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Real Time Lane Detection and Tracking Using Jetson Nano

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***Abstract*—Lane detection is a pivotal technology in the realm of autonomous vehicles, advanced driver assistance systems (ADAS), and traffic monitoring systems. Its ability to perceive and delineate lane markings empowers vehicles to comprehend their position within their surroundings, fostering safer and more efficient navigation. This project delves into the development and implementation of efficient lane detection system, meticulously crafted to address the challenges posed by real-world conditions and deliver accurate lane segmentation. The proposed framework encompasses a meticulous selection of image processing techniques, tailored algorithms, and comprehensive evaluation strategies. It aspires to contribute towards the advancement of lane detection cum lane keeping assist technologies and their seamless integration into real-world applications using Convolutional Neural Network, ultimately paving the path towards a future of intelligent and autonomous transportation systems.**

***Index Terms*— Advanced Driver Assistance Systems, ADAS, Lane detection, Convolutional Neural Network CNN, Jetson Nano.**

I. INTRODUCTION

The ground reality of road traffic crashes has an estimated 1.19 million lives are tragically lost on our roadways, devastating families and communities. This urgent public health challenge demands a proactive approach, one that leverages cutting-edge technology to fundamentally reshape how we ensure safety on our roads. This is where lane detection technology emerges as a critical catalyst for change.

Powered by advancements in computer vision and artificial intelligence, lane detection systems helps vehicles with the remarkable ability to. Using this transformative capability, immediate, proactive interventions can be implemented that actively mitigate the risk of lane departure incidents.

Precise lane-keeping maneuvers: Vehicles automatically adjust their position, gently moving towards the correct lane and eliminating the risk of accidental crossings and potential collisions.

Timely driver warnings: When driver distraction threatens lane departure, the system triggers immediate alerts, to focus attention back to the road before a critical error occurs.

Unwavering lane visibility: Even in adverse weather conditions such as rain, fog, or low light, clear lane boundaries remain visible, ensuring safe navigation despite reduced visibility.

The benefits of lane detection extend far beyond accident prevention. This technology will encourage drivers to have *enhanced confidence and trust on the road*. By actively monitoring lane boundaries, the system is vigilantly watching on the driver, *allowing drivers to focus on the task at hand and navigate with increased peace of mind*. Furthermore, lane detection makes the way for the seamless integration of autonomous vehicles, promising a future of safe and efficient mobility where *human error is no longer a factor in accidents.*

There are six levels of vehicle driving autonomy defined by SAE International in the SAE J3016 standard, which are numbered from 0 to 5:

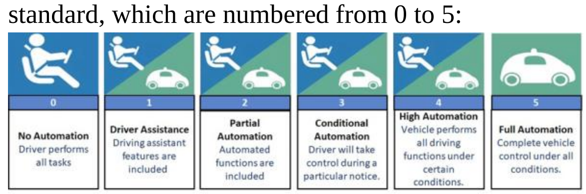

Fig 1.Different levels of automation.

(Source: https://www.mdpi.com/sensors/sensors-21-00706/article_deploy/html/images/sensors-21-00706-g003-550.jpg)

Level 0: No Driving Automation - The driver performs all DDT (Defensive Driving Training) (i.e. full manual driving) while the ADS provides warnings. Lane Detection Warning (LDW) falls into this category.

Level 1: Driver Assistance - Driver performs all DDT not performed by the ADAS and supervises features performed by it. The ADAS is capable of performing either longitudinal or lateral vehicle motion control.

Level 2: Partial Driving Automation - Driver performs all DDT not performed by the ADAS and supervises features performed by it. The ADAS is capable of performing both longitudinal and lateral vehicle motion control. Lane Keeping Assistance (LKA) falls in this or previous category based on its performance.

Level 3: Conditional Driving Automation - The ADAS performs all DDT within its Operational Design Domain (ODD) while engaged and will disengage after requesting the driver to intervene when it detects a situation outside of its ODD or when the driver requests to drive.

Level 4: High Driving Automation - The driver does not need to supervise the ADAS while it is engaged. The ADAS will determine if the condition is safe enough for the user to drive upon request.

Level 5: Full Driving Automation- The vehicle can drive everywhere (i.e. on roadways public and private) in all conditions completely autonomously.

Lane detection is a crucial task in autonomous driving, includes algorithms that can be computationally efficient and runnable on embedded systems with limited resources. Light image processing-based methods are considered a solution, but they face challenges due to weather, lighting, and occlusions. An advanced method would be like using CNN (light DNN) model for lane detection, which is runnable on systems with limited resources on Jetson Nano.

METHODS OF LANE DETECTION

1.1 Traditional method of lane Detection

The Digital image processing method is based on the inherent property of lane marking. The Processing is based on the color, intensity and the edge feature which includes.

1) Image Acquisition: The camera mounted near the upper center of the windshield to get image information of front view of the lane.

2) Preprocessing: Grayscale conversion is done to simply the processing of the converted image. Noise reduction (smoothing): Gaussian blurring is used to reduce noise and improve edge detection. Region of interest (ROI) selection: Crop the image to focus on the relevant area to discard the unwanted area to avoid processing, usually a trapezoidal region of front lane is used. Perspective Transformation (optional): Transform the image into a Bird's eye view (as if one is looking from above the lane). Manu researchers suggest for Inverse Perspective Transformation rather than

3) Lane feature extraction: include Edge detection - Canny Edge detection is used for finding the lane marking. Followed by Color Thresholding: to isolate lane marking based on their color (Yellow or White).

4) Lane model finding: Hough Transform: this method helps in finding the line in detecting the lines from the Edge-Image and group them into potential lines. Then comes Polynomial fitting: we fit the polynomial curve to the detected lane, which popularly used in Sliding window method.

5) Lane Tracking and curve prediction: the information from the previous frame to refine the current lane detection and predict lane curvature. We use polynomial fitting to find the lane curvature Which helps in determining the Steering angle for navigation of the mini car. [14] The algorithm uses image segmentation and Hough transformation to detect lanes as straight lines within a reasonable range for vehicle safety. [13] lane detection techniques, highlighting their effectiveness in identifying straight lanes but neglecting curved lanes, highlighting the need for CLAHE and Improved Hough Transform. [8] The proposed lane tracking algorithm is effective on a self-made test track, despite environmental factors like shadows and illumination changes. It provides accurate lane maneuvering and fulfills real-time operation requirements on a mini-computer.

The limitation over image processing system is that they are sensitive to light condition means the performance can degrade in low light and harsh shadows. Susceptible to occlusion: object obstructing lanes can cause detection failure. Difficulty with curved lane: Fitting accurate models for curved lane can be challenging.

1.2 Machine Learning in Lane Detection

Machine learning generates rules and programs through training, which involves observing inputs and expected outputs. The dataset is divided into training, test, and validation sets to provide enough data for learning an approximation and unseen data for model evaluation.

During training, the model learns a linear/non-linear mathematical function, and a loss function measures model quality by quantifying the difference between expected and predicted outcomes, updating parameters accordingly.

Deep Learning is a subset of machine learning that uses a deep neural network (DNN) as a statistical model. DNNs are graph structures composed of layers of computational units called neurons, which combine weights and biases into a non-linear activation function. [9] hybrid neural network combining CNN and RNN for robust lane detection in driving scenes. The network uses an encoder-decoder framework, abstracting features, processing sequential encoded features, and feeding outputs into the CNN decoder for information reconstruction and lane prediction.

During training, the network's weights are tuned using backpropagation and gradient descent to map inputs to output predictions. These algorithms occur iteratively for all data in the training set until the network is trained, which is called an epoch. Once trained, the network's weights are used to make predictions in a process called inference.

The goal of training is to have the network learn general features in the dataset to correctly predict features in unseen data. However, the model's performance depends on the input data and its loss function. Feeding a model random data will not result in a useful program, and it often takes thousands to millions of well-labeled data points for the model to learn complex tasks. Loss functions must be designed to minimize the error between the data and the label gradually, and they cannot be "one size fits all." [12] Convolutional Neural Networks (CNN) and Deep Neural Networks (DNN) to enable autonomous cars to lane-follow along a simplified indoor track. Where results compared to DenseNet and VGG16, CNN had higher training accuracy but slower prediction rate. {10] proposed multi-line detection algorithm uses pixel histogram statistics to identify line-existing regions in track-following applications. It uses bottom-up sliding windows to obtain pixels on curves, avoiding cross-horizontal lines. [6] Yolov3 algorithm to address the issue of traditional lane detection. [3] a new deep learning-based approach for lane detection, which also includes a lane departure detection system.a vehicle detection algorithm using YOLO is integrated to enhance safety in autonomous vehicles.

Using ML method offers enhanced robustness and adaptability compared to traditional method.

1) Segmentation Based Method - the method treats lane as pixcel-wise clasification task. Also train the CNN to classify each pixel as lane or non-lane. Popular dataset is LaneNet, SCNN, Enet-sad, CuLane, TuSimple.

2) Anchor Based Method - Generate pre-defined lines or curves(anchors) representing potential lane position. Use ML models to predict adjustments to these anchor to match actual lane. Similar to object detection based on YOLO and SSD. [16]

3) Parameter Based Method - Directly predict lane parameter (eg curvature, position) using ML models. Often used with conjunction with traditional technique for efficiency.

1.3 Lane Keeping Assist

Lane Keeping Assist (LKA) is a driver assistance system designed to enhance vehicle safety by helping the driver to keep the vehicle within its lane. It is often part of an advanced driver assistance system (ADAS) and is commonly found in modern vehicles.

Lane Keeping assist uses the following steps for maintaining the car within the lane boundaries. These steps involve Lane Detection, followed by lane tracking and the system gives output to deliver as warning or gives a precise steering angle to overcome the deviation from the center of the lane.

Lane Detection: LKA systems use various sensors, typically cameras mounted on the vehicle's windshield, to monitor the road and detect lane markings. Some systems may also use other sensors like radar or LiDAR.

Lane Tracking: The system continuously tracks the position of the vehicle within the detected lane. This involves analyzing the captured images or sensor data to determine the vehicle's lateral position in relation to the lane markings.

Warning Generation: If the system detects that the vehicle is unintentionally drifting out of its lane (without the use of turn signals), it generates a warning for the driver. This warning can be in the form of visual alerts, audible warnings, or haptic feedback, such as steering wheel vibrations.

Active Steering Intervention: In more advanced LKA systems, if the driver does not respond to the warnings and the vehicle continues to drift out of its lane, the system can provide active steering intervention. This involves making subtle adjustments to the steering to guide the vehicle (mini car) back into the center of the lane. [10] End-to-End steering angle prediction model that combines modified VGG16 and LSTM networks. The model effectively predicts steering angles by considering spatial-temporal information from input images.[7] approaches to lane detection and tracking systems, focusing on preprocessing blocks to enhance input images and improve real-time lane detector accuracy with proper implementation. [5] Waveshare JetRacer AI vehicle's model was tested for autonomous driving using a GPU-based CUDA architecture. The model uses data from the Waveshare IMX219 160 degree FoV camera and sends control signals to the steering system.[4] VGG-gated recurrent unit (VGG-GRU) is a deep-learning-network-based approach for autonomous self-driving vehicles. It uses lane-following planning and steering angle control to maintain a car's path during simulated and real driving scenarios. The VGG-GRU framework also outperforms GPU implementations, taking 45-46 seconds to execute a single epoch. [2] lightweight deep neural network for vehicle control actions, including steering wheel angle, speed, and braking. [1] computer-vision-based and Artificial Neural Network (ANN) was used as two method approach for accurate lane detection.

EXISTING SYSTEM’S WORKING STEPS

1) Image Acquisition: The camera is situated at the upper center of the windshield to obtain images of the front view of the lane.

2) Preprocessing: Grayscale conversion is done to simply the processing of the converted image. Noise reduction (smoothing): Gaussian blurring is a technique utilized to minimize noise and enhance edge detection. Region of interest (ROI) selection: The image is cropped to concentrate on the relevant area, discarding unwanted areas to avoid processing, typically using a trapezoidal front lane region. Perspective Transformation (optional): The image should be transformed into a bird's eye view, as if one is looking from above the lane.

3) Lane feature extraction: include Edge detection - Canny Edge Lane marking is determined through detection, followed by color. Thresholding: to isolate lane marking based on their color (Yellow or White).

4) Lane model finding: Hough Transform: This method aids in identifying lines from the Edge-Image and categorizing them into potential lines. Then comes Polynomial fitting: The polynomial curve is fitted to the detected lane, a popular method in the Sliding window method.

5) Lane Tracking and curve prediction: the information from the previous frame to refine the current lane detection and predict lane curvature. We use polynomial fitting to find the lane curvature Which helps in determining the Steering angle for navigation of the mini car.

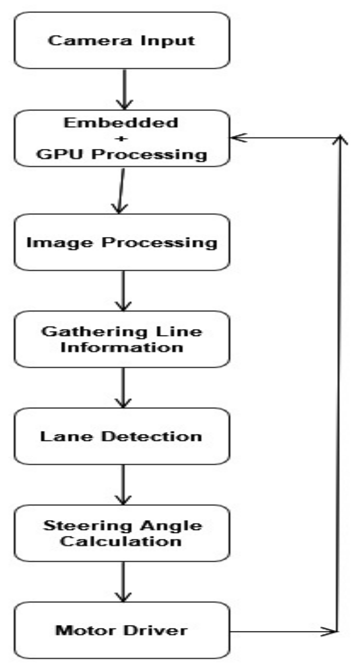

Fig 2. Flow chart of preprocessing step for lane detection and steering assist

The limitation over image processing system is that they are sensitive to light condition means the performance can degrade in low light and harsh shadows. Susceptible to occlusion: object obstructing lanes can cause detection failure. Difficulty with curved lane: Fitting accurate models for curved lane can be challenging

Research Gaps in the Existing Model

While current lane detection technologies excel in navigating straight roads, they face challenges when encountering curved sections. These areas, such as bends and merges, become blind spots, increasing the risk of collisions. Additionally, these systems have not yet fully explored the potential of advanced variations of the Hough Transform, which could significantly improve their accuracy and processing speed. Furthermore, adverse weather conditions like fog present a considerable obstacle, obscuring lane visibility and demanding the development of weather-resistant detection methods, potentially involving fog-specific pre-processing or adaptable algorithm design. Examining a specific algorithm reveals limitations in its ability to address jittery lane markings, particularly on surfaces with imperfections. Refinement of the employed high-order FIR filter or exploration of alternative noise reduction techniques may prove beneficial in achieving smoother lane delineation. Moreover, the algorithm's current focus on straight lanes restricts its applicability in real-world driving scenarios. To overcome this, its capabilities must be expanded to encompass curved sections through techniques such as perspective transformation and poly-fitting lane lines.

However, these limitations extend beyond simple lane detection accuracy. The algorithm currently lacks a well-defined strategy for identifying the region of interest on uphill or downhill inclines, hindering its effectiveness in these prevalent road configurations. Further investigation is required to determine appropriate region-of-interest delineation and to adapt detection methods accordingly. Lastly, proximity to other vehicles presents a further underexplored challenge. Comprehensive testing in such scenarios is crucial for ensuring stable and reliable lane detection performance even amidst potentially congested traffic environments.

By devoting resources to addressing these identified limitations and actively pursuing the development of innovative solutions, we can propel lane detection algorithms to a new level of sophistication and functionality. Such advancements hold the potential to transform our roadways into safer and more intelligent spaces, where every lane functions as a silent guardian of progress and safety, ensuring a future of seamless and safe vehicular navigation

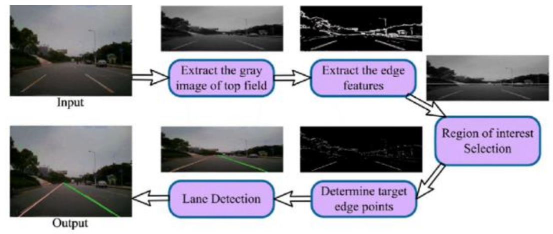

Fig 3. Preprocessing followed by lane detection (Hough Transformation)

(Source: https://www.researchgate.net/figure/Block-diagram-of-lane-detection-method_fig2_301312989)

PROPOSED SYSTEM

Convolutional neural networks (CNN) are used to model spatial information, such as images. CNNs are very good at extracting features from images, and they're often seen as universal non-linear function approximations.

CNNs can capture different patterns as the depth of the network increases. For example, the layers at the beginning of the network will capture edges, while the deep layers will capture more complex features like the shape of the objects (leaves in trees, or tires on a vehicle). This is the reason why CNNs are the main algorithm in self-driving cars.

The key component of the CNN is the convolutional layer itself. It has a convolutional kernel which is often called the filter matrix. The filter matrix is convolved with a local region of the input image which can be defined as:

$$y_j = \omega_{ij} * x + b_j$$

Where:

the operator * represents the convolution operation,

w is the filter matrix and b is the bias,

x is the input,

y is the output.

The dimension of the filter matrix in practice is usually 3X3 or 5X5. During the training process, the filter matrix will constantly update itself to get a reasonable weight. One of the properties of CNN is that the weights are shareable. The same weight parameters can be used to represent two different transformations in the network. The shared parameter saves a lot of processing space; they can produce more diverse feature representations learned by the network.

The output of the CNN is usually fed to a nonlinear activation function. The activation function enables the network to solve the linear inseparable problems, and these functions can represent high-dimensional manifolds in lower-dimensional manifolds. Commonly used activation functions are Sigmoid, Tanh, and ReLU, which are listed as follows:

Sigmoid : $R = \dfrac{1}{1 + e^{-y}}$

Tanh : $R = \dfrac{e^{y} - e^{-y}}{e^{y} + e^{-y}}$

ReLU : $R = max\ (0,y)$

z ReLU is the preferred activation function, because it converges faster compared to the other activation functions. In addition to that, the output of the convolution layer is modified by the max-pooling layer which keeps more information about the input image, like the background and texture.

The three important CNN properties that make them versatile and primary component of self-driving cars are:

local receptive fields,

shared weights,

spatial sampling.

These properties reduce overfitting and store representations and features that are vital for image classification, segmentation, localization, and more.

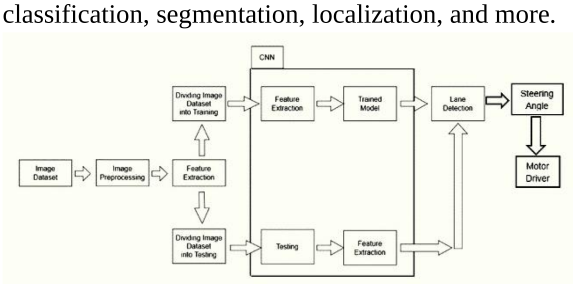

Fig 4. Block Diagram for lane Detection using CNN and Steering angle prediction

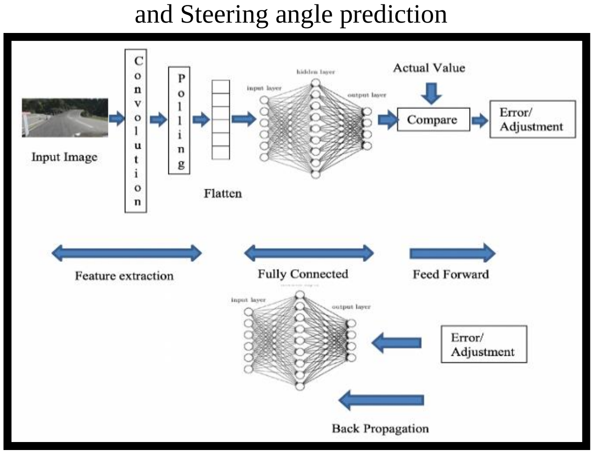

Fig 5. CNN Architecture

The code for detecting lane line in a straight path of a video file is made successfully. The produces output is placed in order in a tabular form as follows.

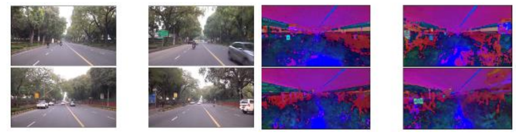

Fig 6. Test image and HSV image

Fig 7. HSL Image and HSL color scale Image

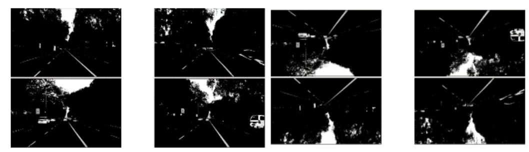

Fig 8. Gray scale Image and Gaussian Smooth

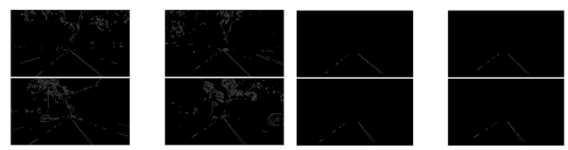

Fig 9. Canny edge Detection and ROI

Fig 10. Hough Transform and Average with extrapolation

Result Analysis

The testing of lane detection was applied on different lane video which are straight road. The test was done on different lanes of 200 – 300 images of different country and lane videos highway, mountain road and tunnels.

Sr. no	No of Frames	Detected frame	Missed frame	Accurate recognition
1	1205	1180	25	97.92%
2	2451	2383	68	97.22%

Srno 1 is for bad weather Condition and 2 is for day light

CONCLUSION

The image processing method have a limitation to work in straight line, in shadow region the out may differ depending on the brightness of the image. CNN have emerged as a powerful tool for lane detection, achieving remarkable accuracy and robustness compared to traditional methods. CNN offer the ability to learn complex relationships within lane markings, handle diverse road conditions, and adapt to variations in lane appearance. However, despite their progress, limitations remain, highlighting the need for further research and development.

Future scope

• Improve accuracy and robustness: Enhance performance in challenging scenarios like poor lighting, shadows, occlusions, and complex lane configurations. Develop models that can generalize well to unseen environments.

• Reduce dependence on training data: Explore semi-supervised and weakly-supervised learning approaches to alleviate the need for large amounts of labeled data, which can be costly and time-consuming to acquire.

• Real-time performance: Optimize CNN architectures and processing algorithms for real-time implementation, particularly crucial for autonomous driving applications.

• Fusion with other sensors: Integrate lane detection with other sensor data like LiDAR and radar to create a more robust and comprehensive understanding of the driving environment.

• Lane change prediction and trajectory planning: Utilize lane detection information to predict lane changes and plan vehicle trajectories, enabling safer and more efficient autonomous driving.

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