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Research Paper

A Study on Vision Based Lane Detection Methods for Advanced Driver Assistance Systems

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Abstract: *- Intelligent driving systems need to find the lines that show where the lanes are present. It can help drivers prevent lane hopping and improve vehicle positioning and identification by providing information about the current road conditions. The lane detection encounters several obstacles, including harsh illumination conditions, missing lane markings, and impediments. Due to their outstanding performance, Artificial Intelligence, machine learning, and deep learning-based algorithms have recently attracted considerable interest in the intelligent driving society. In this paper, we thoroughly analyses different lane detection approaches for lane detection including deep learning based techniques. In addition, we review known datasets about lanes and assessment criteria. It ends with a discussion of current problems and possible directions for a lane detection system.*

Keywords*- ADAS, LKAS, Lane Detection.*

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1. Introduction

Advanced Driver Assistance Systems (ADAS) are systems designed to support drivers in operating vehicles more safely and efficiently. These systems use various technologies such as cameras, Radar, Lidar, and ultrasonic sensors to sense the environment around the vehicle and provide the driver with information and warnings. ADAS features can range from simple technologies such as backup cameras and lane departure warning systems to more advanced systems such as semi-autonomous driving systems, adaptive cruise control, and automatic emergency braking. ADAS aims to decrease the number of accidents produced by human error, such as distracted driving, and improve the overall driving experience. ADAS technologies have seen rapid advancements in recent years, becoming increasingly common in new vehicles. ADAS technologies are expected to play a critical role in developing autonomous vehicles and be a key driver of growth in the automotive industry in the coming years. Some of the most popular ADAS features include lane detection involves detecting road lanes and locating a vehicle inside them. Lane detection informs drivers and autonomous vehicles about lane layout and aids navigation. Lane Departure Warning warns the driver if the vehicle veers out of its lane. Blind Spot Monitoring alerts the driver to vehicles in their blind spot. Adaptive Cruise Control automatically maintains a safe following distance from the vehicle in front. Forward Collision Warning alerts the driver to an impending collision and may automatically apply the brakes.

1.1 Overview of Lane Detection

Lane detection is a computer vision methodology employed to identify lane markings on roads and highways and estimate the precise positioning of a vehicle inside such lanes. The lane information discovered is utilized to ascertain the vehicle's precise position and regulate its steering and navigation. The data, as mentioned earlier, finds utility in a diverse range of applications, including but not limited to autonomous driving, driver assistance systems, and improved navigation systems. The identification of lanes is of utmost importance in the advancement of road safety, the enhancement of the driving experience, and the facilitation of autonomous vehicle development. The main goal of the lane detection system is that it must work well, mostly at low speeds, and can be used for mapping, locating, and understanding. Our short-range system needs to work on both highways and in cities. Since we are looking for lateral lines, cameras on the car's sides make more sense for this task. Figure 1 shows some different ways that primary line detection can be used. On roads, there is more than one line, the "principal line," the longest visible line closest to the car. On the right, it always lines up with the end-of-roadway line. On the left, it could line up with the line between the lanes or the opposite end-of-roadway line when the other is not visible. If a line has dashes, all of the dashes will be counted as part of the main line.

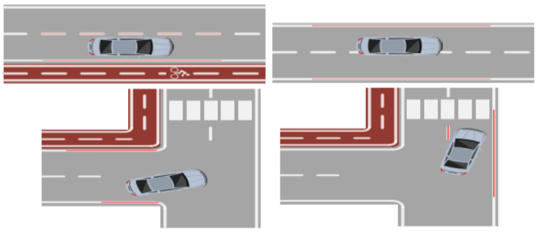

Figure 1: Examples of predominant principal lines detection.

Some of the critical needs for lane detection include:

Safety: Lane detection systems can help drivers stay within their lanes and avoid accidents, especially in adverse weather conditions or low-visibility situations.

Efficient Navigation: Lane detection helps autonomous vehicles navigate the roads efficiently and safely, making them more reliable for passengers and other road users.

Improved Driving Experience: Lane detection systems can provide drivers with real-time feedback on their driving, helping them stay within the lanes and drive more smoothly.

Enhanced Performance: The integration of lane-detecting systems with other Advanced Driver Assistance Systems (ADAS) functionalities, such as adaptive cruise control and autonomous emergency braking, can enhance the overall operational effectiveness of the vehicle.

Cost-Effective Solution: Lane detection systems are becoming increasingly affordable, making them accessible to a broader range of vehicles and drivers.

Lane identification algorithms commonly employ image processing and computer vision methodologies to identify lanes in real-time video streams acquired from vehicle-mounted cameras. Lane detection poses significant hurdles within computer vision and machine learning, necessitating the resolution of several obstacles to get dependable and precise lane detection outcomes. Figure 2 shows various challenges posed by lane detection problems. Lane detection systems must be able to handle complex road scenes, including various types of roads, lighting conditions, and weather conditions. A complex road scene in lane detection refers to a road with various features and challenges that make it difficult for the lane detection algorithm to identify the lane markings accurately. Roads with multiple lanes can pose a challenge for lane detection algorithms, as they must accurately identify and distinguish between the different lane markings. Curved lanes can present a challenge for lane detection algorithms, as the lane markings may become distorted and difficult to identify, particularly at sharp curves. Intersections with multiple roads can challenge lane detection algorithms, as the lane markings may become obscured or distorted by other vehicles or road signs. Weather conditions, such as rain, snow, and fog, can make it difficult for lane detection algorithms to identify lane markings accurately. Varying lighting conditions like shadows and reflections can also challenge lane detection algorithms. Lane detection systems must be able to handle occlusions, such as vehicles, trees, and road signs, which can obscure the view of the lanes. These complex road scenes can make it difficult for lane detection algorithms to accurately identify the lane markings and maintain a safe and efficient vehicle trajectory. Lane detection algorithms must be robust and flexible enough to handle these challenges and provide accurate and reliable results. Lane detection systems must process images in real-time, which requires a balance between accuracy and computational efficiency. Lane detection requires computer vision, machine learning, and engineering expertise to address these challenges and achieve accurate and reliable results.

Figure 1. Various challenges in lane detection. [a] A vehicle occluding nearby lane [b] Presence of shadow [c] Rainy road [d] Extreme illumination on the left side of the image

The difference between lane detection with and without a vehicle primarily lies in the challenges and considerations arising when a vehicle is on the scene. Let's explore the key differences:

Occlusion: A vehicle in the scene may partially or entirely block the view of lane markings, leading to occlusions. This can make it more difficult for the lane detection algorithm to identify and trace the lanes accurately.

Size and Shape Variation: Vehicles come in various sizes and shapes, and their presence on the road can vary significantly. Lane detection algorithms must be robust enough to handle these variations and distinguish between lane markings and other objects.

Dynamic Scene Changes: Vehicles are mobile objects, and their presence in the scene can change rapidly. Lane detection algorithms must adapt to these dynamic changes and track the lanes effectively, even when vehicles move in and out of the frame.

Lane Change Scenarios: When a vehicle changes lanes, the lane detection system should be able to recognize this change and update its understanding of the new lane configuration.

False Positives: The presence of vehicles can introduce false positives in the lane detection process, where the algorithm may mistakenly identify vehicle edges or other objects as lane markings.

Sensor Perspective: Lane detection systems often use cameras mounted on the vehicle. The camera's perspective can affect the appearance of lane markings when a vehicle is nearby, making it necessary to account for this in the algorithm.

To address these challenges, advanced lane detection systems may use more sophisticated techniques such as deep learning-based approaches, fusion with other sensors, and advanced filtering and tracking algorithms. The goal is to create a robust and reliable system that can accurately detect and track lanes even in the presence of vehicles and other dynamic elements on the road.

2. Review of Vision Based Lane Detection Methods

The recognition of lanes plays a vital role in autonomous driving systems, as it allows the vehicle to recognize and monitor the edges of lanes on the roadway. Numerous scholarly articles have put forth a range of methodologies and technologies for identifying lanes. Numerous conventional approaches for lane recognition necessitate intricate manual feature engineering and subsequent post-processing methodologies, rendering them vulnerable to instability when confronted with diverse road scenarios. The lane detection procedure encompasses many stages: picture pre-processing, region of interest (ROI) extraction, lane line identification, and lane tracking. In recent years, sophisticated lane detection systems have proliferated, encompassing technologies like radar sensors and cameras. The reliability and accuracy of these systems have witnessed significant advancements, enhancing the safety and security of autonomous cars. The safety and security of autonomous cars have been enhanced via the development of more precise and dependable systems driven by technological developments. Lane detection is a complex undertaking encompassing many computer vision tasks, including semantic segmentation, object identification, and picture categorization. The problem of lane detection has been tackled through several manually designed approaches, including geometric modelling and traditional procedures. The sequential technique, sometimes called pipelines, is frequently adopted by most classical detection algorithms. The standard pipeline for lane detection has many stages, encompassing picture pre-processing, feature extraction, lane model fitting, and line tracking. The main goal of photo pre-processing is to reduce the level of noise present inside the image. Following this, the attributes of lanes are utilized throughout the feature extraction procedure, facilitating the recognition and retrieval of areas that belong to lanes.

Reviewing existing literature on lane identification with vision sensors uncovers various algorithms and strategies for detecting and tracking lanes. These approaches encompass several methodologies, including pre-processing, edge detection, lane recognition, and tracking. The categorization of vision-based lane identification approaches encompasses three primary classifications: feature-based, model-based, and learning-based. Features-based techniques employ binary pictures to identify lanes, whereas model-based approaches utilize resilient lane recognition models with limited vehicle characteristics. Learning-based methodologies, such as the integration of reinforcement learning techniques with model predictive controllers, can also be employed as a means to mitigate the occurrence of erroneous lane detection.

2.1 Model-Based Methods

The approach employed in this study is model-based. Lane detection techniques refer to a set of methodologies employed to identify and monitor lanes on roadways. These algorithms commonly represent lane lines through geometric forms, such as straight lines, curves, parabolas, or splines. The research community has extensively investigated lane recognition algorithms that are based on models due to their efficacy in addressing complex scenarios, including but not limited to junction merging and splitting, curves, shadows, and straight roadways [1][2]. Moreover, these algorithms can simultaneously recognize numerous lanes. The challenge of lane recognition is then transformed into identifying the suitable model inside the original region [3]. Lane detection in computer vision often involves using conventional image processing techniques to extract relevant pixel characteristics from the lane line. Subsequently, a suitable algorithm for pixel fitting is employed to accomplish the task of lane detection. The approaches may be roughly categorized into two groups: lane identification based on classification and lane detection based on semantic segmentation. Classification-based lane identification systems commonly employ dynamic programming (DP), and Hough transforms algorithms for lane detection [4]. The efficacy of this approach is considerable, yet, it encounters challenges when confronted with intricate road circumstances, such as curving pathways or the presence of many lanes. Using semantic segmentation-based methods for lane identification involves the application of instance segmentation to identify lanes within scenes containing multiple lanes accurately. The model has three components: an auxiliary segment, a lane predictor, and a semantic segment. The procedure consists of three stages: picture pre-processing, lane line segmentation, and lane line fitting. As mentioned, the technique exhibits higher accuracy than the classification-based methodology but requires greater processing capacity.

The lane detection method commonly employs a log-polar transform (LPT) and Random Sample Consensus (RANSAC) to get reliable and resilient performance [5]. The system needs an initial assessment of the road position a human operator provides to extract the ideal lane markers. The lane identification process involves determining the optimal lane shape based on the characteristics of the given picture. In their study, Wang et al. (6) introduced a model-based approach for recognizing lanes, whereby the lane route was represented geometrically through a B-Snake spline arc. The Canny/Hough Estimation of Vanishing Points (CHEVP) technique was employed to derive the geometric model parameters. Špoljar et al. (7) introduced a parabolic line model for lane detection in their study. Identifying the number of lines and their respective placement in the original image involves seven distinct analysis steps. The algorithm has difficulties detecting lines when they are not fully visible.

In their study, Zhou et al. (2018) propose a lane geometrical model that incorporates four essential parameters: the beginning position, the original orientation, the width, and the curvature of the lane (Zhou et al., 2018, p. 8). The algorithm is comprised of three separate steps. The first phase, offline calibration, is performed as a singular event after the installation and stabilization of the camera on the vehicle. Accurately determining the camera parameters used for lane detection is achieved using the 2D calibration approach [9]. The third phase, known as the estimate of lane model parameters and the building of lane model candidates, entails estimating the first three parameters: beginning location, original lane orientation, and lane width. The estimation uses dominant orientation estimation [10] and local Hough transform. Later, the procedure of generating lane model candidates is carried out to achieve the final lane model matching. This signifies the third phase of the comprehensive process. The applied methodology for matching lane modules is designed to ascertain the optimal model. The incorporation of these modules possesses the capability to tackle the inherent difficulties linked to universal lane recognition, which stem from the constraints of edge detection methods, such as the existence of shadows caused by trees and the presence of pedestrians on the roadway. The efficacy of the suggested lane identification algorithm will be substantiated through the exposition of empirical data obtained from real-world traffic circumstances.

The geometric modelling approach was introduced by Akbari et al. [11]. This technique utilizes the region of interest (ROI) for pre-processing, the Canny operator for extracting edge features, and the Hough transform to filter out unwanted edges and generate straight lines. The vanishing point subsequently removes extraneous straight-line segments from the picture. Hence, using B-spline clustering and IPDA filter is incorporated in this study to recognize the road lane effectively. As mentioned earlier, the solutions exhibit expeditious implementation and straightforwardness, yet they need the human entry of parameters.

The assessment of the performance of these algorithms has significance in guaranteeing their correctness and dependability. The efficacy of model-based lane identification is contingent upon the specific model employed and the prevailing road conditions. In general, the mean detection accuracy often falls within the range of 97% to 99%, accompanied by a detection time that spans from 20 to 22 milliseconds. Model-based lane detection is widely employed in several intelligent car systems, including driver assistance, lane departure warning, and autonomous driving. Model-based lane recognition algorithms are crucial in intelligent vehicle systems since they can effectively identify lanes under diverse environmental circumstances. Model-based approaches exhibit reduced susceptibility to weak lane appearance characteristics and noise compared to feature-based methods but at the cost of increased computing resource requirements.

2.2 Featured-Based Methods

Model-based lane identification approaches employ a model to identify lanes, whereas feature-based lane detection techniques rely on low-level data such as edges for detection. Lane recognition algorithms based on features utilize manually designed characteristics to identify lane markers. The abovementioned properties encompass line segments, ridge filters, and spatiotemporal images. Feature-based lane identification algorithms are employed to ascertain the presence of lanes in a given road environment by leveraging the distinctive characteristics of lane edges and colours. Prominent techniques utilized for feature extraction encompass the Canny transform, Sobel transform, and Laplacian transform. Feature extraction employs several approaches, including the Sobel operator, Canny edge operator, FIR filter, and Hough transform. Moreover, several methodologies employ inverse perspective transformation, image augmentation, stereo camera, and wavelet analysis in challenging scenarios.

In their study, Mariut et al. [12] devised a simple way to find lanes, describe them, and figure out the direction of movement. Known as the Hough transform, it was used to find possible lines in the picture. So that lane recognition is reliable, a method was made that focuses on getting the inner edge of the lane. By making the magnitude picture, the edges of the lane can be seen more clearly. T.T. Tran et al. [13] introduced an adaptive method for lane detection that employs the HSI colour model—the initial transformation of the RGB-based image to its corresponding HSI-based representation. The method used to calculate the intensity (I) component from RGB colour images was modified to enhance the HSI colour model. When analyzing the colour photographs of the road scene, the researchers used the HIS colour space's limited colour gamut. Consequently, the H, S, and I components were incorporated into this methodology. The proposed method precisely identifies and labels lane locations with high precision.

K. Ghazali et al. [14] presented an efficient and improved algorithm with the capacity to identify unexpected lane Lines. The authors proposed a technique for lane detection that employs the H-MAXIMA transformation and an improved Hough Transform algorithm. This method commences by identifying the region of interest within the input image to restrict the search area. The image is then separated into the near field and far field. The Hough transform was applied close to the observed area to detect lanes. In their work, Srivastava et al. (15) researched the efficacy of several filtering strategies in decreasing noise in photographs. The main objective of this work was to develop, implement, and evaluate an effective lane detection algorithm capable of producing superior results, even in the presence of signal noise. The study compares several filters, including the median, Wiener, and hybrid median filters.

The lane-detecting system developed by Khalifa et al. [16] is capable of real-time operation. The approach employs video sequences from a vehicle in motion on a roadway. The algorithm demonstrated robustness in its ability to adapt to changes in lighting conditions and the existence of shadows. The lanes were detected using the Hough transformation approach, which included a constrained search region. The possible utilization of this technology extends to many road conditions, encompassing both painted and unpainted surfaces, as well as roadways exhibiting moderate curvature or straight, irrespective of existing weather conditions. Compared to other algorithms, the presented technique showed resilience and satisfactory efficiency in fulfilling real-time requirements. It is well acknowledged that automobiles often traverse roadways characterized by mostly flat and straight stretches, occasionally interspersed with gradual turns. The efficacy of this methodology is less than optimum when confronted with sudden changes in curvature and while functioning in environments with the presence of shadows.

Pomerleau et al. [17] proposed the RALPH technology to regulate the lateral position of autonomous vehicles. The lane curvature and side offsets are determined using adaptive template modification and alignment concerning the averaged scan line intensity profile. Using edge information, Mammeri et al. [18] proposed a method for identifying the borders of lanes. Lane markings are indicated by nearly vertically dazzling lines on a nearly black background. Adaptive filtering extracts and combines quasi-vertical pointed lines into more significant segments. Chen et al. [19] propose a novel LDWS and LEHA based on enhanced grayscale processing, binarization, image flattening, and ROI extraction during the image pre-processing phase. Detection requires less time, thanks to the inventive ROI extraction and Hough transform.

AURORA was developed by Farag et al. [20] to detect lane markings on structured roadways using a colour camera mounted on the side of a vehicle. In each image, lane markings are detected by a single scan line. Using edge recognition, squares angular estimation, and the Hough transform, Zhou S. et al. [21] estimated roadway lanes. The method is effective except for shadow or traffic interference. Chenet et al. [22] proposed a real-time, efficient method for lane recognition. The method utilized a top view of the road image, Gaussian kernel filtering, line identification, and a novel RANSAC spline fitting technique to detect street lanes. This method identified all lanes in urban street photographs under various conditions. This method has problems with crosswalk stop lines, oncoming vehicles, and disorganized writing. Kumar et al.[23] included novel algorithms for lane curvature, worn-out markings, and lane layout alterations such as merging or separating lanes.

The author of Zhang et al. [24] proposed a real-time lane detection technique based on highway video sequences. Using this procedure, lighting and shadows were addressed appropriately. Using a limited search area and Hough transformation, the channels were identified. It operates in all weather conditions, on painted and unpainted roadways and curved and straight roads. Compared to previous algorithms, this one was more robust and rapid enough for real-time applications. Vehicles assume that the road is level, linear, or gently curved. Shadows and sharp contours are problematic with this procedure. Xing et al. [25] presented a novel camera-based robust lane identification system. Using Interacting Multiple Models (IMM), this identification method was coupled with a monitoring strategy. The linear technique was resistant to noise and insufficient markers.

Yahiaoui et al. (26) developed a system that autonomously enhances and identifies lane markings in digital photographs. This methodology acknowledges the presence of lane markings and the determination of driving direction. To achieve precise identification of lane marks, the inner edge of the lane is removed. The efficacy of this strategy is seen to be high in the context of straight roads, whereas its effectiveness diminishes when applied to curved roads. Chen et al. (27) introduced a model with the primary objective of developing an image-processing system that can effectively recognize road lanes and provide alerts for lane departure. A lane departure is determined solely based on the distance between lanes and the bottom centre of the picture. The utilization of the Kalman filter demonstrates enhanced performance in lane recognition compared to the Hough transform method. In contrast to prior systems, the model exhibited high efficiency and viability. As mentioned earlier, the system is deficient in accurately identifying lanes under challenging circumstances.

Feature-based lane identification algorithms are characterized by their simplicity, robustness, and efficiency, which enable them to precisely and effectively retain lane line characteristics. The study of lane recognition and tracking algorithms has demonstrated that feature-based approaches may effectively achieve high levels of accuracy in recognizing lanes across diverse traffic circumstances. Previous studies have demonstrated that feature-based lane recognition algorithms exhibit notable precision in detecting lanes. Previous research has documented an average detection accuracy of 98.49%. Feature-based methods have been found to possess higher efficiency compared to other approaches. However, it is essential to note that these methods are susceptible to the influence of noise and the presence of weak lane appearance characteristics. Model-based lane recognition approaches employ a model to identify lanes, whereas feature-based lane detection techniques rely on low-level data like edges. Model-based approaches exhibit reduced sensitivity to weak lane appearance characteristics and noise compared to feature-based approaches but at the cost of increased processing demands. Feature-based methods have been found to possess higher efficiency compared to other approaches. However, it is essential to note that these methods might be susceptible to the influence of noise and the presence of weak lane appearance characteristics.

2.3 Learning-Based Methods

Lane detection plays a vital role in the functioning of autonomous driving systems, as it facilitates the vehicle's ability to discern and monitor the delineations of lanes on the roadway. Numerous scholarly articles have put forth diverse methodologies and technology for lane detection. Numerous conventional approaches for lane recognition rely heavily on manually designed features and post-processing procedures, rendering them vulnerable to instability when confronted with diverse road situations. Many lane recognition techniques based on deep learning have been suggested to tackle this concern. An example of a study involved introducing a deep network with two parallel branches to identify and track lane characteristics in real-time. Lane identification has been successfully achieved using deep learning approaches, which have shown to be highly effective in accurately detecting lane pictures. The primary focus of this literature review pertains to models for lane detection in the context of deep learning.

Deep learning is a nascent technological advancement that has found utility in lane detection owing to its remarkable capacity for lane identification. Additionally, this technique may be employed for two-class segmentation. It has the advantage of quick detection because of its basic design. Furthermore, it can effectively manage situations when the number of lanes is unclear, eliminating the need for post-processing. In recent times, deep learning methodologies have been employed to tackle the issue of complex situations and computational efficiency. Novel deep-learning methodologies are propelling the advancement of intelligent driving. Individuals demonstrate proficiency in learning through several methods, including reinforcement, independent learning, social learning, and a combination of these approaches. In a broad sense, the field of deep reinforcement learning involves the integration of deep learning techniques with reinforcement learning methodologies. Deep learning can be performed using autoencoders, deep belief networks (including Boltzmann machines), and Generative Adversarial Networks (GANs) even when the training data is unlabelled.

Deep learning methods may be further categorized into single-step models and two-step models. Single-step models employ a singular network for lane detection, whereas two-step models initially extract lane characteristics before the detection process. The efficacy of deep learning methods has been demonstrated in accurately detecting lanes under challenging circumstances, including low illumination, indistinct lane markings, and obstructed views. Deep learning models may be classified into four categories: encoder-decoder networks, region proposal networks, convolutional neural networks (CNNs), and recurrent neural networks (RNNs). Convolutional neural networks (CNNs) have been employed to extract pixel characteristics about lane lines. Subsequently, a suitable pixel-fitting method is utilized to accomplish the task of lane detection.

CNN-LD is proposed by Satti et al. [28] for identifying and following road edge lanes. To extract edge features, the proposed technique employs a convolutional neural network. Normalization was applied to get optimal performance. The proposed CNN-LD performs better than the state-of-the-art methods. Combining CNNs with RANSAC algorithms yields an effective lane-detecting strategy. To increase the practicality of autonomous cars, CNNs are frequently utilized in multi-task learning technologies. The lane line coefficients they generate can be used to fit a second-order polynomial. Since RNNs can extract characteristics from picture slices and infer the lane, they have been employed for lane recognition in driving scenarios. The LSTM-based Lane Position Detection Model, gradient map-based CNN, and RNN Lane Detection Model have been established utilizing RNNs. It has been argued that using semantic segmentation-based approaches for lane detection is inefficient, based on research by Shriyash Chougule et al. [29]. Instead of focusing on outlining the particular form, the segmentation paradigm prioritizes attaining precise pixel-level categorization. Despite the caveats, segmentation-based lane detection algorithms have shown promising results. Many other approaches have been proposed to deal with these problems.

Zhang Jie et al. [30] implemented a multi-task architecture in GCLNet that combines sub-structures for lane segmentation and lane boundary identification to improve performance. Each decoder is linked to an encoder, so complimentary data can easily travel across processes. The capabilities of both decoders can be improved through this iterative process of mutual refining. The thorough analysis of how lane areas and lane borders are related provides valuable information for future r researchers planning to use a multi-tasking strategy. It was first proposed by Vijay John et al. [31] to detect empty areas, discernable lane markings, and road scene labels. This method is comparable to GCLNet in many ways. The innovative and efficient approach provided by Gaurav Singal et al. [32] shows a high degree of accuracy in lane recognition while keeping a low execution time. The model's dimensions were purposefully kept low to guarantee hardware compatibility and to allow for real-time execution. We created and trained a deep Convolutional Neural Network (CNN) model for this task. CNN models were selected because of their track record of success with other picture categorization datasets. We used many networks and optimization criteria as hyper-parameters and provided the one with the highest F1 score. The NVIDIA DGX V100 Supercomputer is used for the training process.

Nevertheless, it is essential to note that deep learning systems lack safety assurances, and at present, no mechanism exists to ensure their operation with a minimal probability of encountering failures. Furthermore, machine learning (ML) based systems cannot adequately meet existing safety requirements due to their limited verifiability and validation. Therefore, more investigation is required to establish strategies for guaranteeing the reliability of deep learning algorithms in self-driving cars. A variety of lane identification methods are centred on learning-based approaches. These algorithms include M^2-3DLaneNet, Curve Modeling, SwiftLane, Structure Guided Lane identification, CondLaneNet, and Robust Lane Detection by Expanded Self Attention.

The efficacy and precision of lane line identification have been significantly enhanced by deep learning techniques, surpassing the performance of conventional detection methods. Nevertheless, there exist certain practical constraints associated with these methodologies. For instance, edge-based systems are more efficient than deep learning algorithms aiming to detect subtle lane appearance aspects. Moreover, implementing deep learning models in cloud computing or edge computing settings might pose challenges owing to the demanding nature of their data processing needs. Moreover, existing techniques for lane recognition encounter difficulties when confronted with scenarios, including several lanes and lane-changing manoeuvres performed by automobiles. Ultimately, it might be argued that conventional lane recognition approaches that rely on image processing techniques may continue to be more appropriate in some situations.

3. DataSets

Lane detection is critical for autonomous driving systems to ensure safe and efficient navigation. Various datasets have been developed and used to train autonomous driving systems to achieve accurate lane detection. These datasets vary in size, complexity, and purpose and can be used for different research applications. Researchers can use these datasets to train and evaluate their lane detection models and compare their models' performance with state-of-the-art methods. These datasets provide annotated images of road scenes to help train deep-learning models for lane detection.

3.1 TuSimple Lane Detection Challenge dataset

The TuSimple dataset, as shown in Fig. 2, refers to a publicly accessible collection of data that focuses on traffic detection, specifically in scenarios characterized by light traffic and visible lane markers. The training dataset's label comprises continuous lane curves that initiate from the lower portion of the input image and extend until the horizon surpasses the vehicles[33]. The dataset comprises substantial amounts of data, encompassing training and testing sets. The testing set consists of 326 instances recorded under bad weather conditions and 2782 instances under ideal weather conditions. The data is collected at different time intervals throughout the day on routes with two, three, or four lanes and additional highway roadways. The RGB input images have a resolution of 1280 by 720 pixels.

Additionally, each image in the collection includes 19 frames with unlabelled data. The annotations are presented in JSON format, displaying the x-position of the lanes at various discretized y-positions. The images are collected from different weather and lighting conditions, and the dataset includes both straight and curved roads.

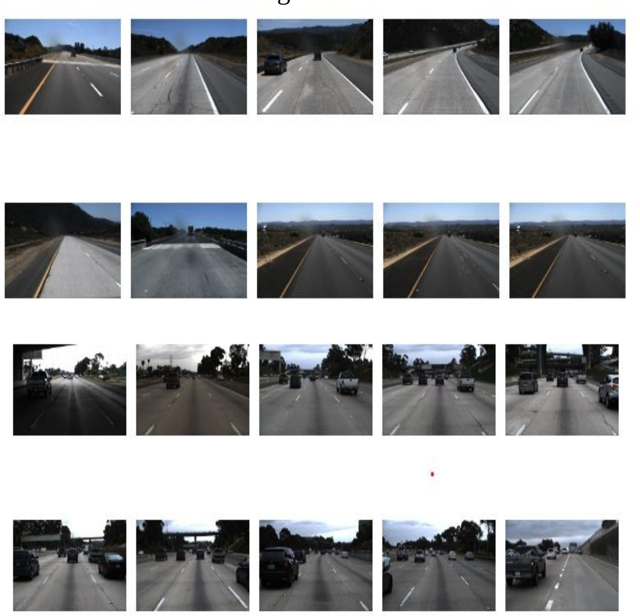

Figure 2: Road Scene images of the TUSimple dataset

3.2 KITTI Vision Benchmark dataset

Jannik Fritsch and Tobias Kuehnl created the KITTI Vision benchmark dataset from Honda Research Institute Europe GmbH [35]. The dataset in Fig 3 encompasses a diverse range of information about the road environment, encompassing colour photographs, stereo imagery, and laser point data. The road and lane estimate benchmark dataset consists of 579 photos, with 289 images designated for training purposes and 290 images reserved for testing. The categorization of road scene photos can be classified into four distinct groups: urban unmarked (UU), urban multiple marked (UMM), urban marked (UM), and hybridization, which encompasses a combination of the categories mentioned earlier. The training dataset comprises 98 photos, whereas the testing dataset comprises 100 images. Generating ground truth in the KITTI dataset involved the manual annotation of photographs. This offering is available in two distinct categories: the road area, which encompasses all lanes collectively, and the lane, which refers to the specific lane in which the vehicle is currently operating.

Figure 3: KITTI dataset images contain (UU), urban marked (UM), and urban multiple marked lanes (UMM)

3.3 CALTECH Lane Dataset

As shown in Figure 4, The dataset comprises four video clips recorded at different times of the day in Pasadena, California[36]. Each video clip has a resolution of 640 x 480 pixels and encompasses a range of lighting conditions, including different levels of illumination, sun glint, and shadows. The clips also feature various lane markings, pavement kinds, crosswalks, and congested surroundings. Furthermore, the dataset encompasses urban streets, including both straight and curved segments, which were subjected to testing using the Caltech dataset.

Figure 4: Images of CALTECH Lane Dataset.

4. Evaluation metrics

The researchers have used various metrics to evaluate the efficiency of their lane detection methods. An evaluation metric or performance measure is used to assess the performance of a lane detection system in both supervised and unsupervised learning scenarios. When evaluating lane detection algorithms, it's essential to consider the specific requirements and constraints of the application. Additionally, ground truth data might not be available for unsupervised learning approaches, making metrics like IoU less applicable. Visual inspection and qualitative evaluation may also significantly assess the system's performance in such cases. We provide various evaluation metrics commonly used for assessing lane detection algorithms:

Mean Squared Error (MSE):
MSE measures the average squared distance between the true and predicted lane positions. Lower MSE values indicate better performance.

$$\mathrm{MSE} = \left(\frac{1}{\mathrm{N}}\right) * \Sigma \left(y_{\mathrm{true}} - y_{\mathrm{pred}}\right)^2 \qquad (1)$$

Where **N**: Number of pixels/points, $\mathbf{y_{\_true}}$: True lane position, $\mathbf{y_{\_pred}}$: Predicted lane position

Root Mean Squared Error (RMSE):
RMSE is the square root of MSE, providing a more interpretable metric in the same units as the lane position. Lower RMSE values are better.

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}} \qquad (2)$$

Mean Absolute Error (MAE):
MAE measures the average absolute distance between the true and predicted lane positions. It is less sensitive to outliers compared to MSE.

$$\mathrm{MAE} = \left(\frac{1}{\mathrm{N}}\right) * \Sigma \left|y_{\mathrm{true}} - y_{\mathrm{pred}}\right| \qquad (3)$$

N: Number of pixels/points, $\mathbf{y_{\_true}}$: True lane position, $\mathbf{y_{\_pred}}$: Predicted lane position
Intersection over Union (IoU):
IoU evaluates the overlap between the predicted lane and the ground truth. A higher IoU indicates better alignment between the lanes.

$$IoU = (Area\ of\ Intersection) / (Area\ of\ Union) \quad (4)$$

Accuracy (for binary classification):
In a binary classification scenario (lane pixel vs non-lane pixel), accuracy measures the proportion of correct predictions overall prediction

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \qquad (5)$$

TP: True Positives, TN: True Negatives, FP: False Positives, FN: False Negatives

Precision (for binary classification):
Precision calculates the proportion of accurate optimistic predictions out of all positive predictions. It focuses on the correctness of positive predictions.

$$Precision = \frac{TP}{(TP + FP)} \qquad (6)$$

Recall (for binary classification):
Recall (also known as sensitivity or true positive rate) measures the proportion of true positive predictions out of all actual positive samples.

$$Recall = \frac{TP}{(TP + FN)} \qquad (7)$$

F1 Score (for binary classification):
F1 Score balances the trade-off between precision and recall. It provides a single metric that combines both measures.

$$F1\ Score = 2 * \frac{(Precision * Recall)}{(Precision + Recall)} \qquad (8)$$

5. Conclusion

This thorough research examines the domain of vision-based lane-detecting algorithms and explores their relevance in advancing Advanced Driver Assistance Systems (ADAS). Lane detection is an essential element of Advanced Driver Assistance Systems (ADAS) since it enables cars to understand and negotiate the intricate aspects of the road, improving safety and boosting the overall driving experience. We analyzed several vision-based lane-detecting systems during our inquiry, encompassing conventional image processing algorithms and cutting-edge deep learning models. Each technique had distinct strengths and limits, compelling us to assess their effectiveness using various criteria. Convolutional neural networks and other advanced designs have played a pivotal role in achieving unprecedented levels of accuracy, hence demonstrating promising outcomes in practical domains.

The findings of a comparative analysis conducted on road and lane recognition in mixed situations revealed that a lane detection algorithm exhibited enhanced accuracy within a range of 9 meters or less. The resilience and accuracy of lane line identification have been significantly enhanced by the advancements in deep learning techniques beyond the capabilities of classical detection methods. Nevertheless, it is essential to acknowledge that certain practical constraints are associated with implementing these approaches. For instance, it has been observed that edge-based methods exhibit higher efficiency compared to deep learning approaches in the detection of subtle lane appearance characteristics. Moreover, implementing deep learning models in cloud or edge computing systems might pose challenges due to their demanding data processing needs.

Moreover, existing techniques for lane recognition encounter difficulties in accurately identifying multiple lanes in complex scenarios and when cars undergo lane changes. Ultimately, it may be argued that conventional lane recognition techniques rooted in image processing continue to exhibit more outstanding suitability in specific contexts. As the study concludes, it becomes apparent that the progress in vision-based lane identification techniques has substantially impacted the development of Advanced Driver Assistance Systems (ADAS), leading to enhanced safety and more autonomy in driving. Nevertheless, further investigation is required to enhance these algorithms, hence increasing their ability to adjust to the ever-changing and intricate driving conditions commonly experienced in real-world scenarios.

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