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SURVEY

Exploring the Current State of Road Lane Detection: A Comprehensive Survey

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Abstract – Road lane identification plays a very role in providing directions to the self-driving car and also gives the accurate positions of the vehicle. Therefore, road lane line detection is one of the critical tasks for self-driving cars. The features contribute significantly improves the efficiency and safety of self-driving cars. In this paper, we identify some methods to avoid the risk of getting into another lane. Comparisons are made based on the available dataset and the robustness of these methods.

Index Terms – Road Monitoring, Lane Detection, Survey, Road transportation, Advanced Driver Assistance Systems (ADAS)

I. INTRODUCTION

Road lane detection is a technique used in self-driving cars and advanced driver assistance systems (ADAS) to identify the location of lane markings on the road. This information is used to help the vehicle stay within its lane and can also be used to detect when the vehicle is drifting out of its lane or to assist with lane changes. The process typically involves using an image or video data from cameras mounted on the vehicle and applying computer vision algorithms to identify and track the lane markings in the images. The detected lane markings are then used to estimate the vehicle's position and trajectory on the road. Several Technologies has been developed for identifying road lane in this paper, and a detailed survey has been done on various technologies used for lane identification. The paper is as follows section 2 presents technologies used for lane identification section 3 follows challenges/issues on road lane detection. Section 4 presents a comparative study section 5 presents a conclusion.

II. TECHNOLOGIES FOR ROAD LANE DETECTION

[1] Rethinking Efficient Lane Detection via Curve Modelling is a research paper that presents a new approach to detecting lanes on the road using a curve modelling technique. The proposed method uses a curve modeling technique that is based on the idea that lanes can be represented as a combination of curves. The paper describes a new lane detection algorithm that uses a combination of edge detection, color information, and a curve fitting method.

[2] A deep-embedded hybrid CNN-LSTM network for lane detection on the NVIDIA Jetson Xavier NX combines the strengths of two types of neural networks: convolutional neural networks (CNNs) and long short-term memory (LSTM) networks. The CNN component is typically used for feature extraction from images. . CNNs are composed of multiple layers, including convolutional layers, pooling layers, and fully connected layers. The convolutional layers are responsible for detecting patterns in the image data, while the pooling layers are used to reduce the dimensionality of the data. The fully connected layers are used to classify the features extracted by the convolutional layer. The LSTM component is used for the sequential processing of the data. [3] Lane detection based on instance segmentation of the BiSeNet V2 backbone network is a specific approach to solving this problem. The BiSeNet V2 is a convolutional neural network (CNN) architecture that is specifically designed for real-time semantic segmentation tasks. It has a lightweight encoder-decoder structure, which makes it well-suited for lane detection in embedded systems. The lane detection algorithm based on this approach typically uses the BiSeNet V2 as the backbone network to extract features from the input image. Then, it applies an instance segmentation module on top of the backbone to separate the different lanes in the image. Finally, it applies a post-processing step to obtain the final lane boundaries.

[4] FastDraw is a lane detection approach that addresses the long tail of lane detection by adapting a sequential prediction network. The long tail in lane detection refers to the fact that there are many rare lane configurations that are difficult to detect using traditional lane detection methods. To address the long tail of lane detection, the FastDraw approach uses a sequential prediction network, a type of neural network that can be trained to predict future states based on past observations. The network architecture used in FastDraw is a variant of the Long Short-term Memory (LSTM) network, which is a type of Recurrent Neural Network (RNN) that is well suited for sequential data. [5] Deep learning for object detection and scene perception in self-driving cars is a rapidly growing field that involves the use of deep neural networks to detect and recognize objects in the environment. There are several popular deep learning architectures for object detection, such as Region-based Convolutional Neural Networks (R-CNN), You Only Look Once (YOLO), and Single Shot Multi-box Detector (SSD). These architectures are able to detect and recognize a wide range of objects, including vehicles, pedestrians, and traffic signs.

[6] Deep learning sensor fusion for autonomous vehicle perception and localization is a field that involves the use of deep neural networks to combine data from multiple sensors to improve the perception and localization capabilities of autonomous vehicles. Sensor fusion is the process of combining information from multiple sensors to improve the overall performance of the perception and localization systems. This can include using data from cameras, lidar, radar, and other sensors to improve the accuracy and robustness of the perception and localization systems. [7] iCurb is a computer program that can identify where the curbs (the edges of the road) are in pictures taken from above (aerial images). It does this by learning from examples provided by humans who have marked the location of curbs in pictures. Once it has learned, it can use that knowledge to find curbs in new pictures on its own.

[8] PolyLaneNet is a lane estimation system for autonomous driving. It is a computer program that can determine the location and shape of the lanes on the road in pictures taken by cameras mounted on the car. The system uses a deep neural network, which is trained on a dataset of images and corresponding

lane line labels. It learns to fit polynomial functions that best represent the lanes in the images. Once it has learned, it can use that knowledge to find lanes in new pictures on its own. Additionally, the system is able to handle multiple lanes and lane changes and able to estimate curved lanes, which is difficult for traditional methods. [9] End-to-end Lane Shape Prediction with Transformers is a method for estimating the shape of lanes on the road for autonomous driving. The goal of this method is to predict the shape of the lanes directly from image data instead of detecting the lanes first and then estimating the shape of the lanes. The method uses a transformer-based neural network, which is a type of neural network that is designed to handle sequences of varying lengths. The transformer network is trained on a dataset of images and corresponding lane shape labels. The labels are represented as a set of points that define the shape of the lanes in the image. During training, the network learns to predict the lane shape in new images by outputting a set of points that define the lane shape

[10] Lane detection is a crucial task in autonomous driving, as it allows the vehicle to understand its position and navigate safely on the road. In recent years, deep learning methods have been widely used for lane detection due to their ability to handle complex and varied scenes. There are several deep learning-based lane detection methods that have been proposed in the literature. One popular approach is to use convolutional neural networks (CNNs) to extract features from the input image and then use these features to predict the lane markings. For example, in the paper "Real-time Lane Detection using Deep CNNs and Recurrent Networks," the authors propose a CNN-RNN architecture that can detect lanes in real time with high accuracy. Another approach is to use fully convolutional networks (FCNs) to directly predict the lane markings from the input image. For example, in the paper "LaneNet: Real-time Lane Detection Networks," the authors propose an FCN-based method that can detect lanes in real time with high accuracy and robustness. Yet another approach is to use object detection methods to detect lane markings as objects in an image. For example, in the paper "Towards End-to-End Lane Detection: an Instance Segmentation Approach," the authors propose a method that uses a Mask R-CNN to detect lane markings as instances in an image.

In addition to CNN's, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have also been used for lane detection. These methods are useful for handling temporal dependencies in videos, where lane markings may change over time. [11] The proposed framework uses a combination of IoT devices and deep learning algorithms to detect lanes under artificial colored light. IoT devices, such as cameras and sensors, are used to collect data from the road in real time, and this data is then processed by deep learning algorithms to detect the lane markings. The deep learning algorithm used in this framework is a convolutional neural network (CNN) that is trained to detect lane markings under different colored light conditions. The CNN is trained on a large dataset of images of lane markings under different colored light conditions, including red, green, blue, and white.

[12] LIDAR-camera fusion is a technique that combines data from LIDAR sensors and cameras to improve the performance of road detection. LIDAR sensors use laser beams to measure the distance to objects, while cameras capture images of the environment. Combining these two types of data can provide complementary information that can improve the accuracy and robustness of road detection. One approach to LIDAR-camera fusion for road detection is to use fully convolutional neural networks (FCNs). FCNs are a type of deep learning algorithm that can be used for image segmentation tasks, such as road detection.

[13] Robust lane detection and tracking is a key requirements for many real-time applications, such as autonomous vehicles and advanced driver-assistance systems (ADAS). To meet this requirement, several methods have been proposed in the literature for robust lane detection and tracking. One approach is to use a combination of computer vision techniques and machine learning algorithms. Computer vision techniques, such as edge detection, Hough transform, and RANSAC, are used to extract features from the input image, such as lane markings. These features are then used to classify the image into one of two classes: lane or non-lane. Machine learning algorithms, such as decision trees and random forests, are then used to learn the patterns and features that are indicative of lanes. Once the algorithm has been trained, it can be used to detect lanes in new images. Another approach is to use deep learning algorithms, specifically convolutional neural networks (CNNs), to detect lanes. CNN's have been shown to achieve high accuracy in detecting lanes in images and videos, and they can be trained on large datasets of labeled data to improve their performance.

[14] LaneNet is a real-time lane detection network for autonomous driving that has been proposed in the literature. The network uses a deep convolutional neural network (CNN) to detect lanes in images captured by a camera mounted on a vehicle. The CNN is trained on a dataset of images of lane markings, and it learns to identify the patterns and features that are indicative of lanes. One of the main features of LaneNet is its ability to perform real-time lane detection

III. CHALLENGES/ISSUES INVOLVED IN ROAD LANE DETECTION

- Lighting conditions: Variations in lighting conditions, such as shadows, glare, and reflections, can make it difficult to accurately identify road lanes.
- Occlusions: Objects such as vehicles, bicycles, and pedestrians can occlude part of the road lane, making it difficult to identify.
- Weather conditions: Rain, snow, and fog can make it difficult to see the road lanes, which can lead to inaccuracies in identification.
- Road surface variations: Different road surfaces, such as concrete, asphalt, and gravel, can affect the appearance of road lanes, making it difficult to identify them consistently.
- Curvature and slope: Road lanes can be curved or sloped, which can make it difficult for an algorithm to accurately identify the lane markings.
- Lane marking variations: Lane markings can be different colors, widths, or styles, which can make it difficult for an algorithm to identify them consistently.
- Self-Driving Cars: Self-driving cars require a high level of accuracy in identifying road lanes because any error can lead to a serious accident.
- Urban Environments: Urban environments are more complex than rural areas, with more obstacles and variations in road conditions, making it more difficult to identify road lanes.

IV. COMPARATIVE STUDY OF LANE DETECTION TECHNOLOGIES

Various technologies are compared in the below table that performed well for lane detection.

Table. 1: Comparative Study and Technique Analysis

Author and year	Method	Description
Zhengyang Feng, Shaohua Guo, Xin Tan, Ke Xu, Min Wang, Lizhuang Ma;	Rethinking efficient lane detection via curve modeling	This method they use the curve model technique to identify lane
YassinKortli[abc]SouhirGabsi[c]Lew F.C. Lew YanVoon, MaherJridi, MehrezMerzougui MohamedAtri[cd] 15 March 2022	Hybrid CNN–LSTM network for lane detection on NVIDIA Jetson Xavier N	This method uses CNN and LSTM to identify lanes
Sun yang, Li yunpeng & Liu yu 2022	Lane Detection Based on Instance Segmentation of BiSeNet V2 Backbone Network	This method uses BiSeNet V2 is, a convolution neural network
Jonah Philion	Fast draw: Addressing the long tail of lane detection by adapting a sequential prediction network	This method uses a sequential prediction network. It is a type of a neural network.
Gupta 2021	Deep learning for object detection and scene perception in self-driving cars: Survey, challenges, and open issue	This method uses R-CNN and YOLO technique
J Fayyad	Deep learning sensor fusion for autonomous vehicle perception and localization:	This method uses the sensor fusion technique
Z Xu · 2021	iCurb: Imitation Learning-Based Detection of Road Curbs Using Aerial Images for Autonomous Driving.	This method uses icurb technique
L Tabelini · 2020.	PolyLaneNet is a lane estimation system.	This method use a polynet system based on a deep neural network
R Liu · 2020	End-to-end Lane Shape Prediction with Transformers	This method uses a transformed neural network for the identification of lane

March 2021, JigangTang[ab]SongbinLi[ab]PengLiu[ab]	A review of lane detection methods based on deep learning	This method uses CNN approach for identificatiuon of lanes
S Ghanem · 2021	Lane detection under artificial colored light in tunnels and on highways: an IoT-based framework for smart city infrastructure	This method uses a deep learning approach to identify lanes.
L Caltagirone · 2018	LIDAR–camera fusion for road detection using fully convolutional neural networks	This method uses lidar to detect the lanes
C Lee · 2018	Robust Lane Detection and Tracking for Real-Time Applications	This method uses CNN technique to detect lanes
Z Wang · 2018	LaneNet: Real-Time Lane Detection Networks for Autonomous Driving	This method uses CNN and Lanenet systems to identify lanes

V. CONCLUSION

Road lane detection is a crucial task in the field of autonomous vehicles, as it allows the vehicle to understand its position on the road and navigate safely. There are several methods for detecting lanes, including traditional computer vision techniques, such as edge detection and Hough transform, as well as more recent deep learning methods, such as convolutional neural networks. These methods have been shown to be effective in detecting lanes in a variety of conditions, including different lighting and weather conditions, and have the potential to improve the safety and efficiency of autonomous vehicles. Overall, road lane detection is an active area of research, with ongoing efforts to improve the accuracy and robustness of the methods used.

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