DEEP LEARNING BASED SELF DRIVING CARS

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Abstract: Self-Driving car, is a car that can sense its surrounding and move on its own through traffic and other obstacles with minimum or no human input. This is the current upcoming technology in the automobile industry and even though it has been discussed and worked on for a long time, it was successfully manufactured by TESLA. These cars began to roll out in foreign markets as private and public vehicles (taxis, etc.) in recent years. Many companies like Waymo, UBER, Nissan, and Nvidia are involved in this product development. With this type of car, the whole automotive transportation's safety, security, and efficiency are increased, and human errors can be eradicated whilst the drive is made to its best. This project has infused the idea of traffic signal responding which is absent in the current models and the above-mentioned advantages can be achieved with much more ease and at a low cost. This type of system can bring a revolution in transporting for differently abled people and help blind people travel dependently.

Index Terms: *TESLA, UBER, CNN.*

1. INTRODUCTION

The main motive for this work is to avoid the need to recognize specific human-designated features, such as lane markings, guard rails, or other vehicles, and to avoid creating a set of it, then, else rules, based on the observation of these features. Convolutional Neural Networks (CNNs) and other deep architectures have accomplished huge outcomes in the field of computer vision.

With recent advances in artificial intelligence (AI), machine learning (ML) and deep learning (DL), various applications of these techniques have gained prominence and come to the fore. One such application is self-driving cars, which are anticipated to have a profound and revolutionary impact on society and the way people commute. Although the acceptance and domestication of technology can face initial or prolonged reluctance, these cars will mark the first far-reaching integration of personal robots into human society. The last decade has witnessed growing research interest in applying AI to drive cars. Due to rapid advances in AI and associated technologies, cars are eventually poised to evolve into autonomous robots entrusted with human lives, bringing about a diverse socio-economic impact. However, for these cars to become a functional reality, they need to be equipped with perception and cognition to tackle high-pressure real-life scenarios, arrive at suitable decisions, and always take appropriate and safest actions.

Embedded in self-driving vehicles, AI is a visual recognition system (VRS) that encompasses image classification, object detection, segmentation, and localization for basic ocular performance. Object detection is emerging as a subdomain of computer vision (CV) that benefits from DL, especially convolutional neural networks (CNNs). This discusses the self-driving cars' vision systems, and the role of DL to interpret complex vision, enhance perception, and actuate kinematic manoeuvres in self-driving cars. This surveys methods tailor DL to perform object detection and scene perception in self-driving cars.

The first self-driving car was invented in 1989, it was the Automatic Land Vehicle in Neural Network (ALVINN). It used neural networks to detect lines, segment the environment, navigate itself and drive. It worked well, but it was limited by slow processing powers and insufficient data. With today's high-performance graphics cards, processors and huge amounts of data, self-driving is more powerful than ever. If it becomes mainstream, it will reduce traffic congestion and increase road safety.

The main motive for this work is to avoid the need to recognize specific human-designated features, such as lane markings, guard rails, or other vehicles, and to avoid creating a set of it, then, else rules, based on the observation of these features. This discusses the preliminary results of this new effort. Convolutional Neural Networks (CNNs) and other deep architectures have accomplished huge outcomes in the field of computer vision.

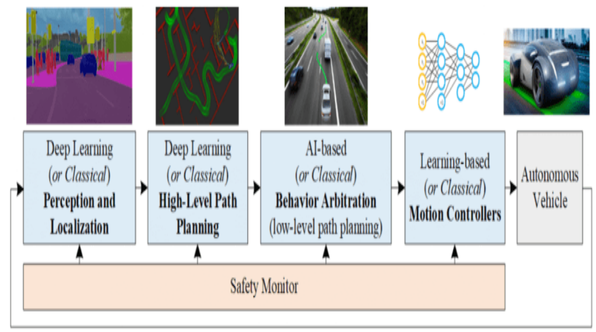

Fig 1 A modular perception-planning-action pipeline

Previously, pattern recognition problems were manipulated through a pre-processing phase of hand-created feature extraction followed by a classifier. A key advantage of CNNs is that high-level features can be automatically extracted from training data which can be used intensively in image recognition tasks. The task is to predict a self-driving car's steering wheel actions based on the input of a camera placed in front of the car. Our deep convolutional neural network does this mapping.

At the heart of it, we find techniques such as 3D CNNs (Convolutional Neural Networks) or PointNet. These are the fundamentals of 3D Deep Learning. These days, LiDAR detection using Deep Neural Networks is booming. That's one of the most active areas of research in self-driving cars.

2. LITERATURE SURVEY

Deep Learning for Reliable Mobile Edge Analytics in Intelligent Transportation Systems

Intelligent transportation systems (ITSs) will be a major component of tomorrow's smart cities. However, realizing the true potential of ITSs requires ultra-low latency and reliable data analytics solutions that can combine, in real-time, a heterogeneous mix of data stemming from the ITS network and its environment. Such data analytics capabilities cannot be provided by conventional cloud-centric data processing techniques whose communication and computing latency can be high. Instead, edge-centric solutions that are tailored to the unique ITS environment must be developed. In this paper, an edge analytics architecture for ITSs is introduced in which data is processed at the vehicle or roadside smart sensor level to overcome the ITS latency and reliability challenges. With a higher capability of passengers' mobile devices and intra-vehicle processors, such a distributed edge computing architecture can leverage deep learning techniques for reliable mobile sensing in ITSs. In this context, the ITS mobile edge analytics challenges about heterogeneous data, autonomous control, vehicular platoon control, and cyber-physical security are investigated. Then, different deep-learning solutions for such challenges are proposed. The proposed deep learning solutions will enable ITS edge analytics by endowing the ITS devices with powerful computer vision and signal processing functions. Preliminary results show that the proposed edge analytics architecture, coupled with the power of deep learning algorithms, can provide a reliable, secure, and truly smart transportation environment.

Navigating Self-Driving Vehicles Using Convolutional Neural Network

In this paper, a method for the navigation of self-driving vehicles is proposed. Although the research on this problem has been carried out for several years, we noticed that elevated accuracy results have not been achieved yet. Therefore, the method using a convolutional neural network (CNN) for training and simulation of unmanned vehicle models on the UDACITY platform has been made. Details, we used three cameras mounted in front of a vehicle to follow three directions left, right and centre positions to collect data. The data are the images that were captured from three cameras. The number of samples image is 15504. In this research, the label with two parameters, the steering angle and speed from each image would also be created. After collecting the data, these parameters will be achieved by training CNN used to navigate the vehicle. With the combination of three cameras, the accuracy of this navigation task is improved significantly. When the vehicle deviates to the left, we will compute the error of the steering angle value between the middle and left positions. Afterwards, the steering angle value will be adjusted to control the vehicle to run in the centre of the lane. Similarly, in the case when vehicles deviate to the right. Based on the simulation platform of UDACITY, we simulated and obtained the result with accuracy was 98, 23%.

Real-time lane detection for autonomous navigation

A lane detection method based on a road model or feature needs the correct acquisition of information on the lane in an image. It is inefficient to implement a lane detection algorithm through the full range of an image when it is applied to a real road in real time because of the calculating time. The paper defines two search ranges for detecting a lane in a road. First is a search mode that searches the lane without any prior information about the road. Second, is a recognition mode, which can reduce the size and change the position of a search range by predicting the position of a lane through the acquired information in a previous frame. It allows us to extract accurately and efficiently the edge candidate points of a lane without any unnecessary searching. Using an inverse perspective transform that removes the perspective effect on the edge candidate points, we transform the edge candidate information in the image coordinate system into the plane-view image in the world coordinate system. We define a linear approximation filter and remove faulty edge candidate points by using it. The paper aims to approximate more correctly the lane of an actual road by applying the least-mean square method with the fault-removed edge information for curve fitting.

From Big Data to Better Behavior in Self-Driving Cars

Diversity and heterogeneity are the key aspects of big data. Including both structured and unstructured data. Understanding and making sense of the huge amount of data requires better approaches for deduction and novel learning systems to address the different difficulties in many domains of application, especially in transportation. Autonomous cars are the future of transportation, in this paper, we will discuss the best combination of big data; text analytics, image processing and big data sensors, from unstructured data and then we will showcase how this fusion of data gathered by different sources can improve reliability and efficiency in self-driving and, may lead us to rethink new theories and models altogether, and finally develop a behaviour vehicle, Capable, like a human, to develop a better understanding from perception and intuition.

Mobile edge computing towards 5G: Vision, recent progress, and open challenges

Mobile Edge Computing (MEC) is an emerging technology in the 5G era which enables the provision of cloud and IT services within the proximity of mobile subscribers. It allows the availability of cloud servers inside or adjacent to the base station. The end-to-end latency perceived by the mobile user is therefore reduced with the MEC platform. The context-aware services can be served by the application developers by leveraging the real-time radio access network information from MEC. The MEC additionally enables the execution of the compute-intensive application in the resource constraint devices with collaborative computing involving the cloud servers.

This paper presents the architectural description of the MEC platform as well as the key functionalities enabling the above features. The relevant state-of-the-art research efforts are then surveyed. The paper finally discusses and identifies the open research challenges of MEC.

3. METHODOLOGY

Various image recognition tasks were handled in the image recognition field by combining image local features manually designed by researchers and machine learning methods. Using SVM algorithm is used to object recognition. By combining the image local features with machine learning, practical applications of image recognition technology are used for self-driving cars.

Drawbacks:

1. The problem is to check whether the object is in the image.

2. In image verification, the distance between the feature vector of the reference pattern and the feature vector of the input image is calculated.

3. Machine learning algorithms have less accuracy for object detection. Keeping in view all problems.

Benefits:

This work empirically demonstrated that CNNs can learn the entire task of lane and road following without manual decomposition into road or lane marking detection, semantic abstraction, path planning, and control.

The performance of the neural network is tested using testing data also taken from the simulator, the system learned to drive the car autonomously.

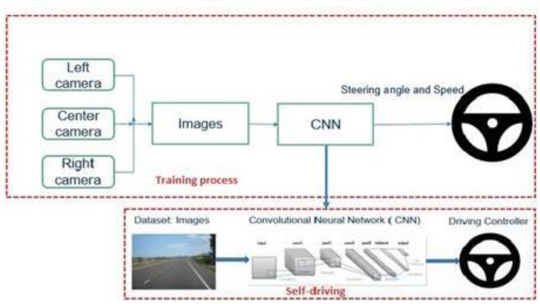

Fig 2 Proposed Architecture

Training data contains single images sampled from the video, paired with the corresponding steering command (1/r). Training with data from only the human driver is not sufficient; the network must also learn how to recover from any mistakes, or the car will slowly drift off the road. The training data is therefore augmented with additional images that show the car in different shifts from the centre of the lane and rotations from the direction of the road.

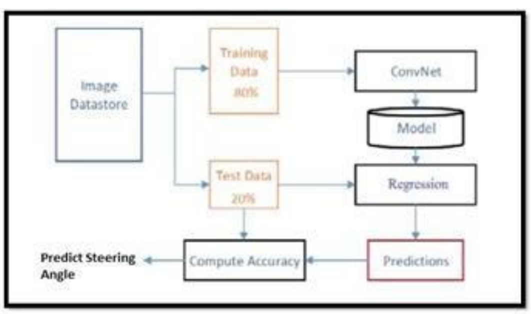

Fig 3 Block Diagram

Modules:

Self-driving cars are autonomous decision-making systems. They can process streams of data from different sensors such as cameras, LiDAR, RADAR, GPS, or inertia sensors. This data is then modelled using deep learning algorithms, which then make decisions relevant to the environment the car is in. The image Fig 1 shows a modular perception-planning-action pipeline used to make driving decisions. The key components of this method are the different sensors that fetch data from the environment.

To understand the working of self-driving cars, we need to examine the four main modules:

1. Perception
2. Localization
3. Prediction
4. Decision Making

4. IMPLEMENTATION

Algorithms

CNN:

A Convolutional Neural Network (CNN) is a type of Deep Learning neural network architecture commonly used in Computer Vision. Computer vision is a field of Artificial Intelligence that enables a computer to understand and interpret the image or visual data. When it comes to Machine Learning, Artificial Neural Networks perform well. Neural Networks are used in various datasets like images, audio, and text. Different types of Neural Networks are used for different purposes, for example for predicting the sequence of words we use Recurrent Neural Networks more precisely an LSTM, similarly for image classification we use Convolution Neural networks. In this blog, we are going to build a basic building block for CNN.

In a regular Neural Network, there are three types of layers:

Input Layers: It's the layer in which we give input to our model. The number of neurons in this layer is equal to the total number of features in our data (number of pixels in the case of an image).

Hidden Layer: The input from the Input layer is then fed into the hidden layer. There can be many hidden layers depending on our model and data size. Each hidden layer can have different numbers of neurons which are generally greater than the number of features. The output from each layer is computed by matrix multiplication of the output of the previous layer with learnable weights of that layer and then by the addition of learnable biases followed by activation function which makes the network nonlinear.

Output Layer: The output from the hidden layer is then fed into a logistic function like sigmoid or SoftMax which converts the output of each class into the probability score of each class.

The data is fed into the model and output from each layer obtained from the above step is called feedforward, we then calculate the error using an error function, some common error functions are cross-entropy, square loss error, etc. The error function measures how well the network is performing. After that, we backpropagate into the model by calculating the derivatives. This step is called Backpropagation which is used to minimize the loss. Convolutional Neural Network (CNN) is the extended version of artificial neural networks (ANN) which is predominantly used to extract the feature from the grid-like matrix dataset. For example, visual datasets like images or videos where data patterns play an extensive role.

CNN architecture

A convolutional Neural Network consists of multiple layers like the input layer, Convolutional layer, Pooling layer, and fully connected layers.

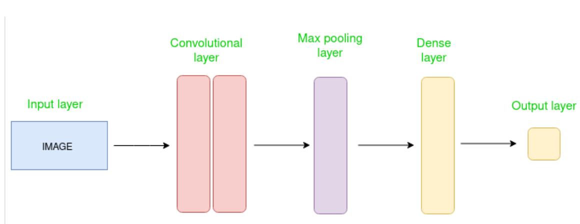

Fig 4 CNN architecture

The Convolutional layer applies filters to the input image to extract features, the Pooling layer downsamples the image to reduce computation, and the fully connected layer makes the final prediction. The network learns the optimal filters through backpropagation and gradient descent.

The equation for CNN is.

Convolution	$z^l = h^{l-1} * W^l$
Max Pooling	$h^l_{xy} = \max_{i=0..s, j=0..s} h^{l-1}(x+i)(y+j)$
Fully-connected layer	$z_l = W_l * h_{l-1}$
ReLu(Rectifier)	$ReLU(z_i) = \max(0, z_i)$
Softmax	$softmax(z_i) = e^{z_i} / \sum_j e^{z_j}$

5. EXPERIMENTAL RESULTS

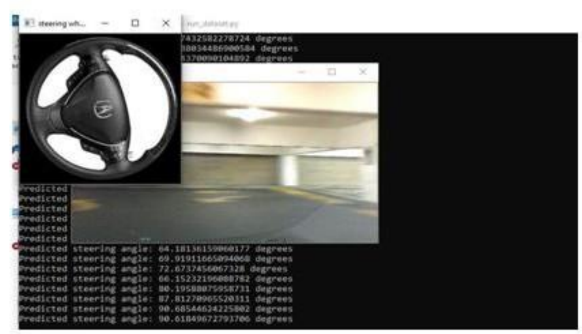

Fig 1 Car turning right.

Fig 2 Car stopping at the signal.

Fig 3 Car continuing in a straight direction.

6. CONCLUSION

Since Self Driving Car is the major gradation in the automatable industry in future, this project focuses on bringing changes in road safety and commuting and significantly reducing accidents and human errors through continuous learning by the system. This project will be a revolution in transporting differently-abled people and blind people can drive independently. With our product as base mobile applications can be developed where the owner summons the vehicle via the app and produces a fully autonomous car on passing the law.

7. FUTURE SCOPE

Without steering wheel and driver's seat, self-driving cars will have new interior outlooks and spaces that can be used for enhanced infotainment services. For travelling people, self-driving cars will be new places for engaging in infotainment services. Therefore, self-driving cars should determine the infotainment contents that are likely to entertain their passengers. However, the choice of infotainment content depends on passengers' features such as age, emotion, and gender. Also, retrieving infotainment contents at the data centre can hinder infotainment services due to high end-to-end delay. To address these challenges, we propose infotainment caching in self-driving cars, where caching decisions are based on passengers' features obtained using deep learning. First, we proposed deep learning models to predict the contents that need to be cached in self-driving cars and the proximity of self-driving cars in multi-access edge computing servers attached to roadside units. Second, we proposed a communication model for retrieving infotainment contents to the cache. Third, we proposed a caching model for retrieved contents. Fourth, we proposed a computation model for the cached contents, where cached contents can be served in different formats/qualities based on demands. Finally, we proposed an optimization problem whose goal is to link the proposed models into one optimization problem that minimizes the content downloading delay. To solve the formulated problem, a block successive majorization-minimization technique is applied.

8. REFERENCES

[1] M. Daily, S. Medasani, R. Behringer, and M. Trivedi, "Self-driving cars," Computer, vol. 50, no.12, pp.18–23, 2017.

[2] A. Ferdowsi, U. Challita, and W. Saad, "Deep learning for reliable mobile edge analytics in intelligent transportation systems: An overview," IEEE Veh. Technol. Mag., vol. 14, no. 1, pp. 62–70, Mar. 2019.

[3] F. Sullivan. (Mar. 2018). Global Autonomous Driving Market Outlook, 2018. Accessed: Jun. 22, 2019. [Online]. Available: https://info. microsoft.com/rs/157-GQE-382/images.

[4] G. Jarvis, "Keeping entertained in the autonomous vehicle," TUAutomotive Detroit, Detroit, MI, USA, Tech.Rep. TUAuto-[Tele.Jarvis.2017.12.08],

Jun.2018.Accessed: Jun. 22, 2019. [Online].

Available: http://pages.tu-auto.com/Detroit18-AVReport

[5] F. Fathi, N. Abghour, and M. Ouzzif, "From big data to better behaviour in self-driving cars," inProc.2ndInt. Conf. Cloud Big DataComput. (ICCBDC), 2018, pp. 42–46.

[6] Y. C. Hu, M. Patel, D. Sabella, N. Sprecher, and V. Young, "Mobile edge computing—A key technology towards 5G," ETSIWhitePaper, vol.11, no. 11, pp. 1–16, Sep. 2015.

[7] A. Ndikumana et al., "Joint communication, computation, caching, and control in big data multi-access edge computing," IEEETrans. Mobile Comput., to be published.

[8] Next Analytics.YouTube Video Appeal Demographics. Accessed: Jun. 22, 2019. [Online]. Available: https://www.nextanalytics.com/excel-youtube-analytic-insights-and-data-mining/page/4/

[9] A. Ndikumana, S. Ullah, T. LeAnh, N. H. Tran, and C. S. Hong, "Collaborative cache allocation and computation offloading in mobile edge computing,".

[10] L. Divine, J. Kurihara, and D. Kryze, "Auto-control of vehicle infotainment system based on extracted characteristics of car occupants". U.S. Patent 13 192629, Jan. 31, 2013.