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Autonomous Lane Line Detection Using Poly-Lanenet and Polynomial Regression

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ABSTRACT

One of the most revolutionary developments in AI is the autonomous driving vehicle. The most crucial stage of current sophisticated driver aid systems is lane detection (ADAS). An autonomous vehicle is capable of doing anything a skilled human can do and can travel anywhere a traditional vehicle can go. We can identify the lane lines by using the the lane's relationship to the surrounding road surface, we need to detect edges for lane detection. To prevent collisions, lane markers serve as the vehicles' driving zones. In order to recognize lane line detection in binary images mostly uses thresholding based on gradient and hue lightness saturation, which can handle a variety of lanes, cope with lane alterations, and more. We devised a novel approach for lane detection using a forward-looking camera image as an input and deep polynomial regression to generate polynomials corresponding to each lane marking in the image.We made use of Poly-net, a cutting-edge lane-line recognition technology that use deep learning to distinguish between lane lines. The system uses convolutional neural networks to train the enormous datasets of lane line images and movies. It is shown in the tu-Simple dataset that the suggested strategy can compete with modern state-of-the-art techniques while maintaining its efficacy.

Keywords—*Autonomous vehicles, Lane Detection, ADAS, Vision-based technologies, Polynomial Regression.*

INTRODUCTION

Nowadays, both academic and commercial computer vision and robotics research is mostly focused on fully autonomous cars. In each scenario, The goal is to fully comprehend the world around the vehicle by utilising a range of sensors and control modules.Lane line detection is the process of locating lane lines in an image or video. As it enables the automobile to keep its lane attention and avoid collisions, it is an essential part of autonomous driving technology. The advent of deep learning has significantly altered the perception problems connected to this field. The vehicle can then be guided in a safe driving style using the detected lane lines. Convolutional neural networks are used in the method of polynet for lane line recognition to identify lane lines in an image or video.The polynet is used to identify after beingtrained on a collection of lane line images.It can be employed to find parking spaces, road signs, etc.The study of autonomous driving is a difficult area that has attracted a lot of interest recently. The developments in deep learning have had a significant impact on the perceptual issues associated to this discipline.

Autonomous vehicles should be able to estimate traffic lanes in particular because each lane not only serves as a spatial restriction but also offers distinct visual cues dictating the drive. The polynet is used to identify after being trained on a collection of lane line images. To produce accurate results, Polynet mostly uses data that is based on probability. It can be a quick and effective approach to find lane lines. It can be employed to find parking spaces, road signs, etc.The study of autonomous driving is a difficult area that has attracted a lot of interest recently. The developments in deep learning have had an important effecton the perceptual issues associated to this discipline. Autonomous vehicles should be able to estimate traffic lanes in particular because each lane not only serves as a spatial restriction but also offers distinct visual cues dictating the drive. Additionally, the surroundings themselves are various by nature: there can be a lot of traffic .There may be a large number of onlookers or it may just be a clear road. Besides, due to a variety of weather factors (such as rainfall, snow, sunshine, etc.), lighting conditions, and other factors, these conditions might change quickly while you're driving (such as day, night, dawn, tunnels, etc.). The usual method for estimating (or detecting) lanes begins with manually constructed feature extraction and concludes with a curve-fitting procedure. Although this method typically works well in certain, everyday situations, it is generally not as consistent as required in challenging situations (as the aforementioned ones). Following a deep learning is currently popular for many computer vision taskshas recently been applied to learn strong features and improve the lane marking estimate technique. The actual lanes can be identified once additional processing is done to identify the lane markers. But there are still issues that need to be resolved. Many of these models are based on deep learning, to start.

LITERATURESURVEY

In this research, an instance segmentation strategy for end-to-end lane detection is proposed. The model is constructed using a single-stage Mask R-CNN with a unique loss function for each lane. The suggested model performs better in terms of accuracy and resilience than the current lane detecting methods, according to experiments. The model can also recognise lanes in difficult situations including curved roadways, shadows, and poor sight.[1]

This paper discusses efficient algorithms for vision-based automated vehicles. It covers perception, planning, and control techniques, as well as performance evaluation metrics.The authors suggest that their algorithms can improve the safety, reliability, and robustness of automated vehicles. Finally, the paper outlines several improvements to the current state of the art. [2]

This paper describesa cutting-edge method for lane recognition and tracking using the front monocular camera of a car. To identify and track lanes from the perspective of camera, the method makes use of picture segmentation and a lane model. Then, an estimate of the lane borders and the vehicle's position within the lane is generated using a Kalman filter.On a driving dataset, the method's effectiveness is shows improved accuracy and robustness compared to existing methods. [3]

Presented here is a vision-based lane detection system. method for structural highway with both straight and curving roads. The method includes a straight-curve model to differentiate straight and curving lanes. The suggested approach can precisely recognize the lane boundaries and curvature of both straight and curved lanes, according to experimental results on real-world highway photos. It is possible to increase the safety of autonomous driving on highways by using the suggested strategy. [4]

A deep convolutional network and a Wasserstein Generative Adversarial Network are combined to create the innovative lane line detection network ripple-GAN, which enhances the effectiveness of lane line detection.The Wasserstein distance is used by the network's specially created loss function to increase the reliability of the results of lane line detection. In addition, Ripple-GAN introduces a dual-stream architecture to more effectively capture lane line characteristics and a new attention layer to further boost the accuracy of outcomes of lane line recognition [5]

This paper presents a method of analyzing driving behavior of intelligent vehicles by using a vision-sensor system for lane detection. It focuses on the lane detection accuracy, which can be improved by pre-processing, feature extraction and lane detection algorithms. The results show that the system can achieve higher accuracy when compared to traditional lane detection methods. The system can also provide valuable information for driving behavior analysis.[6]

Polynominal regression is used for lane line fitting in the deep learning-based lane estimation method PolyLaneNet. A convolutional neural network is used to estimate the polynomial coefficients before building the lane lines in the image. PolyLaneNet offers cutting-edge performance in lane estimation, according to experiments on the TuSimple benchmark dataset.[7]

This study presents a reliable multi-lane detection method for autonomous city driving based on affinity fields (AF). A single image is used in the technique to learn the lane features using an encoder-decoder architecture. A lane affinity field map, which encodes the laneness and connectivity of lanes, is produced using the encoder's output. The suggested method surpasses existing lane detection approaches with improved accuracy and robustness, according to tests on the BDD100K dataset.[8]

This paper describes a generic approach for lane detection utilizing end-to-end estimation and point instance segmentation.It is based on a Mask-RCNN model, which provides a unified architecture for lane and instance segmentation of point clouds.Experiments on the KITTI dataset show competitive results with state-of-the-art methods and show that the model is able to detect lanes in different driving scenarios.The proposed approach offers a practical solution for lane detection in autonomous driving applications.[9]

In order to precisely recognise lane borders in intricate road situations, a new lane detection method is proposed in this study that makes use of a curve modelling approach. The suggested solution accurately adapts to the road geometry by using region growth and a Bezier curve fitting algorithm. The suggested method is suitable for real-time lane detection and performs superior to current techniques in terms of accuracy and efficiency, according to experiments. [10]

Keep your Eyes on the Lane is a paper that proposes a real-time lane detection system using an attention-guided approach. It uses an end-to-end network to detect roads while considering global and local contexts. The system is tested on multiple datasets, achieving state-of-the-art results and real-time performance.[11]

Lane detection using color-based segmentation is a technique for detecting lanes in a camera image.It involves converting the camera image from RGB to HSV color space and then applying a threshold to identify the lanes.The output of this technique is a binary image which indicates the presence of a lane line in the image.This technique is suitable for detecting lanes in a variety of conditions such as bright and dark lighting.[12]

For precise real-time lane recognition, PointLaneNet is an effective end-to-end Convolutional Neural Network (CNN). PointLaneNet effectively extracts lane features utilizing an encoder-decoder architecture, from the source imagewith an encoder feature pyramid network. After that, it reconstructs and classifies lane lines using a number of convolutional layers. The PointLaneNet model delivers state-of-the-art accuracy in real-time lane detection thanks to training on the expansive BDD100K dataset..[13]

Differentiable least-squares fitting is a lane detection technique that uses a differentiable least-squares cost function to model lane boundaries. It fits the detected lane boundaries by minimizing the differences between the model and the detected boundaries. The model is based on a low-order polynomial curve, which is then refined through an iterative optimization process. This method can be used to accurately detect lane boundaries, even in challenging scenarios, such as curved roads and lane changes.[14]

Real-time lane detection in autonomous vehicles is accomplished through the use of computer vision and machine learning techniques. It aids in the accurate and safe navigation of autonomous vehicles on highways. Vehicles can reliably forecast turns and navigate curves by identifying lane boundaries. In order to discover additional lanes, the system fits a mathematical model to the detected lane markers using image processing algorithms.[15]

A real-time stereo vision technology called GOLD is used to detect lanes and obstacles. It is made to work in parallel across several CPU cores. After capturing stereo images using a set of stereo cameras, the system employs feature extraction and stereo matching to find obstacles and lanes. The identified objects can also be tracked and classified by it. GOLD is made to be quick and precise and can be used in autonomous vehicles.[16]

VARIOUS METHODS OF LANE DETECTION

A. *Edge Detection*

Edge detection can be used to identify lane line boundaries so that a line can be drawn over the lane line.By observing changes in pixel intensity, algorithms are used to identify the edges of objects in an image.

Steps in Edge Detection:

1. Image pre-processing:This step comprises boosting the contrast and brightness of the image, grayscale conversion, and smoothing the image to reduce the amount of noise in the image.
2. Edge Detection: This entails using different algorithms, including Sobel, Prewitt, Canny, Roberts, and Laplacian, to identify changes in the image's intensity.
3. Edge Thinning: This involves reducing the detected edges to a single pixel width.
4. Edge Linking: This involves connecting the detected edges and grouping them together, to produce a continuous line.
5. Edge Enhancement: This involves sharpening the edges to make the details more prominent.

B. *Hough Transform Method*

The Hough transform method can be used to locate lines in a picture. Straight lines are detected with it, and it is widely employed in lane detection. These points are used by the Hough transform to construct a line over the lane line by looking for points in the image that form lines.

Steps in Hough Transform:

1. Pre-processing: Pre-processing the image is the initial stage. This involves the elimination of noise, improvement of contrast, and conversion to binary picture.
2. Edge detection: This technique is used to identify the edges in a previously edited image.
3. The Hough Transform is employed to identify any lines or curves in a picture. In this stage, edge points are transformed into a parameter space, which is a representation of the image's lines or curves.
4. Fourth, lines or curves are found in the parameter space, and the relevant line or curve is drawn in the image.

C. *ConvolutionalNeuralNetwork*

Deep learning algorithms known as convolutional neural networks (CNNs) are used to identify objects in images. They can be used to identify lane markings and mark the lane with a line.

Steps in CNN:

1. Pre-processing: The input image is first enhanced with lane lines and noise reduction.
2. Region of Interest: To concentrate the search for lane lines, a Region of Interest (ROI) is established around the lane lines.
3. To locate straight lines in the area of interest, apply the Hough Line Transform. Thus, the lane lines will be detected.
4. Lane Line Extraction: Left and right lane lines are extracted from the detected lane lines.
5. Polynomial Fit: Each of the lane lines is fitted with a polynomial. A continuous line will be drawn along the lane lines using this polynomial.
6. Output: The algorithm's result is an illustration of the lane lines superimposed on the input image.

D. *Color Thresholding*

To locate the lane lines in an image, utilise colour thresholding. It distinguishes the lane markings from the other parts of the picture. using particular colours. Lane markings are often painted in white or yellow. Then, a line can be drawn over the lane line using the colours of the lane lines.

Steps used in Color Thresholding:

1. To make it simpler to quantify the colours, the colour image is first converted to a grayscale.

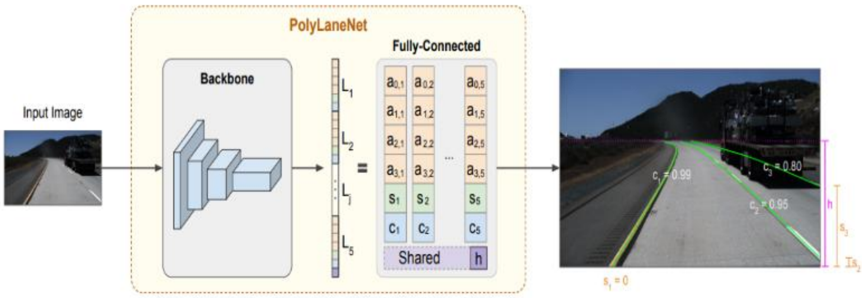
2. Use Gaussian blur to eliminate details and noise from the image that are unimportant for lane detection.
3. Obtain the gradient of the image: A gradient is a change in direction of colour or intensity in an image..
4. Use colour thresholding: Color thresholding is a technique for identifying areas of an image that fall inside a specific colour range.
5. Use Canny edge detection to identify object boundaries in a photo.
6. Use the Hough line transform to identify straight lines in a picture.This technique is used to locate the lanes.
7. Apply the area of interest mask to the image: The region of interest mask is used to draw a border around the image's main topic.

E. *PolyLane-Net*

PolyLaneNet is a deep learning model developed for autonomous driving. It utilizes a multi-task learning framework, combining lane detection and lane change recognition tasks. The model is based on a fully convolutional neural network, which allows for real-time performance.

Steps for PolyLane-Net:

1. Preprocessing: The images from the dataset are preprocessed
2. Network Architecture:The CNN takes the preprocessed images as input and outputs the polynomial coefficients.
3. Training: The training set consists of preprocessed images and their corresponding polynomial coefficients.
4. Evaluation: The trained model is evaluated on the test set.
5. Post Processing: Once the polynomial coefficients are estimated, the lane markings can be reconstructed using the polynomial equations. The lane markings are then used for further applications, such as lane detection, tracking, and control



F. *Polynomial Regression:*

Polynomial regression may be used in lane identification to forecast where lanes will be along a given section of road. The lane locations may be precisely predicted by fitting a polynomial to the data, enabling lane identification and tracking.The association between a predictor variables (in this case, lane detection) and one or more target variable(such as road curvature, lane width, etc.) is modelled as an nth degree polynomial in polynomial regression.

Steps in Polynomial Regression:

1. Establish the required lane line first.
2. Compile data points from the lane photos.
3. Fit the data points using a polynomial.
4. Calculate the curve's coefficients using the polynomial.
5. To draw the polynomial line, use the coefficients.
6. Reduce the error between the data points and the fitted line to improve the polynomial line fit.
7. After identifying the best polynomial line, use it in order to find the lane markings in the picture.

TABLEI:COMPARISION OFDIFFERENTMETHODS

Author Name	Methodandtoolsused	Merits	Demerits
Naven et al.	1.ConvolutionalNeuralNetwork(CNN) 2. Instance Segmentation 3. Multi-Scale Feature Extraction	a lane border probability map and a lane instance map are combined in an efficient instance segmentation method for lane detection.	The paper uses a single model which cannot be optimized for different lane sizes and shapes.
Qian, Y., Dolan, J. M., & Yang	1. Control algorithms 2. Reinforcement learning	This study describes effective algorithms for vision-based automated cars' perception, planning, and control, and shows how useful they are through actual-world tests..	It discusses the implications of using deep learning for these algorithms and the unique safety considerations that must be taken into account.
D. C. Andrade et al.	1.Support Vector Machine (SVM) 2.Canny Edge Detection 3. Histogram of Gradients	This novel strategy was vehicle's forward monocular camera is the foundation of this unique lane recognition and tracking technique, making it a low-cost and low-power option.	The suggested technique fails to recognise the lane.in challenging weather conditions.
H. Wang, Y. Wang, X. Zhaoet al.	1.curve-fitting model	This structural highway straight-curve model allows for more accurate lane detection when the road has curved sections.	This model may not be suitable for roads with many intersections and abrupt changes in the lane boundaries, as it is designed to detect straight and curving sections of the road.
Zhang, Y., Lu, Z., Maet al.	1. Convolutional Neural Network (CNN) 2. Ripple Line Detection Network (RLDN) 3. Generative Adversarial Network (GAN)	Ripple-GAN is an effective method for lane line identification under difficult circumstances. It combines the Ripple Network and the Wasserstein GAN to detect lane lines accurately.	Ripple-GAN necessitates a large amount of instruction data and is therefore not suitable for applications with a limited amount of training data.
D. K. Dewangan and S. P. Sahu	1. Machine Learning Algorithms 2. Feature Extraction 3. Computer Vision Algorithms	It offers a more efficient and accurate way of detecting lanes on roads, as compared to traditional methods.	The accuracy of the system is limited by the resolution of the camera and other sensors used.
Tabelini, L., Berriel, Ret al.	1. fully convolutional neural network (FCN) 2. PolyLaneNet algorithm 3. polynomial regression	PolyLaneNet uses deep polynomial regression to generate lane estimation in a more accurate and robust manner than traditional methods.	PolyLaneNet requires a sufficient training data sets toachieve good accuracy, which can be difficult to obtain.
Abualsaud, H., Liuet al.	1. Multi-Lane Detection 2. Affinity Field (AF) 3. Robustness Enhancement (RE)	LaneAF is a robust lane detection approach that adopts a unified framework for lane detection with affinity fields.	LaneAF is computationally expensive and large amount of data for training required.
Ko, Y., Lee, Y., Azamet al.	1.Edge Detection 2. Hough Transform 3. RANSAC (Random Sample Consensus)	It is a simple and straightforward approach that requires low computational complexity.	It is sensitive to camera calibration errors.

Feng, Z., Guo, S., Tanet al.	1.image processing	Efficient Lane Detection via Curve Modeling is a novel method that allows for faster and more accurate lane detection.	Efficient Lane Detection via Curve Modeling is a complex algorithm and requires more computational power than traditional lane detection methods.
Tabelini, L., Berriel,et al.	1. Convolutional Neural Networks (CNNs 2. Attention-based Models	The real-time lane identification offered by Keep your Eyes on the Lane is attention-guided.system that is capable of accurately detecting lanes in complex driving scenes.	The system relies on a deep neural network which requires large amounts of computing power and memory, making it difficult to deploy on low-end hardware.
Chiu, K. Y., & Lin, S. F	1.K-Means Clustering 2.Otsu's Method	Easy to implement: Color-based lane detection is relatively easy to implement and requires minimal computational power.	Not suitable for all scenarios: Color-based lane detection may not be suitable for all scenarios, such as in cases where there is a lot of reflection or shadows.
Chen, Z., Liu, Q., & Lian, C.	1. Convolutional Neural Networks (CNNs) 2. Lane Marker Refinement (LMR) Module	PointLaneNet is a lightweight yet accurate real-time lane detection system that uses efficient end-to-end convolutional neural networks.	PointLaneNet is not suitable for detecting curved or curved lanes due to its limited field of view.
Van Gansbeke, W.,et al.	convolutional neural network	Lane detection from end to end using differentiable lowest fittingis a straightforward and effective method because it only necessitates minimal data pre-processing.	The final lane detection method necessitates the collection of a lot of data,which can be expensive to acquire.
Assidiq, A. A., Khalifa,et al.	1. Image Segmentation 2. Edge Detection 3. Support Vector Machines (SVMs)	Real-time lane recognition is a crucial component of autonomous vehicles, and this study offers a thorough analysis of the methods currently in use, as well as their benefits and drawbacks.	The statements stated in the paper are not supported by any data or experiments in the publication.
Bertozzi, M., & Broggi, A.	1.Scene Interpretation 2.Feature Extraction	This research presents a parallel real-time stereo vision system for general lane and obstacle recognition.	The technology may not be appropriate for various sorts of terrain because it has not been tested in a range of situations.

CONCLUSION

Deep polynomial regression was recommended as a method for lane detection. The proposed method is competitively accurate while being both rapid and effective when relative to cutting-edge techniques. It is challenging to undertake in-depth comparisons of the variations among approaches, despite some works adopting cutting-edge techniques with somewhat increased accuracy. The majority of these works do not offer source code to duplicate their results. Our method is computationally efficient and will be made available to the public, providing future research on the recognition of lane markings with a starting point and a point of comparison. We have also shown problems with the metrics that are employed to rank lane markings detection methods. Future research can study metrics that can be used to multiple lane identification strategies (such segmentation) and that better show the inadequacies of lane detection systems.

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