Realtime Road Lane Detection

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Abstract- *These are many cases of people dying each year in road accidents due to driver's lack of attention. Over the years many new technologies have helped to overcome such cases. Detecting lanes have proven to be useful for drivers. The main purpose of lane detection system is to avoid such accidents. These systems are designed to detect the lane marks and to warn the driver if the vehicle tends to depart from the lane. Detecting lanes is an important aspect of an intelligent transport system. Future is of driverless car technologies; this system is not only useful for drivers but also for driverless vehicles. Few challenges that this system might face are varying road conditions, weather conditions. In previous years different approaches for lane detection were proposed and demonstrated. In this paper, a comprehensive review of the literature in lane detection techniques is presented. The main objective of this paper is to discover the limitations of the existing lane detection methods.*

Key words: **Lane detection, Intelligent Transport Systems**

1. INTRODUCTION

With the drasticincrease of urban traffic, safety of traffics has become more mandatory. Breaking the lane causes about more than 30% of accidents on highways, and these are due to inattention or fatigued driver. Thus, a system that provides analert message to drivers if any danger having great potential to save lives. Advanced driver assistance systems are technologies that are designed to aid drivers while driving a car (ADAS). Many systems such as adaptive cruise control, collision avoidance system, night vision, blind spot detection and traffic sign detection are a part of ADAS [1]. Lane departure system is also a part of this category. The system's goal is to identify the lane marks and notify the driver if the vehicle tends to leave or change the lane. Lane detection is the process to detect lane markers on road and then present these locations to an advanced system. In intelligent transportation systems [2], intelligent vehicles cooperate with smart infrastructure to achieve a safer environment and better traffic conditions. The applications of a lane detecting system could be as simple as pointing out lane locations to the driver on anexternal display, to more complex tasks such as predicting a lane change in the instant future to avoid collisions with other vehicles. Other interfaces included that can detect lanes are cameras, laser range images, LIDAR and GPS devices[3].

This paper is organised as follows. Section II presents the Related Work. Section III presents the Literature Survey. Section IV describes the Gaps in the existing Systems. Section V presents the Proposed System. Section VI gives the detailed System Implementation Details. The last section concludes the article.

2. RELATED WORK

2.1 Image processing

An important part of lane detection is image processing in order to achieve an accurate result. The first step in image processing is to convert the image into grayscale i.e., converting the images into gray ones. The first step in image processing is grayscale processing, which converts color images into gray ones. Grayscale processing is used to carry out the next step, binarization, in which the gray image is turned into a black-and-white image. Many algorithms were proposed on how to implement binarization. A new algorithm was proposed [9] in 2017 to improve the traditional algorithm by using an adaptive threshold instead, which improves binarization performance for old images.

2.2 Lane detection

The first step of the lane detection stage is to identify the range of detected objects in the image, also known as the region of interest (ROI). There are two types of ROI in images, namely static ROI and dynamic ROI. In [10] an image's near vision field is divided into a near vision field area, a far vision field area, and the sky field is divided into static ROIs. The sky field accounts for 5/12 of the image, and the far vision field accounts for half the near vision field. Most algorithms utilise the ROI-processed picture after getting itedge detection to extract essential road lane characteristics from the picture that has been provided. Canny edge detection is the most widely used edge detection technique (CED). Hough transfer is utilised for lane line detection once the pixels with large brightness variations have been marked. [10] employed standard Hough transfer in its algorithm. The approach determines the lane lines for the straight line by using the starting point and finishing point. For the straight line, the method uses the beginning point and the end in order to determine the lane lines. In the case of a curve, the approach calculates the bending direction of the curve on the right base and determines the waveform using the least square fit. Wei et al. [14] used points of disappearance and some pixels around points, the classic Hough transfer was improved. The Hough Transform is a technique for locating lines by identifying all of their points. This can be performed by representing a line as points. These points are represented as lines/sinusoidal (depending on Cartesian/Polar co-ordinate system). If multiple lines/sinusoidal pass through the point, we can deduce that these points lie on the same line.

2.3. Lane departure recognition

While the gap between the car and the left lane line is much less than the distance between the vehicle and the right lane line, the car starts to flow to left, otherwise, the automobile starts off evolved to flow proper. The deviation distance of the car, in truth, can be calculated by way of the ratio of the deviation distance and driveway inside the picture. Whilst the deviation distance exceeds a selected cost, LDWS works and warns the driving force to adjust again to the safe using range inside the driveway.

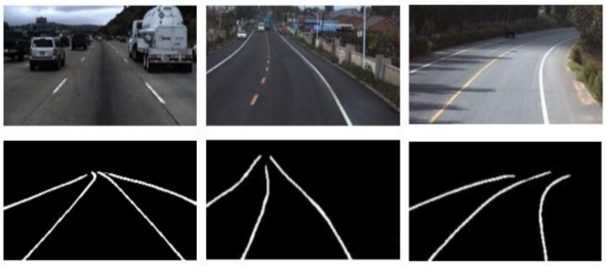

Fig1. Lane Departure Recognition

3. LITERATURE SURVEY

3.1. Data Collection and Processing Methods for the Evaluation of Vehicle Road Departure Detection Systems

In recent years, off-road collision avoidance / mitigation off-road collision detection systems (RDDS) have been developed and installed in some production vehicles. To support and provide standardized and objective performance assessments for RDDS, this paper describes the development of the data acquisition and data post-processing systems for testing RDDSs. Seven parame are used to describe road departure test scenarios overall structure and specific components acquisition system and data post-processing syster evaluating the vehicle RDDS will be developed and presented.The sensing system and data post-processing system captured all required signals and accurately displayed the testing vehicle's motion profile, according to the results. The suggested data collection system's effectiveness is demonstrated by test track testing under various scenarios.

3.2. A Lane Detection Method for Lane Departure Warning System

The vision-based Lane Departure WarningSystem (LDWS) is an effective way to prevent Single Vehicle Road Departure accident. In fact, a lot of complex noise makes it very difficult to quickly and accurately identify a lane, that is, to define a lane, a set of image processing method which can give results fast and accurately in the non-ideal conditions is the primary work. This document proposes a lane detection method for the Lane Departure Warning System. Experimental comparisons determine the Canny algorithm as the edge detection method and the Hough transform as the efficient method for air wire detection. To meet real-time requirements, the Region of Interest (ROI) is defined to reduce noise and speed up for accurate ramping. Finally, experimental results show that this lane detection method can efficiently and accurately extract lane information from captured road images.

3.3. Real-time illumination invariant lane detection for lane departure warning system

Lane detection is an important factor in improving driving safety. This paper proposes a real-time, lighting-invariant lane detection method for the Lane Departure Warning System. There are three primary components to it. First, it detects vanishing points based on the voting map and defines an adaptive region of interest (ROI) to reduce computational complexity. Second, we take advantage of lane colours' unique nature to achieve illumination invariant lane marker candidate detection. Finally, use a clustering technique to find the main track from the lane marker candidates. In the event of a lane departure situation, our system will send a warning signal to the driver. Experimental results show satisfactory performance with an average detection rate of 93% under a variety of lighting conditions. In addition, the overall process requires only 33MS per frame.

3.4. A Robust Lane Detection Method Based on Vanishing Point Estimation Using the Relevance of Line Segments

This article proposes a robust lane detection method based on vanishing point estimation. Estimating the vanishing point helps identify the lane because the parallel lines in the 2D projected image converge to the vanishing point. However, for images with complex backgrounds, it is not easy to determine the vanishing point correctly. Thus, a robust vanishing point estimation method is proposed that uses a probabilistic voting procedure based on intersection points of line segments extracted from an input image. The proposed voting function is defined by the strength of the line segment, which represents the relevance of the extracted line segments. Then select a candidate lane segment, taking into account geometric constraints. Finally, the host trace is detected using the proposed score function designed to remove outliers for the candidate line. In addition, the detected host traces are improved using interframe similarity that takes into account the position consistency of the detected host traces and the estimated vanishing points of consecutive frames. In addition, we suggest using a look-up table to reduce the computational cost of the vanishing point estimation process. Experimental results show that the proposed method efficiently estimates the vanishing point and recognizes lanes in a variety of environments.

3.5. A Framework for Camera-Based Real-Time Lane and Road Surface Marking Detection and Recognition

In this paper Vision based, integrated framework based on spatio-temporal incremental clustering coupled with curve fitting and Grassmann manifold learning technique for lane detection is used. It is only restricted by the type of road surface markings present in the training data.

3.6. New Lane Detection and tracking strategy based on vehicle forward monocular camera

A new strategy for lane detection and tracking that is suitable as a functional prerequisite for using DAS features such as lane departure warning and lane departure warning. Here the visibility of the lane markings was compromised by several factors, such as the reflectivity of the lane, the camera's glare, and the presence of shadows and the deterioration of the paint.

3.7. A Portable Vision-Based Real-Time Lane Departure Warning System: Day and Night

Here embedded advanced RISC machines (ARM)-based real-time Lane Departure Warning System is proposed. The limitation being this system will poorly perform if there is no sufficient illumination.

3.8. Automatic Detection and Classification of Road Lane Markings Using Onboard Vehicular Cameras

It is a new approach for road lane classification using an onboard camera using Bayesian classifier but it limits the rapid detection of transitions and removal of isolated misdetections.

3.9. Lane Departure Identification for Advanced Driver Assistance

This approach reduces the computational time required for the lane departure estimation and reduces the false warnings but does not estimate the real-world coordinates of a vehicle with respect to both lane boundaries.

3.10. Robust Road Lane Detection from shape and color feature fusion for Vehicle Self-Localization

It used a system to extract the region of interest, perform Hough transformation and calculate the vehicle position. The only limitation is the vehicle's controller limitations arise for a maximum speed of 70 km/h in sharp turns.

3.11. Lane Detection Algorithm using Vanishing point

It proposed a system using Canny edge detection, kalman algorithm to extract the region of interest but same limitation as mentioned in the above paper, The vehicle's controller limitations arise for a maximum speed of 70 km/h in sharp turns.

3.12. Lane Detection Algorithm using Vanishing point

Lane detection method using the vanishing point according to the perspective feature of the camera. Here the limitation is that image processing takes a long time. It is a major factor affecting the system's real-time feature.

4. GAPS IN EXISTING LITERATURE

A literature search found that most existing literature ignores one of the following:

- The survey has shown that the existing methods provides good accuracy for high quality images but sometimes provide poor results for poor environmental conditions like fog, haze, noise, dust etc.
- The majority of existing solutions work well for straight lanes but not so well for curved roads.
- Because most lane detection approaches are based on the conventional Hough transform, they can be tweaked to improve accuracy even more.

5. THE PROPOSED WORK

In many proposed systems [4], lane detection consists of finding specific primitives such as lane markings on the surface of painted roads. Parked and moving vehicles, poor quality lines, trees, buildings, shadows from other vehicles, sharp curves, irregular lane shapes, converging lanes, lettering and other markings on the road, unusual road surface materials Various challenges, such as different grades, cause lane detection problems. There has been active research on lane detection and a wide variety of algorithms of various representations, detection and tracking techniques, and modalities have been proposed [5].

Single vehicle road departure (SVRD) accidents account for a high percentage of all highway accidents. In 2006, SVRD accidents accounted for about 20% of road accidents and 40% of fatalities across the United States, according to AASHTO (American Association of State Highway Traffic Authority) statistics. According to a Mercedes-Benz research report on road accidents, the reasons for this can be divided into five columns: leaving the road (equivalent to 19% of all traffic accidents), changing lanes and merging (equivalent to 4%). Crossings (equivalent to 29%), rear-end collisions (equivalent to 26%). , And other reasons account for about 22%. The study also shows that more than 80% of accidents are associated with unintentional or dozing drivers, and that a 0.5 second warning can avoid 60% of accidents. If a one-second warning is given, 90% of accidents can be averted. Lane Departure Warning System (LDWS) is one of the most important aspects of Intelligent Vehicle (IV) technology, which is an active safety system to prevent unintended lane departure that can lead single vehicle roadway departure, lane change/merge, and rollover crashes. LDWS uses a forward-looking monocular camera to capture lane information and determine the vehicle's position with respect to the lane. If a lane change occurs and the vehicle's turn signal is not in use, LDSW warns the driver when the vehicle exceeds a certain speed threshold.

Many approaches have been applied to lane detection, which can be classified as either feature-based or model-based [7-8]. Feature-based methods detect lanes by low-level features like lane-mark edges [9-11]. The feature-based methods are highly dependent on clear lane-marks, and suffer from weak landmarks, noise, and occlusions. The model-based method represents lanes as a kind of curved model that can be determined by some important geometric parameters. The model-based method is less sensitive to weak lane appearance features and noise than the feature-based method. However, a model created for one scene may not work in another, making the process less adaptable. In addition, the best possible estimation of model parameters requires the application of a relatively time-consuming iterative error minimization algorithm.

The general procedure for lane detection is to first capture an image of the roadway using a camera mounted on the vehicle. The image is then converted to grayscale to minimize processing time. Second, the presence of noise in the image interferes with correct edge detection. Therefore, it is necessary to apply a filter such as a bilateral filter, Gabor filter, or trilateral filter to remove noise. It then uses an edge detector to generate an edge image by preserving the edges with an automatic threshold canny filter. Then, after detecting the edge, the edge image is sent to the line detector to create the left and right lane boundary segments. Lane boundary scan uses the information in the edge image captured by the Hough transform to perform the scan. The scan returns a series of points on the left and right. Finally, a pair of hyperbolas fits into these data points and represents the boundaries of the lane. For visualization purposes the hyperbolas are displayed on the original colour image.

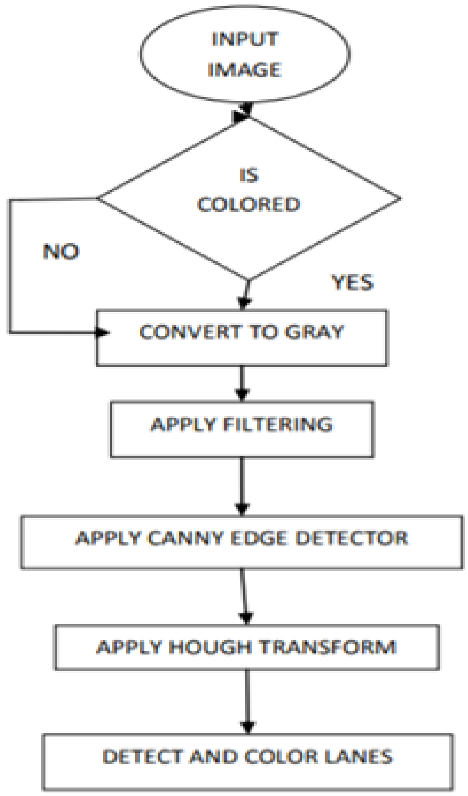

Fig 2. Flowchart

5.1. Raspberry PI zero module

The Raspberry Pi is a popular single board computer (SBC) because it is a complete computer packaged in a single circuit board. The Raspberry Pi 3 and its predecessors are likely recognisable to many people. These are the most recognized form factors today. The Raspberry Pi is offered in an even smaller form factor. With the introduction of the Raspberry Pi Zero, it's now possible to integrate an entire computer into a smaller project. The Raspberry Pi Zero Wireless, the latest iteration of the Zero line with an integrated WiFi module, is described in this guide. These steps should work for most versions and form factors of the Raspberry Pi, but the focus is on the Pi Zero W.

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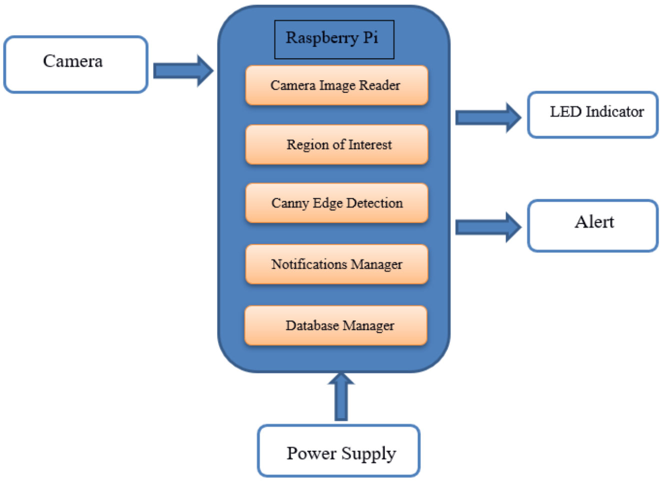


Fig 3. System Architecture

5.2. Image Processing

After acquiring the image information in front of the vehicle, the lane marking features are first extracted by image processing, and then the lane is adapted from these features. In reality, light and evasive manoeuvres and a variety of complex noises make it difficult to detect lanes quickly and accurately. As a result, establishing a series of image processing methods is one of the key technologies of LDWS that can provide fast and accurate results under the condition of the acquired image information. This is not ideal.

- Edge Detection
- Linear Model Fitting
- Setting of the Region of Interest (ROI)

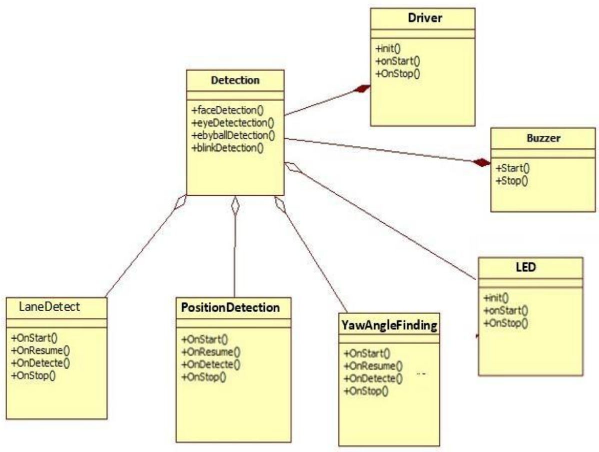


Fig 4. Class Diagram

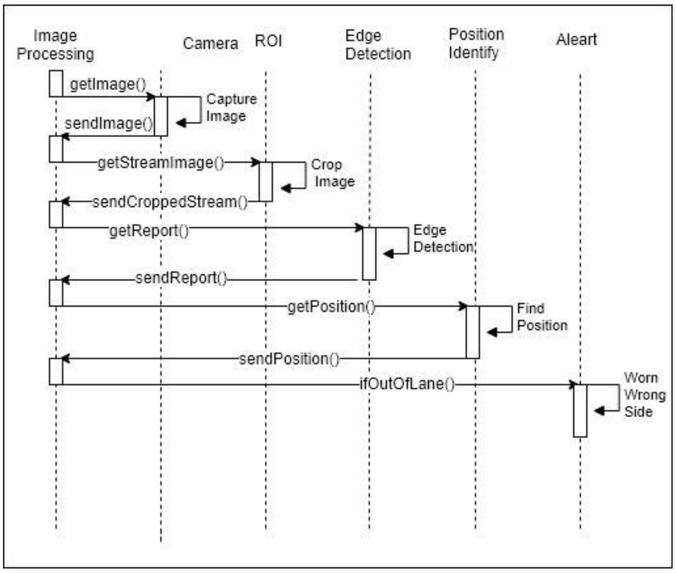


Fig 5. Sequence Diagram

5.3. Overview of Project Modules

Identifying the lanes of a road is a very common task for a human driver. This is important to keep the vehicle in the lane. This is also a very important task that self-driving cars must perform. And a very simple lane detection pipeline is possible with simple computer vision technology. This report describes a simple pipeline that can be used for simple lane detection using Python and OpenCV.

We have provided following features into our system:

1. Hardware can capture the images
2. Hardware can detect the road lanes
3. Hardware can give notification via buzzer/speaker when driver crossed the lane
4. Hardwar can give notification via buzzer/speaker when zebra crossing is detected
5. Hardware can detect any Road Signs and give notification via buzzer/speaker

6. IMPLEMENTATION DETAILS

6.1. Lane Detection Pipeline:

1. Convert original image to grayscale.
2. Darkened the grayscale image (this help in reducing contrast from discoloured regions of road)
3. Convert original image to HLS colour space.
4. To make yellow mask, isolate yellow from HLS. (For yellow lane markings)

5. Isolate white from HLS to get white mask. (For white lane markings)
6. Bit-wise OR yellow and white masks to get common mask.
7. Bit-wise AND mask with darkened image.
8. Apply slight Gaussian Blur.
9. Apply canny Edge Detector (adjust the thresholds—trial and error) to get edges.
10. Define Region of Interest. This helps in weeding out unwanted edges detected by canny edge detector.
11. Retrieve Hough lines.
12. Consolidate and extrapolate the Hough lines and draw them on original image.

Fig 6. Original Image

6.1.1 Convert to grayscale

Converting original image to grayscale has its benefit. We need to detect yellow and white lanes, and changing the original image to grayscale,improve the lanes' contrast with the road. increases the contrast of lanes with respect to road.

Fig 7. Converted to Grayscale

6.1.2. Darken the grayscale image

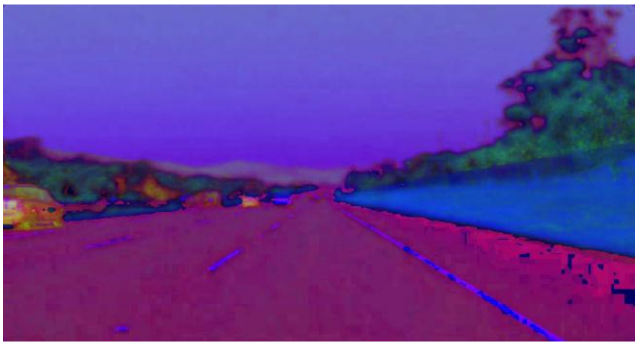
This is done with the intent of reducing contrast of discoloured patches of the road.

Fig 8. Darken the grayscale image

6.1.3. Convert original image to HLS colour space

The original image is RGB, but you should also look at other color spaces such as HSV and HLS. If you look at them side by side, it's easy to see that in the HLS color space, you can get better color contrast from the streets. This may help in better colour selection and in turn lane detection.

(A) Convert original image to HLS



(B) Convert original image to HLS

(C) Convert original image to HLS

Colour Selection

6.1.3.1. Colour Selection

To acquire the mask between the threshold and hold value, we utilise OpenCV's inRange function. We can determine the threshold range after some trial and error.

For yellow mask:

- Hue value was used between 10 and 40.
- We use higher saturation value(100–255) to avoid yellow from hills.

For white mask:

- We use higher lightness value (200–255) for white mask.

We bit-wise OR both masks to get combined mask.

Below images show combined mask being bit-wise AND with darkened image.

(A) Bit-wise AND with darkened image

(B) Bit-wise AND with darkened image

6.1.4 Gaussian Blur

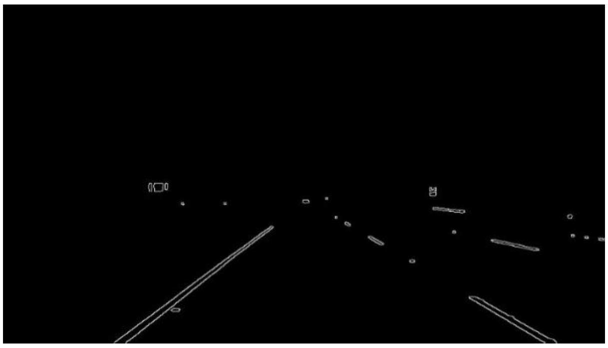
Gaussian blur (Gaussian smoothing) is a pre-processing step used to reduce (or smooth) image noise. Use this pre-processing step to remove many of the detected edges and keep only the most prominent edges in the image.

GaussianBlur from OpenCV expect kernel size(odd value) for blurring. After trying some values, we used 7.

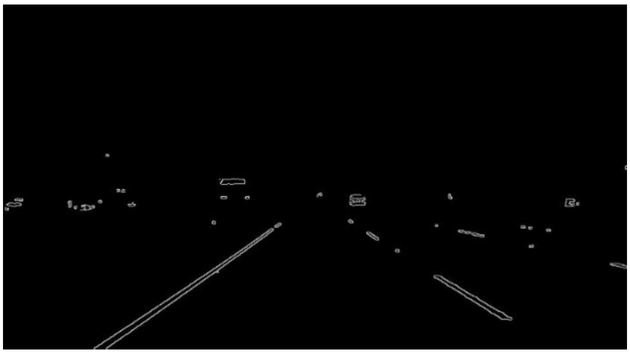
6.1.5. Canny Edge Detection

Now we apply Canny Edge Detection to these Gaussian blurred images. The algorithm Canny Edge Detection recognises edges based on gradient change. Despite the fact that picture smoothing with default kernel size 5 is the first stage of Canny Edge detection, we still use explicit Gaussian blur in the prior phase. The other steps in Canny Edge detection include:

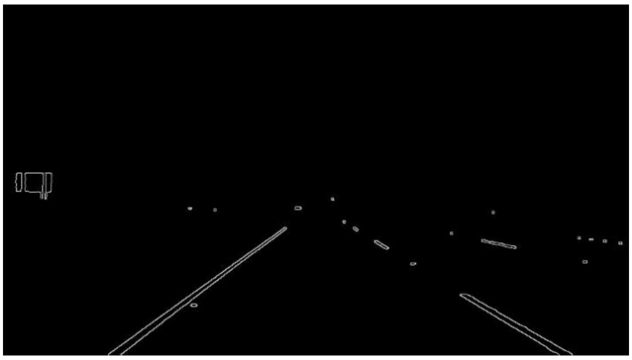
- Finding Intensity Gradient of the Image
- Non-maximum Suppression
- Hysteresis Thresholding



(A) Canny Edge Detection



(B) Canny Edge Detection



(C) Canny Edge Detection

(D) Canny Edge Detection

6.1.6. Select Region of Interest

Many non-lane edges are detected even after applying canny edge detection. Regions of interest are polygons that define the regions in the image that the edges are interested in.

Note that the image's co-ordinate origin is in the top-left corner, with rows increasing top-down and columns increasing left-right.

The assumption is that the camera will remain in the same position and that the lanes will be flat, allowing us to "guess" the region of interest.

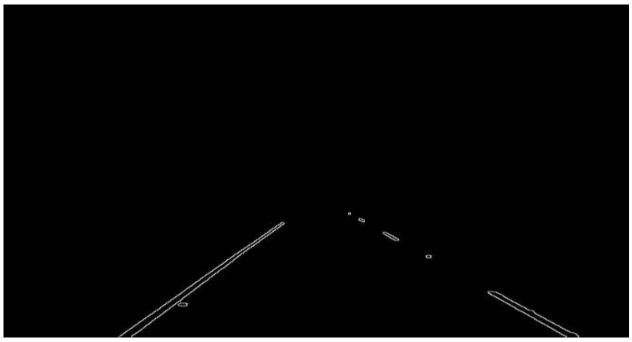


Fig 9. Selecting Region of Interest

6.1.7. Hough Transformation Lines Detection

The Hough transform is a technique for finding a line by identifying every point on the line. This is done by representing the line as a point. Points are also represented as lines / signs (depending on the Cartesian / polar system). If multiple lines / sine waves pass through a point, we can conclude that these points are on the same line.

Fig 10. Hough Transformation and Line Detection

7. Conclusion and Future work

Lane recognition technology plays an important role in intelligent transportation systems. In this paper, we considered how to detect lanes. Most of them resulted in inaccurate results. Therefore, further improvements can be done to enhance the results. Soon, one can modify the existing Hough Transformation so that it can measure both the curved and straight roads. Various steps should be taken to improve the results in different environmental conditions like sunny day, foggy day, rainy day etc.The proposed system and system implementation give the detailed implementation which will result in high accuracy while tackling the limitations of the other systems discussed in the literature survey.The lane detection shall have proved to be an efficient technique to prevent accidents using Intelligent Transportation Systems. Our algorithm will increase the detection accuracy of the system. From the results of the experiment, our method gets lane change and warning goals.It is expected that the proposed algorithm shall detect more than 98% details in the image with good condition, and over 96% details in less-than-ideal weather conditions. A database can be used to store the record of already visited potholes, blockages on the road which may have been visited in the past while passing through the same route.And aim to reduce the number of accidents caused on the roads and also to improve the seriousness of such accidents.

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