A Review on Self-Driving Car

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Abstract - *This article briefs about the development of self-driving cars. This review article describes in detail the deep learning methods that are used for self-driving cars. It focusses on the recent methods used for lane detection, path planning and detection of traffic signs. It also discusses the experimental results obtained on each of the above methods.*

Key Words: Self-driving cars, Deep learning, Lane detection, Path planning, Traffic sign detection

1.INTRODUCTION

A self-driving car also known as autonomous vehicle is a vehicle that is capable of sensing its environment and moving safely with little or no human input [1][2]. The first semi-autonomous car was developed by Japan's Tsukuba Mechanical Engineering Laboratory. A landmark autonomous car appeared in the 1980s with Carnegie Mellon University's Navlab and ALV projects funded by United States' Defense Advanced Research Projects Agency. The research of National Automated Highway System was successful in 1997. In March 2021, Honda began leasing in Japan a limited edition of 100 Legand Hybrid Ex Sedans equipped with approved Level 3 automated approved Level 3 equipment for "Traffic Jam Pilot" driving technology which allowed drivers to legally take their eyes off the roads.

Self-driving cars aid in reducing the accidents caused due to human errors. The other advantage of self-driving cars is traffic efficiency, cost savings, better access and mode of transportation. It also results in an environmentally friendly environment.

2. DEVELOPMENT OF SELF-DRIVING CARS

The ascension and development of the artificial Intelligence (AI) and Internet economy has promoted the progress of autonomous cars. The measure and market demand of self-driving cars are increasingly notable. At present, many research institutions and enterprises have invested during this field. The giants which have participated within the research and development of Autonomous cars are Google, Nissan, Audi, General Motors, BMW, Ford, Honda, Tesla, Apple, Toyota, Mercedes, Nvidia, and Volkswagen. Google is an internet company, which is one among the leading company in self-driving cars, because of its solid substructure in computing. Two Google self-driving cars were tested on the road on June 2015. So far, quite 3.2 million km of tests are accumulated by Google vehicles. Tesla stands second company that has made great progress within the field of self-driving cars. The first company to devote self-driving technology in field of production is Tesla. It's "auto-pilot" technology has made major breakthroughs in recent years, followed by the Tesla models series. In line with the national highway traffic safety administration (NHTSA), tesla's autopilot technology is just considered Level 2 stage because it is one amongst the foremost successful companies in autopilot system application to this point. Tesla shows that under certain conditions, the car has realized automatic driving.

The main objective of the autonomous decision system is to create some decisions for the autonomous car including path planning, navigation, obstacle avoidance and so on. As an example, within the path planning, the autonomous decision system plans a worldwide path in keeping with the target location and current location firstly, then plans a neighborhood path for the self-driving car by combining the local environment information provided by the environment perception system and also the global path.

3. THEORETICAL BACKGROUND OF DEEP LEARNING METHODS USED FOR SELF-DRIVING CAR

During the last decade, deep learning has demonstrated to be a wonderful technique within the field of Artificial Intelligence. Deep learning methods are used to solve various problems like image processing [3,4], speech recognition [5,6], and linguistic communication processing [7,8]. As deep learning can learn robust and effective feature representation through layer-by-layer feature transformation of the initial signal automatically, it is an honest capability to deal with some challenges within the field of self-driving cars.

To introduce the applications of deep learning within the field of self-driving cars clearly, the theoretical background of four varieties of deep neural networks is reviewed, which are the common deep learning methods applied to self-driving cars.

3.1. Convolutional Neural Network

Convolutional Neural Network (CNN) is out and away one in all the foremost popular deep neural network architectures, usually consisting of an input layer, one or more convolution and pooling layers, a full connection layer and an output layer at the top (see Figure 1).

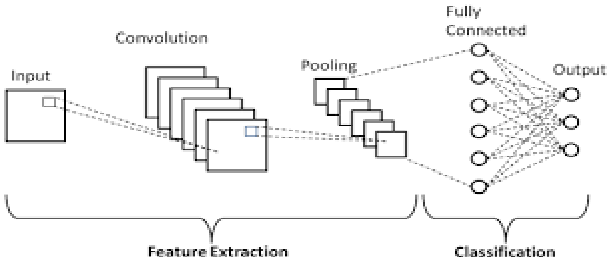

Fig - 1: The network structure of Convolutional Neural Network (CNN)

Convolution layer is the core component of Convolutional Neural Networks although the precise structures of Convolutional Neural Networks could also be different. The convolution kernel (i.e., filter matrix) is convolved with a neighborhood region of the input image, namely

$$yj = \sum wij * x + bj \,,$$

where the operator ∗ represents two-dimensional discrete convolution operation; w represents the filter matrix and b is that the bias parameter; x is that the input feature map and y represent the output of the feature map. The convolution kernel is mostly initialized as a little matrix of three × 3 or 5 × 5. Within the training process of the network, the convolution kernel is constantly updated through learning and eventually get an inexpensive weight.

The Convolutional Neural Network has yielded outstanding ends up in computer image and general image classification tasks recently. Because many self-driving cars technologies depend on image feature representation, they can be easily realized to support Convolutional Neural Networks for obstacle detection, scene classification and lane recognition.

3.2. Recurrent Neural Network

As the self-driving car functions reckoning on the data from the perception of regularly changing the encircling environment, it is important to induce a more complete representation of the environment by storing and tracking all the relevant information obtained within the past. Recurrent Neural Network (RNN) will be used to house this problem efficiently, which is especially wont to capture the time dynamics of video fragments. Recurrent Neural Network maintains the memory of its hidden state for a period of time through a feedback loop and models the dependence relationship between this input and also the previous state [9]. A special form of Recurrent Neural Network is Long Short–Term Memory (LSTM), which controls the input, output and memory state to find out long-term dependencies [10] (see Figure 2).

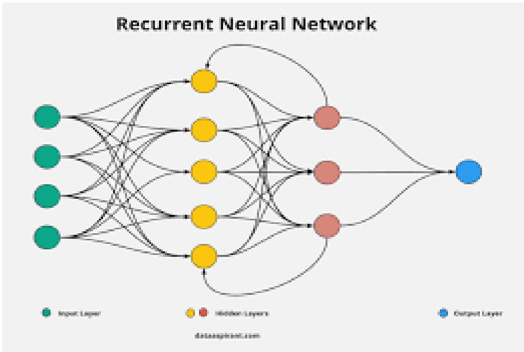

Fig - 2. The network structure of Recurrent Neural Network (RNN)

4. APPLICATION OVERVIEW

Automated vehicles are increasingly present in modern society. Lane detection, path planning, detection of traffic signs are all crucial factors for operation of self-driving cars. This paper focuses on review of all the recent methods used for these operations in order to increase the performance and efficiency of autonomous vehicles and self-driving cars.

4.1. Lane Detection

1) Lane Detection Techniques using Image Processing:

For lane detection, there are two approaches. Among the two approaches, the initial steps are same, that is thresholding and warping [11].

Thresholding:

The image obtained from video which are in BGR format are converted into HSV. HSV is mainly used for color-based image segmentation which is used in separating the road from its surrounding. Thresholding converts the image into binary image i.e., the color of the path is detected as white color and the remaining part is shown in black.

Warping:

Warping used to get the top view of the image by changing its perspective. It is done by passing the coordinates of image to OpenCV library function. The main idea of warping is to convert rectangular shape when road is straight.

Approach 1:

After warping and thresholding, the lanes are located using histogram. To remove unwanted pixels in the image threshold is used. The average histogram value of ¼th part of the image is considered as base point or center of the path. The average histogram value of whole image is considered as middle point. Curve value is the difference between middle point and base point. It is used for obtaining steering angle.

Approach 2:

In this approach, edges of path are considered instead of entire road pixel. The image is pre-processed to get clear edges of the path and it is used to determine the curvature. The imperfections are smoothened out by applying gaussian blurring method. The lane boundaries are extracted from threshold binary image.

Canny Edge Detection:

Canny edge uses multi-stage algorithm for detecting edges in the image by identifying large changes in gradients of pixels. Hysteresis thresholding is used to detect real edges. The edges with intensity gradient more than the maximum value are accepted as edges and edges with below minimum value are removed. The edges between maximum and minimum values are classified based on connectivity.

Sliding Window Algorithm:

The input image is divided into horizontal slice and a rectangular region of fixed width and height. Best fit curve on the line is obtained by applying fitting function. The values of both left and right edges are stored and subtracted with each other to find the curvature value.

The first approach gives the approximate turning value without using the edge positions and offset value cannot be determined. The second approach is applied for both lane marking and no lane marking roads. Offset value can be measured using second approach. So, the second approach is more accurate than the first approach.

2) A Deep Learning Approach for Lane Detection:

Lane detection systems are mainly based on convolutional image processing techniques. To minimize the effect of environmental factors, data driven approach is used for feature extraction.

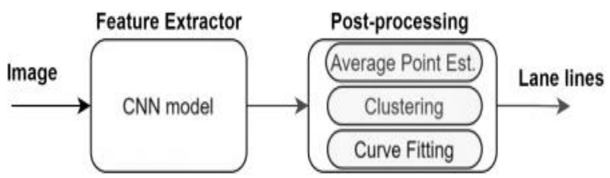

Fig - 3. Block diagram representation of the proposed lane detection framework.

The main objective is to extract lane features in various environmental condition using deep convolutional neural network. A small image patch is selected from the input image and prediction is performed on each image patch. The proposed system consists of three convolutional layers. One is maximum pooling layer and other three are fully connected layers. The input is in the form of image patch of size 16 x 64 pixel and output is binary classification result.

The patches with low confidence value for lane marking are removed at pre-processing level. Clustering method that uses Euclidean distance and angle as a criterion is applied on the group of points with same lane boundary. To avoid overlapping, the clusters are sorted on the basis of number of points in the cluster [12].

The lane boundary is considered as correct only when more than 70% of the sample points should have error less than a defined threshold. Otherwise, the prediction is considered as incorrect.

4.2. Path Planning

Path planning plays a pivotal role in autonomous driving. There are lots of methods used for path planning, such as Particle Swarm Optimization, Genetic Algorithm and so on. However, these conventional and traditional planning algorithms are not very suitable and efficient for the path planning task of self-driving cars under complex environments.

Owing to impressive advantages in maximizing performances in roads without lanes, NMPC (nonlinear model predictive controller) is promising.

1) Path and Trajectory Planning for Self-Driving Car on Roads without Lanes

Rotem Levy and Jack Haddad describe the "Path and Trajectory Planning for Autonomous Vehicles on Roads without Lanes" [13]. In this paper, researcher focused on trajectory planning and control for self-driving cars without considering the lane marks.

Maximizing vehicles' performances while using the full road width and not keeping the center of the lane, provide new options for self-driving car path and trajectory planning. In this paper, an NMPC was developed for path planning for autonomous vehicles to enhance the traffic flow performance, which includes maximizing all vehicles' progress on track with minimum control efforts, under road geometry layouts and vehicle dynamics constraints. The NMPC controller for path and trajectory planning was implemented in the MATLAB environment, where the Casadi framework and the IPOPT library were used to solve the non-linear optimization problem at each time step.

The defined controller was tested on three case study simulations for several vehicles to examine the benefits of the lane-free road and two-lane road concept for path and trajectory planning of autonomous vehicles. The results have shown that:

(i) The time lap of the lane-free concept was faster in at least 11.3% from the corresponding time lap of the conventional lane road concept
(ii) Depending on the road geometry layout, the order of the vehicles on the road changes,

(iii) The NMPC controller has the capability to increase the road density and capacity.

2) Path Planning for Self-Driving Cars with Dynamic Lane Mapping and Obstacle Avoidance

The core of autonomous driving capabilities includes Path Planning and obstacle avoidance is a fundamental part of autonomous vehicles.

Ahmed El Mahdawy and Amr El Mougy described the "Path Planning for Autonomous Vehicles with Dynamic Lane Mapping and Obstacle Avoidance" [14]. This research paper focuses on trajectory model with static and moving obstacle avoidance potential, LiDAR-based localization and dynamic lane mapping corresponding to road width. In this paper, information about the position of static obstacles or objects and the position and velocity of moving obstacles are integrated to provide a cost for each lane waypoint. And finally, a pure pursuit algorithm is used for trajectory planning.

The project implementation is based on Robot Operating system, a framework designed to assist the development of robot software.

Simulator experiments

A SVL simulator by LG was used to test the static and moving obstacle avoidance capabilities of the proposed system by two means: Simulating a static obstacle ahead of the vehicle position in the same driving lane and simulating a moving obstacle moving laterally in front of the vehicle (i.e., a person crossing the road). The distance from the obstacle to the vehicle and the deceleration of the vehicle are evaluated. The simulator integrates with the ROS platform, providing a vehicle model which can be controlled using ROS commands and simulates sensors typically used in autonomous driving such as camera, LiDAR and GPS.

Simulation result

During the test, the vehicle managed to stay within a safe distance from all introduced obstacles. The vehicle initiated a lane change approximately 14 meters away from the obstacle in the static obstacle tests.

In the moving obstacle tests, a moving obstacle models a pedestrian crossing the road. If the direction of movement of the obstacle is lateral to the road, all lines are blocked and the vehicle needs to stop completely.

Field experiments

A live demo of the path planning modules was performed using a modified electric golf cart. Data processing and vehicle control is done locally on a computer running the ROS platform.

Field Results

Two trials were performed in this area: A first trial where the vehicle makes a full route with no obstacles/objects and a second trial with a simulated pedestrian crossing, once the vehicle reaches the target speed. The vehicle's position, velocity data and heading were recorded for the duration of the two runs.

In the first run, the vehicle managed to maneuver around the sharp corner.

For the second trial, three pedestrian crossing events were initiated during the test. In each event, a simulated obstacle/object was placed seven meters ahead of the current position in the path of the vehicle and removed a few seconds later. The distance between the object/obstacle position and vehicle was recorded. The vehicle starts to decelerate as soon as the obstacle is detected and manages to stop an average of about three meters away of the obstacle in the three events.

The approach was evaluated by means of a simulation test, as well as a real-world scenario by implementation of model and running the model on a vehicle modified to allow self-driving functionalities.

4.3. Detection of Traffic Signs

1) Traffic sign classification using CNN and Computer Vision:

Today's advanced technologies are furthering our goals with automation in every field making the need for a human in those areas invalid because a human is prone to make mistakes, but the role of a machine would certainly be more efficient, both in terms of speed and accuracy. Deep learning and Machine Learning have played a very important role. This research aims to develop a product that would help people learn about one of the most underrated, yet very important parts of our daily life, a traffic sign. In the past and recent times, there have been many road accidents where the main reasons are inadequate knowledge of road and traffic signs. And speed is considered to be one of the main reasons for such incidents.

Image detection on traffic signs is done through deep learning, image processing by OpenCV. GTSRB – German Traffic Sign Detection Benchmark is the dataset that is being used. GTSRB is a well-known dataset that is being used by Kaggle for traffic signs. For training, validation and testing purposes, this data set has more than 50000 images and forty classes of images. The data set is divided into training sets, validation sets and testing sets. The dataset is also very diverse. The type of network which is being used is the Convolutional Neural Network (CNN). The two constraints faced were, firstly the amount of computational power to train the network was high and not easily accessible. Secondly, transferring images from the dataset for training and testing also needs a good amount of computational power [15].

Nvidia GTX 1080 will provide a comparatively better computational power for the training of the deep learning model. The main step was resizing the images to a lower size for ease of computation. The color of the images will not be changed as the images have to retain the maximum of their properties for the model to learn. When an image is processed in a model, it has to be passed between two convolution layers. And then it is followed by a maximum pooling layer with pooling size (2,2). A maximum pooling layer has been utilized to lower the dimensions but still retain the details of an image. This set is repeated two times and then it is flattened and passed to a fully connected dense layer network. The functions used are rectified linear functions, followed by a fully connected layer that runs through a SoftMax layer in order to predict the class of the traffic sign.

2) Neural Network model for Traffic Sign:

Traffic accidents that occur in bad weather conditions like fog and snowy are due to poor visibility. Traffic sign recognition systems have played an important role in autonomous vehicles. It has reduced the risk of accidents and improved the driving experience. TSRS can be categorized into two sub-tasks, i.e., detection and classification. Detection is used to identify the target objects from the images and classification is used to classify the detected traffic signs into types. The fast development of Convolutional Neural Networks (CNN) has detailed data from raw images extracted and hence traffic sign recognition has obtained such importance.

Convolutional neural network (CNN) has reduced the parameters, improved the network speed and reduced redundancy. Detection of the position and class of an object is required to extract the features of the image. Different traffic scenes from all types of roads like a highway, rural and urban are recorded during daytime and twilight under various weather conditions. The signs are divided into four different types, i.e., mandatory, prohibitory, danger and others. Traffic signs occupy most of the image in GTSDB. The subcategory of the sign to which it belongs can only be determined by algorithms can. The collected images are then classified into classes and each class has a unique name [16].

Better quality of categorization can help in distinguishing the traffic sign and give proper instructions to the driver. In a dataset, if 100000 images are considered, then only about 10 % images have traffic signs and the rest 90% of images do not contain any traffic signs. Due to the large dataset, only 10% of the images can contribute to training. LabelImg is used to annotate the images for each traffic sign with a bounding rectangle drawn with the corresponding category provided.

Some images contain partly hidden traffic signs. A software called LabelImg was used to marginalize the images for each traffic sign. Annotated images can be saved as JSON files automatically. It contains the bottom right and top left positions of the bounding rectangle in the assigned class of the image. And the annotated images are ready for training.

CONCLUSION OF REVIEW

Vision experts of today are focusing on developing self-driving cars without human intervention. Self-driving cars aid in reducing road accidents and also help in having an environmentally friendly environment. This article describes in detail the latest deep learning methods that are used for lane detection, path planning and traffic sign detection in autonomous vehicles. A discussion is also held on the experimental results of the above methods.

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