Summer Internship Project Report on

LANE DETECTION USING DEEP LEARNING

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Contents

Chapter 1

Introduction

An autonomous vehicle is also known as self-driving vehicle or driverless vehicle is a vehicle which uses a combination of sensors, cameras, radar and artificial intelligence (AI). A qualified autonomous vehicle should be able to navigate without human input and can travel to the predetermined destination over roads. The need for autonomous vehicles is increasing day by day as autonomous control implies good performance under significant uncertainties in the environment for extended periods of time and the ability to compensate for system failures without manual intervention. These vehicles are capable of sensing lanes, pedestrians and objects on the road for the smooth navigation without human input. Hence they can greatly reduce human fatigue as they relieve the vehicle occupants from driving and navigation chores.

1.1 Levels of autonomy in self driving cars

- **Level 0 :** The human driver does all the driving.
- **Level 1 :** An advanced Driver Assistance System(ADAS) on the vehicle assists the human driver.
- **Level 2 :** The ADAS of vehicle can control both steering and breaking or accelerating simultaneously under some circumstances. The human driver must continue to pay full attention and perform all other driving tasks.
- **Level 3 :** An Automated Driving System(ADS) on the vehicle can perform all driving tasks under some circumstances. The driver must be ready to take the wheel and drive outside of those set circumstances.
- **Level 4 :** An ADS on the vehicle can perform all driving tasks and monitor the road in certain circumstances. The human does not have to pay attention in those circumstances.
- **Level 5 :** An ADS on the vehicle does all the driving in all circumstances. The human occupants are just passengers and are never involved in driving.

1.2 Advantages of self driving vehicles

- Reduced accidents
- Last mile services
- More efficient parking
- Transportation accessibility
- Reduced traffic congestion
- Increased lane capacity
- Lower fuel consumption
- More effective & affordable taxis
- Reduced carbon dioxide emissions
- Reduced travel time & transportation cost

1.3 Disadvantages of self driving vehicles

- Jobless Drivers
- No one is guilty
- Problems related to weather
- Reduction of driving experience
- Privacy concerns
- Security worries
- Change of Road System
- The threat of terrorists
- The price of the self driving cars is high
- The possibility of even worst crashes
- Difficulty of understanding human behavior

1.4 Pedestrian Detection

It is considered as the essential & significant task in intelligent video surveillance system, virtual reality and intelligent vehicle systems, as it provides the fundamental information for semantic understanding of the video footages. It is also used as canonical instance of object detection.It is one of the most challenging tasks in the research of computer vision due to many different types of noise, created by the appearance of pedestrians and the changes of postures and illumination, in addition to being brought about by complex backgrounds and perspectives. Its application includes car safety, surveillance, robotics etc

Challenges of pedestrian detection are;

- Different backgrounds
- Variety of appearances
- Different body sizes
- High resolution datasets needed
- Distance of the pedestrian from the camera

1.5 Object Detection

Object detection deals with detecting objects of a certain class (such as humans, buildings, or cars) in images and videos.

Challenges of Object detection are;

- Dynamic Background
- Occlusion
- Clutter
- Camouflage
- Presence of Shadows
- Motion of the Camera
- Bootstrapping
- Video Noise

1.6 Lane detection

Lane detection is the process of locating lane markers on the road and then these locations are feed to an intelligent system. Some of the interfaces used to detect lanes include cameras, laser range images, LIDAR and GPS devices.

Challenges of lane detection are;

- Parked and moving vehicles
- Bad quality lines
- Shadows of trees
- Buildings and other vehicles
- Sharper curves
- Irregular lane shape
- Merging lanes
- Writings and other markings on the road
- Unusual pavement materials
- Dissimilar slopes

1.7 Problem Statement

Many people die each year in roadway departure crashes caused by driver inattention. Lane detection systems are useful in avoiding these accidents as safety is the main purpose of these systems. Such systems have the goal to detect the lane marks and to warn the driver in case the vehicle has a tendency to depart from the lane. A lane detection system is an important element of many intelligent transport systems. Lane detection is a challenging task because of the varying road conditions that one can come across while driving. In the past few years, numerous approaches for lane detection were proposed and successfully demonstrated.

1.8 Motivation

Autonomous cars has the ability to transport passengers from one point to another, autonomously in a safe manner. In order to achieve this goal, the vehicle should have some form of road following system, traversing through both rural and busy urban streets while abiding all the existing traffic laws. An increasing safety and reducing road accidents, thereby saving lives are one of great interest in the context of Autonomous Driving Vehicles. The aim of lane detection is to detect what constitutes a lane marking from a digital image/video feed. These lane markings deduced are useful for obstacle detection, lane changing and avoiding accidents. In this paper, a comprehensive review of the literature in lane detection techniques is presented.

Chapter 2

Literature Survey

Two approaches for lane detection are;

- **Feature based method :** Detects lanes by low level features like lane mark edges. The feature based methods are highly dependent on clear lane marks, and suffer from weak lanemarks, noise and occlusions.

- **Model based mthod :** It is a methods which represents the lanes as a kind of curve model and it can be determined by a few critical geometric parameters. They are much more better than feature based methods since they are less sensitive to weak lane appearance features and noise. This method is less adaptive.Because the model constructed for one scene may not work in another scene.

  Challenges of lane detection are;

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  - Merging lanes
  - Writings and other markings on the road
  - Unusual pavement materials
  - Dissimilar slopes

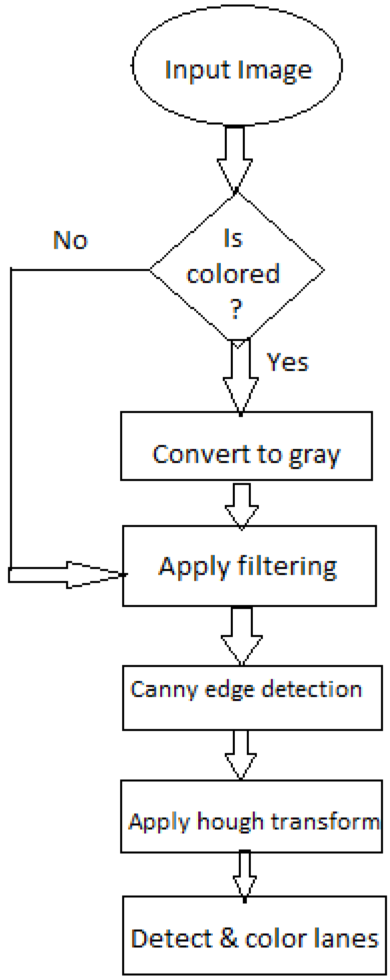

Figure 2.1: Algorithm of Lane Detection

Figure 2.1 represents the basic algorithm of lane detection. First take an image of road with the help of a camera fixed in the vehicle. Convert the captured image to a grayscale image. This process is done in order to minimize the processing time. Presence of noise in the image will hinder the correct edge detection. So we have to remove such noises by using filters like bilateral filter, gabor filter, trilateral filter. Then the edge detector is used to produce an edge image by using canny filter with automatic thresholding to obtain the edges. After detecting the edges, this edged image is feed as the input of line detector which then produces a right and left lane boundary segment. Using the information in the edged image,we perform scanning on these lane boundary. The scan returns a series of points on the right and left side by applying Hough transform. To represent the lane boundaries, we are fitting pair of hyperbolas to these data.

2.1 Semantic Segmentation

Semantic segmentation is a natural step and it is used in the progression from coarse to fine inference:

- The origin could be located at classification, which consists of making prediction for a whole input.
- Then we perform localization or detection step. The output of this step is not only the classes but also it additionally provides information regarding the spatial location of those classes.
- Finally, semantic segmentation get fine-grained inference. This is achieved by making dense predictions inferring labels for every pixel. so that all those pixels are labeled with its own enclosing object class or region class.

Existing Semantic Segmentation approaches

Semantic segmentation architecture consists of an encoder network followed by a decoder network:

- The encoder is a pre-trained classiffication network .
- Decoder projects the discriminative features (lower resolution) learnt by the encoder semantically onto the pixel space (higher resolution) to get a dense classiffication.

2.2 VGG-16

VGG16 was an attempt to usurp OverFeats dominance in object classication and detection by exploring the eects of extreme layer depth. A 16-layer and 19-layer model was produced, setting new benchmarks on localization and classication in the ImageNet ILSVRC 2014 Challenge.

2.3 FCNN

Fully Convolutional Network-Based Semantic Segmentation is an approach which plays a vital role in the decoding mechanism and it is an extension to the classical CNN. The task of FCNN is to map pixels to pixels, without extracting the region proposals. It only have convolutional and pooling layers. These layers give them the ability to make predictions on arbitrary-sized inputs.

Chapter 3

Project Design

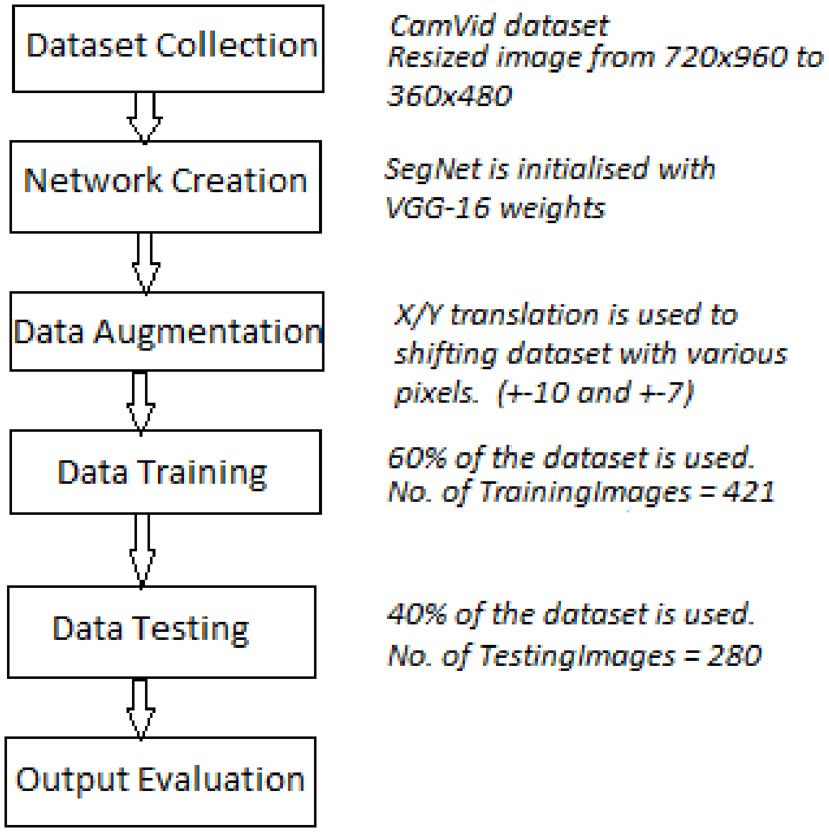

Figure 3.1: Proposed System

3.1 Snap shots

Figure 3.2: Input Image

Figure 3.3: Output Image

Figure 3.4: Input Image

Figure 3.5: Output Image

Figure 3.6: Input Image

Figure 3.7: Output Image

Figure 3.8: Input Image

Figure 3.9: Output Image

Figure 3.10: Input Image

Figure 3.11: Output Image

3.2 Testing Procedure

3.2.1 Dataset

:

- CamVid dataset is a real world dataset from Cambridge University
- It contains real world images obtained from driving car in real time
- The dataset contains pixel to pixel labels
- Thus our model classifies every pixel and pixels once classified are combined into their respective classes
- Images are resized from 720x960 to 360x480 to reduce training time
- The dataset contains 32 classes which we have grouped together into two classes i.e car and road which are of our interest

3.2.2 Creating Network

:

- A segmentation network i.e SegNet is initialised with VGG-16 weights.
- These weights are transferred to the SegNet and additional layers are added to network required for semantic segmentation.
- Class weighting is used to deal with the unequal number of instances in each class. Egnumber of instances of fences are less than that of sky.
- This class weighting is done to improve training and subsequently the accuray.

3.2.3 Data Augmentation

:

- We created minor changes in already available dataset so as to increase the current dataset and subsequently increase the accuracy of our code.
- We have tried many augmenters of which X-Y translation worked best
- X/Y translation we tried shifting dataset with various pixels.
- +-10 and +-7 delivered best results
- Other parameters can also be chosen after empirical analysis for hyperparameter tuning.

3.2.4 Training

:

- 60% of the dataset is used for training
- 60/40 split of data
- numTrainingImages = 421
- numTestingImages = 280
- We tried a wide variety of options during training like sgdm, Momentum, InitialLearningRate, L2Regularization, Max Epochs, MiniBatchSize, CheckpointPath, Shuffle and Verbose Frequency.
- We took values judiciously while coding so as to reduce the training time.

3.2.5 Testing

:

- 40% of the dataset is used for testing.
- 60/40 split of data
- numTrainingImages = 421
- numTestingImages = 280
- The obtained model is tested for any number of images.
- The colour labels are over layed on the images in two classes i.e road and car.
- The results are then compared with actual results thus following supervised learning.
- We have also used intersection over union to prevent classes overlap also known as Jaccard Index which is really important for deep learning applications.

3.2.6 Evaluation

:

- We minimised batch-size to 4 to reduce the memory usage by the GPU.
- We calculated the Global Accuracy, Mean Accuracy among other metrics.
- Class Accuracies were also checked using Class Metrics.

Global Accuracy	Mean Accuracy	Mean IOU	Weighted IOU	Mean BFScore
0.89428	0.87142	0.63592	0.80043	0.62715

	Accuracy	IoU	Mean BFScore
Road	0.96273	70.92816	0.73825
Car	0.92551	0.77295	0.73029

Chapter 4

Implementation details

1. We have performed semantic segmentation on real-world dataset i.e Camvid dataset from University Of Cambridge for testing and training process.
2. Semantic segmentation refers to complete image understanding and is very useful for applications like self-driving vehicles, cancer detection and more.
3. VGG16 weights are assigned to SegNet from the start and more layers are added to the SegNet while training process.
4. The training is lengthy process and takes approximately 5 hours on Nvidia Titan X.
5. As the name suggests semantic segmentation using deep learning segments the image into a number of classes of which we are using only 2 classes i.e road and car.
6. We have narrowed down the number of classes from 30 to 2 in the original dataset code.

4.1 Project Development Time Schedule

- **Week 1** - Workshop on Deep learning and building concepts on same.
- **Week 2** - Detailed study about project and installation process was done. Moreover data collection was started.
- **Week 3** - Data collection was completed and model was trained.
- **Week 4** - Testing Process was conducted and documentation was done.

Chapter 5

Conclusion

Lane detection is a key problem in any driving assistance system, and one of the privileges of computer vision. The lane detection problem, at least in its basic setting, does not look like a hard one. In this basic setting, one has to detect only the host lane, and only for a short distance ahead. While current implementations of LIDAR-based autonomous driving systems are capable of road following and obstacle avoidance, they are still unable to detect road lane markings, which is required for lane keeping during autonomous driving sequences. In this paper, we present an implementation of semantic image segmentation for lane marking detection. In the last decade several advancements occurred in this field. Lots of progress has been attained but there is still scope for enhancement due to the variability in the lane environments.

5.1 Limitations

1. Can not detect bad quality lanes.
2. Shadows effect the proper finding of lanes.
3. Dissimilar slopes will also effect the technique.

5.2 Future Scope

- Future enhancement incudes system for extreme weather conditions such as rain and snow, which are currently not handled by our system.
- By enabling the model to detect lanes in video, a device can be installed in vehicle which will capture video in real time and beware driver about lanes
- It can be linked to GPS system which along with the route will show the condition of road according to the lane.

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