle constraints to the Hough transform and propose a new method for the dynamic ROI Hough transform. Experiments show that it has a good detection effect on different road conditions on structured roads.

The authors in [8] improved the Hough transform algorithm and combined it with methods such as region of interest and adaptive binarization to achieve good detection of the lane where the vehicle is located in various environments.

A lane detection algorithm capable of detecting longer and farther lanes is proposed in [17]. This algorithm first extracts the ROI followed by perspective transformation and binarization using the Sobel operator. Finally, the slider method is used to fit the lanes. Experiments show that the algorithm can effectively detect long-distance lanes.

A lane detection method based on RGB channels is proposed in [31]. The input image is first separated by RGB channels, and then the lanes are extracted by the characteristic color transfer function and morphologically processed to obtain the detection result. Experiments show that this algorithm has a better detection effect for yellow lanes.

A lane detection method mainly oriented to yellow lanes is proposed in [22]. This method utilizes the prior information of lanes in HSV color space to speed up the calculation and improve the detection effect.

Multilane detection based on the Hough transform is proposed in [18], in which the dynamic ROI extraction method is leveraged to obtain the ROIs. Afterwards, lanes are detected by the Hough transform and sliding window search. Finally, the potential interference is removed with a compensation postprocessing step. The robustness and stable detection performance are validated with RGB images captured from a vehicle-mounted camera in the Caltech dataset under different scenarios, e.g., sunny, cloudy, and rainy days.

However, a difficulty of the traditional inverse perspective is that a fixed transformation matrix is often difficult to adapt to situations such as ramps. The HP-net proposed in [5] can dynamically generate a transformation matrix according to the image. The detection results can be effectively improved by projecting the results output by the SCNN to a bird's-eye view and fitting and outputting them.

2.2. Deep Learning Models

A convolutional neural network with an encoder and decoder is a successful deep learning method applied to lane detection. A lane detection model based on vertical spatial convolution is proposed in [32]. First, a three-stage encoder network is applied to the original image to generate feature maps, where vertical spatial convolution enhances the representational ability of the model by enhancing the message passing between pixels. After that, the results of the encoder are fed into the decoder to produce the final prediction, while a classification network is used to confirm whether the decoder has produced a lane. Experiments on CULane and TuSimple demonstrate the effectiveness of the model. A network with structural priors is proposed in [2]. By improving the convolutional structure and loss function, this model achieves close results on CULane with a much lower computational load than state-of-the-art methods.

The attention mechanism and transformer structure are also applied to the lane detection task. A network based on an attention mechanism and residual blocks is proposed in [6]. The encoder network is divided into two parts, where the first part consists of downsampling and convolution and the second part consists of residual blocks and attention modules. Benefiting from fewer downsampling times and the application of residual blocks and attention modules, the network can better learn the information in the image. The decoder then uses the output of the encoder to generate lane information of the same size as the input image. Experiments on the TuSimple and LLAMAS datasets demonstrate that the attention module produces some improvement in the performance of the model.

An anchor-based one-stage model is proposed in [20]. First, the backbone extracts feature maps from the image, and then the generated features of the attention module are connected with anchors that are projected onto the feature maps. The last two-layer network outputs the prediction result. Experimental results on TuSimple, CULane, and LLAMAS show that this model is superior to state-of-the-art models.

A lane detection method with a row-column self-attention module using a transformer structure is proposed in [7]. The input image is first passed through a ResNet backbone to obtain row and column features. Meanwhile, the module predicts anchor boxes and ROIs from the input. The output of the backbone is fed into a transformer encoder with a row-column attention mechanism and self-attention mechanism. The last transformer decoder is designed to predict the location of the final lane. Experiments on CULane and TuSimple demonstrate that this method is effective.

A network with a bionic attention mechanism is proposed in [33]. By incorporating an attention mechanism into the encoder, this model can better notice details in the input. Experiments on TuSimple and Caltech demonstrate the effectiveness of this attention mechanism.

There are also models that use special mechanisms, such as recurrent neural networks and graph neural networks, or multiple images as input. A model capable of detecting lanes containing complex topologies is proposed in [15]. The input image first enters the backbone composed of ResNet and FPN to extract features of different resolutions. The features then go into the proposal head and the conditional shape head; the former is used to find the starting point of the lanes, while the latter generates results that can describe the lanes. To resolve lanes with complex topologies, RIM is applied in the proposal head. Experiments on Curve Lanes, CULane, and TuSimple demonstrate that the model works very well even with a complex topology of lanes.

The authors in [10] use graph neural networks instead of convolutional neural networks to detect lanes. In this work, a hat filter is applied to the input image to build a graph model. A graph neural network then selects subgraphs representing lanes in the constructed graph model. The experimental results on KIST and Caltech prove that this model can balance speed and accuracy.

There are also some works that attempt to optimize the detection accuracy with continuous information (such as video). A lane detection method with prealignment and a spatial-temporal attention mechanism is proposed in [4]. The author first proposes an algorithm that can extract feature points in weak texture areas to align multiple consecutive images. After that, a model with spatial-temporal attention processes multiple images and produces the final result. Experiments on ApolloScape and Tusimple demonstrate that this model has higher F1 scores and fewer false predictions than other models using one image.

A lane detection method based on an affinity field is proposed in [1]. In this approach, the model no longer predicts the lane result directly but a vector field. In this field, each pixel is represented as a 2D vector pointing to the center of the lane. Some postprocessing is then used to cluster this field into lane instances. Experiments on CULane and LLAMAS demonstrate that this method is very effective.

A method with a deep Hough transform is proposed in [14]. Through a novel loss function that exploits knowledge of lane geometry in Hough space, the model can take advantage of very cheap and large amounts of unlabeled data. Experiments on CULane and Tusimple demonstrate that this model can significantly improve performance by learning from a large amount of unlabeled data.

There are also some works that focus on the computational speed and computational load of the model. A lightweight attention deep neural network with 4 modules and two branches is proposed in [28]. The input image goes through the global context embedding module, which encodes long-range contexts, and the explicit boundary regression model, which encodes low-level high-resolution feature maps in parallel after light downsampling. Finally, transpose convolution is used to mix the GCE and EBR outputs and generate the final predictions. Experiments on TuSimple and CULane prove that this model can find a better balance between performance and cost. A lightweight lane detection model is proposed in [2]. The authors evaluate several encoder and decoder combinations and verify the accuracy and speed on TuSimple.

A lightweight lane detection model is proposed in [10]. The image is first passed through ResNet14, a simplified version of ResNet16, and then passed through two fully connected layers to generate predictions. The final prediction result is output after false positive suppression and curve fitting. Experiments on CULane demonstrate that this model runs very fast while being competitive in terms of accuracy.

2.3. Challenges and Opportunities

Based on the above literature review, it can be found that different lane detection methods have different advantages and disadvantages. For traditional methods, the calculation is relatively simple, but it is often difficult to adapt to complex situations. Although the method based on model fitting greatly improves the stability of the output, the output is often a curve. However, for more complex lanes, the preset model will have a limitation on the output. Although machine learning methods can adapt to more complex situations, they often require a high computational load. The number of lanes output by many models is often fixed, which will result in computational waste when there are few instances of lanes and may not be enough when there are many instances. At the same time, the dependence of machine learning on a large amount of labeled data makes it very difficult to create new datasets that contain more situations.

For the lane detection task, the following current challenges exist:

1 Lanes are often not complete. The occlusion of other vehicles and natural wear cause the lanes to be incomplete most of the time, which greatly increases the difficulty of detection.
2 The detection of lanes will be affected by the environment. Different seasons, weather and time will lead to differences in the collected road information, resulting in lower recognition. Rain, dust, or snow on the camera may change the perspective and viewing range of the camera, causing errors in the result.
3 There is a lack of a unified benchmark dataset of suitable difficulty to more accurately evaluate the performance of each method.
4 Few models pay attention to the fact that the lanes are continuous. The vast majority of methods focus on the detection of a single image rather than continuous images. This results in very important sequence information being almost wasted.

Some future research directions are thus proposed as follows.

1 It is necessary to design a benchmark dataset with suitable difficulty to more accurately evaluate the performance of each method.
2 An attempt should be made to combine multiple models to optimize performance, e.g., vision Transformers and graph neural networks [11-13, 35].
3 The computing load of the application platform should be considered when designing the new model, e.g., lightweight models and model compression [24, 34].

3. Dataset Collection

In recent years, autonomous driving technology has gained much attention in both academia and industry. One of the most basic and challenging tasks is lane detection in real scenes. However, due to the existence of harsh scenes such as occlusion, haze, strong light, and darkness, it is extremely challenging to accurately detect lanes.

Most of the existing lane detection methods tend to focus on the lane detection of a single frame image, which causes the model to often fail to make good use of continuous stance data. Therefore, extending the image dataset to the video level is worthy of research. Some works [4] have demonstrated that video-level datasets can provide temporal contextual information and help to better improve the stability of the output results.

In this section, the most widely used lane detection datasets in the literature are collected and a comparison among these datasets is presented.

3.1. Dataset Description

3.1.1. TuSimple

The TuSimple dataset is a highway-oriented lane detection dataset. The training set of this dataset contains 3626 video segments, each segment is recorded for one second and divided into 20 frames, the last of which is annotated. The test set contains 2782 similar fragments. These clips were all shot during the day when the weather was good. There are at least 2 lanes in each frame, and most frames are marked with 4 lanes. Specifically, the ordinates of multiple lanes are the same, and a JSON file gives the horizontal direction of each lane.

3.1.2. CULane

The CULane dataset is a commonly used dataset and a challenging dataset. Six vehicles in Beijing collected 55 hours of video and extracted 133,235 frames. The frames were split into 88,880 training samples, 9,675 validation sets, and 34,680 test sets. For each frame, cubic splines are used to label the lanes. On the particular note, this dataset also annotates lanes that, although occluded and lossless, should still semantically be recognized as lanes.

3.1.3. BDD-100k

BDD100K is a multitask oriented dataset that collects data from multiple sensors, such as GPS and IMU, in addition to the camera. This dataset is vast, with 100,000 videos and 120,000,000 images, and is annotated with detailed attributes of lanes, such as solid or dashed, double or single.

3.1.4. Caltech

The Caltech Lanes dataset is a relatively small dataset consisting of four clips taken at different times of the day. Includes 1225 individual frames. The dataset is divided into four separate clips: cordova1 has 250 frames, cordova2 has 406 frames, washington1 has 337 frames, and washington2 has 232 frames. Because it was proposed earlier and the amount of data is not large, it is common in the experiments of many traditional methods.

3.1.5. VPGNet

Some datasets pay special attention to rain, such as VPGNet. With approximately 20,000 images, VPGNet divides scenes into no rain, rain, heavy rain, and night. Interestingly, the images for this dataset are given in.mat format instead of the common picture format. This means that intuitive observation of this dataset is not as convenient as several others. The vanish point is also marked in the dataset.

3.1.6. DET

Different from the common datasets that use ordinary RGB cameras, the DET dataset uses Dynamic Vision Sensors (DVS). DVS is a special camera that can only output pixels that change, which reduces the pressure of computing and can better adapt to some special environments (such as drastic changes in light). The DET dataset contains 5,424 DVS-based images and has the highest resolution of 1280x800 among all DVS datasets. The dataset contains a variety of complex scenes, and all 17103 lane instances are manually annotated.

3.1.7. CurveLanes

CurveLanes is a new dataset for lane detection with complex scenes, including more lanes and curves. As the largest lane detection dataset to date, CurveLanes has 150K images annotated with cubic splines, which are divided into a 100K training set, 20K evaluation set and 30K test set. The resolution of this dataset is also high, reaching 2650×1440.

3.1.8. Comma2k19-LD

Comma2k19 LD is a dataset that contains information such as driving speed and vehicle angle. This dataset contains 200 images annotated with left and right lanes. At the same time, this dataset ensures that the driving speed corresponding to all pictures is above 48 km/h.

3.1.9. SDLane

SDLane is a new dataset for lane detection. The 39K training set and the 4K test set contain challenging scenes of highways and urban areas. The lanes of all courseware on the road are marked with each frame, and the position of each lane relative to the leftmost lane is also recorded.

3.1.10. VIL-100

VIL-100 is a video instance lane detection dataset consisting of 100 videos with a total of 10,000 frames. The data include a variety of weather and traffic scenarios. All frames are annotated as instance-level lanes, and the type of lanes is also recorded.

3.2. Dataset Comparison

A summary of the lane detection datasets is shown in Table 1. Most of the discussed datasets are publicly available and widely used in the literature. A further dataset usage statistic in the relevant studies is shown in Table 2. It can be found that the usage of these open datasets is highly imbalanced. Two datasets, namely, CULane and TuSimple, are widely used, with ratios of 65% and 59%, respectively. The remaining datasets are less used, and 45% of the discussed datasets are only used once.

All in all, each dataset has its own specific direction and intends to solve a specific situation in the lane detection task. TuSimple focuses on the detection of lane lines on highways in fine weather. The lane lines are very clear, with little intersection and occlusion. Caltech includes urban roads under better weather, and less occlusion. Since it was proposed earlier, it can be seen that many traditional methods also use this data set. SDLane includes both city and highway scenes. CULane's images have a large amount of occlusion, which may be caused by traffic jams. CurveLanes contains a large number of intersecting and curved samples, just like its name. VPGNet pays attention to the vanishing point in the image, and provides samples of rainy day and nighttime. In addition to scenes, more diverse sensors are also a direction of interest. DVS is used in DET to provide a different data source than RGB cameras. Comma2k19-LD records data such as vehicle speed, BDD100k contains MPU and GPS data, and VIL-100 provides time dimension information and more weather and scenes in the form of video. People have used different datasets according to their research direction. Interestingly, many challenging datasets are applied less frequently, probably because they are too challenging.

Table 1
A summary of lane detection datasets (- denotes not available)

name	number of pictures	Number of lanes	multi-city	multi-weather	multi-time	multi-sensor	resolution	Download Link
TuSimple	6408	-	N	N	N	N	1280×720	https://github.com/TuSimple/tusimple-benchmark/issues/3
CULane	133235	-	N	Y	Y	N	1640×590	https://drive.google.com/drive/folders/1mSLgwVTiaUMAb4AVOWwlCD5JcWdrwpvu
BDD100k	120000000	-	Y	Y	Y	Y	1280×720	https://bdd-data.berkeley.edu/ https://www.bdd100k.com/
Caltech	1224	4172	Y	-	Y	N	-	http://www.mohamedaly.info/datasets/caltech-lanes
VPGNet	21097	-	N	Y	Y	N	1288×728	https://github.com/SeokjuLee/VPGNet#vpgnet-dataset
DET	5424	-	N	-	-	N	1280×800	https://spritea.github.io/DET/
CurveLanes	150000	-	Y	Y	Y	N	2650×1440	https://github.com/SoulmateB/CurveLanes
Comma2k19-LD	2000	-	-	Y	Y	N	1164×874	https://github.com/commaai/comma2k19
SDLane	42949	-	N	N	N	N	1920×1208	https://www.42dot.ai/akit/dataset/
VIL-100	10000	-	N	Y	Y	N	640×368 to 1920×1080	https://github.com/yujun0-0/MMA-Net
OpenLane	200000	880000	N	Y	N	N	1920×1280	https://github.com/OpenPerceptionX/OpenLane/blob/main/data/README.md
KIIT	579	-	N	N	N	Y	-	https://www.cvlibs.net/datasets/kitti/eval_road.php
Cityscapes	5000	-	Y	N	N	N	-	https://www.cityscapes-dataset.com/
ApolloScape	143906	-	N	Y	Y	N	1280×720	http://apolloscape.auto/trajectory.html
Mapillary	25000	-	Y	Y	Y	Y	-	https://help.mapillary.com/hc/en-us/articles/115000967191-Object-detections
3D Lane Synthetic Dataset	7499	-	-	-	-	-	1920×1080	https://github.com/yuliangguo/3D_Lane_Synthetic_Dataset

Table 2
The statistics of dataset usage in the relevant studies

Study	Caltech	CULane	TuSimple	LLAMAS	Curve Lanes	KIST	ApolloScape	Total
[5]	1							1
[32]		1	1					2
[6]			1	1				2
[15]		1	1		1			3
[28]		1	1					2
[10]	1					1		2
[5]		1						1
[20]		1	1	1				3
[6]		1						1
[4]			1				1	2
[1]		1		1				2
[7]		1	1					2
[2]			1					1
[33]	1		1					2
[14]		1	1					2
[2]		1						1
[10]		1						1
Total	3	11	10	3	1	1	1	
percentage	18%	65%	59%	18%	6%	6%	6%	

4. Proposed Dataset and Numerical Evaluation

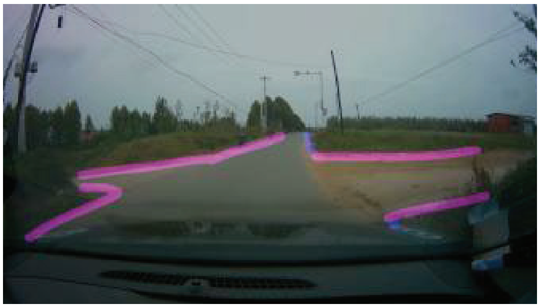
In the following years, it might be hoped that the lane detection algorithm can detect those semantic lanes, even those that are occluded or broken. Furthermore, lane detection algorithms are now expected to detect semantic road boundaries rather than lanes themselves. As mentioned in Table 2, there are already a lot of urban-oriented lane datasets. However, in addition to urban roads, another type of road that deserves attention is suburban roads. Suburban roads and urban roads have significantly different topology, materials and textures. Therefore, a new suburban-oriented dataset named MudLane, is proposed, in which all road boundaries are annotated as lanes.

As shown in Figure 1(a), suburban roads may be cement or soil, while urban roads are mainly asphalt. As shown in Figure 1(b), suburban roads often have many forks, and because the main road is very narrow, these forks can be in the middle of the image with a near-horizontal attitude. Whether these horizontal lanes are necessary for detection is worth discussing. If these lanes are to be detected, many data set labeling methods cannot label horizontal lanes, and the result output methods of some methods do not support horizontal lanes. As shown in Figure 1(c), there are also some special cases, some things that do not appear in the city will block the road, such as large swathes of corn.

MudLane was shot by a driving recorder at 1920*1080@25FPS in Qingdao, Shandong, China and is dominated by rural roads. All road boundaries are

Figure 1
Some examples from the proposed MudLane dataset

(a)



(b)

(c)

annotated as lanes. All 275 original videos are in the origin-video folder. Each video is sliced into the corresponding directory of the picture folder with the frequency of one image every five seconds. There is also a txt file and a png file for each image, which contains the position and mask of the lanes in the image. It is worth noting that some file just has a json file and there is no txt file. The reason is that these image have forks, thus it was attempted to train these images and some model just crashed when training. All images with only two lane lines were filtered and txt files for these images were generated, and the pictures with more lane lines were left for later work. This subset is called MudLane2, where 2 is the number of lanes not the version of the dataset. The data format in txt is similar to CULane, each line is a lane line, and the points on the lane line are arranged in the order of x y. A list of training sets, test sets and validation sets can be found in the list folder, again in a format similar to CULane. my dataset can be download at https://pan.baidu.com/s/1v0QNsqJ5rEUz9iGl6UTFpg?pwd=ptny. MudLane2 is tested on some well-known method as the baseline in the numerical experiments. The results are shown in Table 3, in which CondLane achieves the best F1 performance.

Table 3
Evaluation results of baselines on MudLane2

	F1
CondLane	0.64
LaneATT	0.60
RESA	0.61
SCNN	0.60

For the vast majority of simple scenes, the performs of the models are very well.

Figure 2
Performance of different models on suburban roads

Ground Truth CondLane LaneATT RESA SCNN

However, in some scenarios, the performance of the models drops significantly. It might be explained that some differences in suburban roads in the dataset might be the reason for limiting the performance of the network.

For cities, since most of the data sets are collected in one city, the lane lines in a data set often have high similarity. However, the road boundaries of suburban roads are quite different, and road boundaries can be composed of various materials, which have distinct characteristics and textures, but are all semantic road boundaries. It can be seen that when there are some rare situations in the road boundary, the performance of the network has dropped significantly.

In addition, there are cases that have similar characteristics but cannot be judged as road boundaries, such as the case of an obstacle existing in the middle of a lane. It is more obvious that the grass in the middle of the lane

Figure 3
Performance of different models on city roads

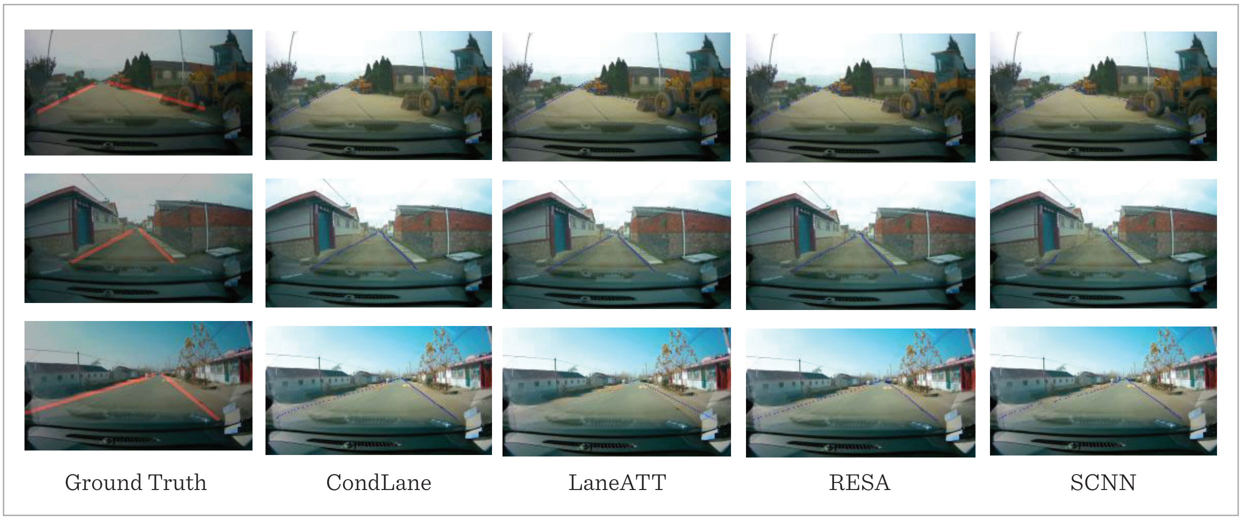


Figure 4
Performance of different models with road boundaries

Figure 5
Performance of different models on intersections

makes the two sides of the grass have similar characteristics to the real road boundary, which is almost impossible on urban roads. Humans can clearly recognize that these are two routes, and choose the outermost two as road boundaries to drive vehicles, but for machines, this is more challenging. Nevertheless, it was found that the models performed very well in this case.

Another noteworthy experimental result is that the network does not perform as well as it should at intersections. Although it has been mentioned above, since the current models are difficult to deal with horizontal lane lines, the horizontal lane lines at intersections are ignored. However, the experiment found that the lane lines recognized by the model did not end at the intersection, which is very dangerous, especially the T-shaped intersection in the picture.

5. Conclusion

To fill in the research gap that there lacks of a latest collection of existing lane detection datasets, the paper presents a comprehensive literature review for lane detection and the latest collection of lane detection datasets. Deep learning models are seen as the state-of-the-art solutions. A novel lane detection dataset, named MudLane, is proposed, which focuses on the lane detection task on suburban roads, and the performance of several deep learning models on the proposed new dataset is evaluated.

Data Sharing Agreement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declaration of Conflicting Interests

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