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NAVIGATING SELF-DRIVING VEHICLES USING CONVOLUTIONAL NEURAL NETWORK

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Abstract

a method for navigation of self-driving vehicles is proposed. Although the research for this problem has been performed for several years, we noticed that the elevated accuracy results have not been achieved yet. Therefore, the method using a convolutional neural network (CNN) for training and simulation of unmanned vehicle model on the UDACITY platform has been made. Details, we used three cameras mounted in front of a vehicle to follow three directions were left, right and centre position to collect data. The data are the images that captured from three cameras. The number of samples image is 15504. In this research, the label with two parameters are 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 vehicle deviates to the left, we will compute the error of the steering angle value between the middle and left position. Afterward, the steering angle value will be adjusted to control the vehicle could 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%.

I INTRODUCTION

Today, with the considerable development of technology and transportation, many vehicles are equipped with the self-driving mode to support the driver to maintain health while driving long distances as well as to reduce traffic accident risk. Navigating trajectory for vehicles was one of the most important aspects of the development of the unmanned vehicle model. There were many methods to do this, but the way to get the best results and match with Industrial Revolution 4.0 is using an algorithm regarding Machine Learning field. Specifically, we made the convolutional neural network (CNN) algorithm to navigate for autonomous vehicles. Deep learning is a subfield of machine learning that is inspired by an artificial neural network. A specific kind of such a deep network

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is the convolutional neural network, which is commonly referred to as CNN or ConvNet. The difference of CNN, in comparison to the traditional neural network, is the number of neural in a class may be reduced but the number of hidden layers is greater and called a deep network. They are trained by backpropagation strategy. So it can build the intelligent systems with high accuracy.

II LITERATURE SURVEY

End-to-End Learning for Self-Driving CarsWe trained a convolutional neural network (CNN) to map raw pixels from a single front-facing camera directly to steering commands. This end-to-end approach proved surprisingly powerful. With minimum training data from humans and no explicit program for road detection, the CNN learns to drive in traffic on local roads with or without lane markings and on highways. It also operates in areas with unclear visual guidance such as in parking lots and on unpaved roads. The system automatically learns internal representations of the necessary processing steps, such as detecting useful road features with only the human steering angle as the training signal. We believe that end-to-end learning leads to better performance and smaller systems. This approach also demonstrates the potential for using CNNs as a general-purpose control algorithm for autonomous driving across varied environments.

Conditional Imitation Learning for Driving in Urban Environments

Autonomous driving in urban environments poses unique challenges due to the complexity of the surroundings. In this paper, we propose a novel approach called Conditional Imitation Learning (CIL) to address this problem. Our method enables a self-driving agent to learn driving policies directly from human demonstrations, conditioning on the surrounding context. Specifically, we utilize a convolutional neural network (CNN) to map sensory inputs from a monocular camera to driving commands. The architecture of our network incorporates both spatial and temporal components to capture dependencies in the sensory input. By introducing conditional elements in the network, we allow the model to adapt its behaviour based on contextual information, such as the presence of pedestrians, traffic lights, and other vehicles. We train and evaluate our approach using the CARLA simulator in various urban scenarios. Our experiments demonstrate that the learned policies generalize well to unseen portions of the environment and even transfer effectively to new environments with different layouts. Conditional imitation learning shows promising results for enabling autonomous driving in complex urban environments

Learning a Driving Simulator

Autonomous driving presents a complex challenge that requires learning models capable of understanding and navigating real-world environments. In this paper, we introduce a novel approach to training end-to-end driving models for autonomous vehicles utilizing large-scale datasets collected from a realistic driving simulator. Leveraging the efficiency of deep Q-learning, we train deep neural networks to control a simulated vehicle based on high-level navigation goals. Our method enables the models to learn to navigate diverse environments without the need for fine-tuning or additional interventions. Through extensive experimentation, we demonstrate that pre-training on vast and diverse datasets obtained from simulation environments can significantly enhance the learning process. Moreover, our analysis reveals that the learned models exhibit robustness to changes in the distribution of training data, including variations in simulator characteristics. These findings underscore the potential of large-scale, diverse simulation datasets for effectively training deep visuomotor policies that can seamlessly transfer to real-world scenarios

DeepRoad:Gaze-based Fast-Response Autonomous Driving in a Simulated Environment.

Autonomous driving systems require fast and responsive decision-making to ensure safe and efficient navigation in dynamic environments. In recent years, gaze-based control has emerged as a promising approach for enabling real-time interaction between human operators and autonomous vehicles. This literature survey explores the use of gaze-based control in the context of fast-response autonomous driving, with a focus on the Deep Road framework implemented in a simulated environment.

We begin by providing an overview of traditional methods for autonomous driving and the challenges they face in achieving rapid response times. We then introduce the concept of gaze-based control and its potential to enhance the responsiveness of autonomous vehicles by leveraging the human operator's visual attention.

Our survey delves into the Deep Road framework, which integrates gaze-based control with autonomous driving algorithms in a simulated environment. We review the architecture of Deep Road, which combines deep learning models for perception and decision-making with real-time gaze tracking technology.

Furthermore, we examine the experimental setup and evaluation metrics used in studies involving Deep Road, including measures of response time, accuracy, and safety. We discuss the advantages and limitations of using simulated environments for training and testing gaze-based autonomous driving systems, highlighting the potential for scalability and reproducibility.

Additionally, we review related research efforts that explore alternative approaches to gaze-based control and fast-response autonomous driving, providing insights into the broader landscape of research in this field.

Through this literature survey, we aim to provide a comprehensive understanding of the principles, methodologies, and applications of gaze-based fast-response autonomous driving, with a particular emphasis on the Deep Road framework. By synthesizing existing knowledge and identifying areas for future research, we hope to contribute

III EXISTING SYSTEM

Formerly, there were many studies on navigation for vehicles, including methods lane detection such as Real-time Lane detection for autonomous navigation [1], a lane tracking system for intelligent vehicle application [2], lane detection with moving vehicles in the traffic scenes [3] or the other papers regarding this method are mentioned in [4], [5]. Although this method gives convincing accuracy about lane detection there are several reasons make the unsuccessful detection.

The first reason is subjective. After detecting two lines we need to calculate and draw a virtual line at the centre then estimate the offset angle between the body of the vehicles and the virtual line to adjust steering of the car so that the vehicles are always in the middle of two lines under any circumstance. The calculations of steering angle that are mentioned above are complicated and can cause many errors.

The second reason is objective. Several of the roads are lack of lane or the lane marking is blurred. Also, when the vehicles are running in the sloping street, the camera was mounted at previous will head to the sky and do not keep up with lane at the ahead. This can also lead to detection will be incorrect.

DISADVANTAGES:

• Using given methods, it is not easy to follow the guidelines.

• Chances of increasing accidents

IV PROPOSED SYSTEM

we demonstrate autonomous driving in a simulation environment by predicting steering wheel angles and speed value from raw images which trained through CNN. Data was collected from three cameras later are pre-processed and fed into a CNN that then calculates value steering angle and speed. The proposed command is compared to the desired command for that image and the weight of the CNN are adjusted to obtain the better result.

ADVANTAGES:

• Gives exact directions using radar, lidar, gps and computer vision.

• Easy to track.

V IMPLEMENTATION

Data Collection: Sensors and cameras mounted on the vehicle capture real-time data about the environment. This data includes images, videos, and sensor readings like lidar and radar. It provides crucial information about the surroundings, allowing the CNN to make informed decisions.

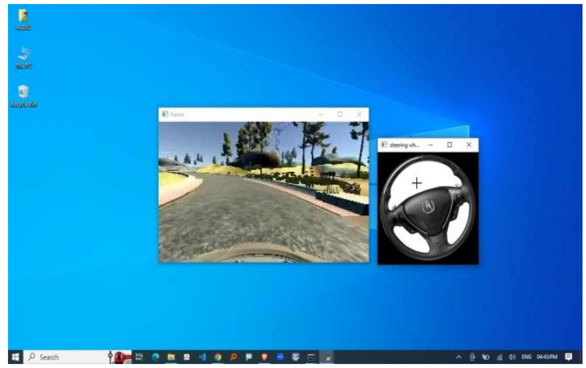
CNN Algorithm: The CNN is the core algorithm used for analysing the visual data. It consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. These layers help the network learn features and patterns from the input data, enabling it to recognize objects, road signs, and other relevant information.

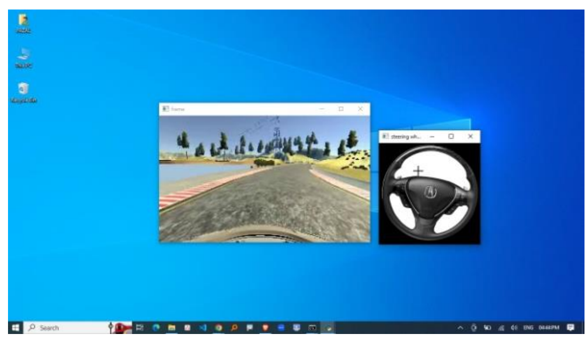
Steering Adjustments: The CNN's output determines the vehicle's actions, such as steering. By analysing the input data, the CNN predicts the appropriate steering angle. This prediction is then used to adjust the steering mechanism of the self-driving vehicle, ensuring it stays on the correct path.

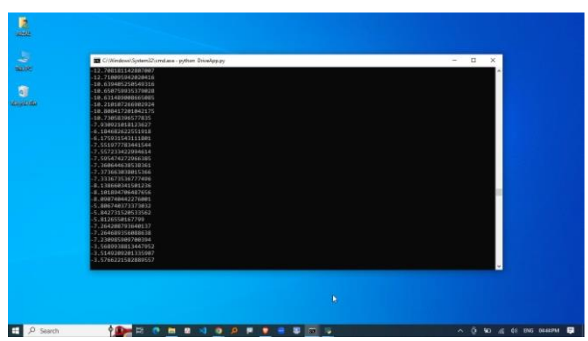
Prediction: The CNN's main task is to predict the appropriate actions based on the input data. It uses the learned features and patterns to make these predictions. For example, it may predict the steering angle, acceleration, or braking needed to navigate the road safely.

Accuracy: To evaluate the performance of the system, accuracy is a crucial metric. The accuracy module assesses how well the CNN's predictions match the actual actions taken by the self-driving vehicle. This evaluation helps identify areas for improvement and fine-tuning, ensuring the system operates with high precision and reliability.

VI RESULTS







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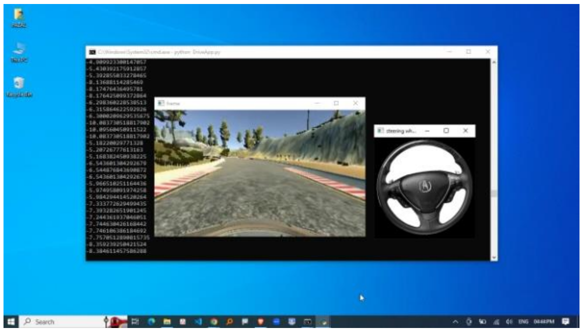

VII CONCLUSION

Advantages of this research are authors have improved and obtained a persuading outcome. Data are one of the most important matter lead to the accuracy of our model (Table 1). Collecting data through three cameras to calibration offset steering angle and ensure the vehicle always runs in the centre of the lane, which is key to enhance the accuracy. Moreover, increasing the epoch so that the model approaches the convergence position is a way to have a model with the persuading result.

On the contrary, in this work has several drawbacks. Firstly, because the simulated environment is so ideal hence the noise from the outside environment is almost non-existent. The second is the matter about the mechanical error of the vehicle is also ignored. With the restrictions mentioned above, authors will soon experiment real-time autonomous vehicle to prove robust of network architecture. In short, authors have created a model which predicts the steering wheel angles and speed for a vehicle using a convolutional neural network. In spite of having obtained a satisfactory outcome but in the near future we are going to approach the several research following: 1) Real-time Self-Driving Car navigation using the deep neural network will be the matter that we interested. 2) Experiment with a more complicated landscape. 3) Take into consideration with the model rely on ResNets/VGG through transfer learning method. 4) Consider reinforcement learning as an alternate method to improve the driving ability.

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