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Artificial Neural Network Based Automated Escalating Tools for Crises Navigation

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ABSTRACT

Autonomous driving technology has made significant advances in recent years. In order to make self-driving cars more practical, they are required to operate safely and reliably even under adverse driving condition. The object detection based on deep learning is an important application in deep learning technology, which is characterized by its strong capability of features learning and feature representation compared with the traditional object detection method. After analyzing the characteristics of videos shot by the camera, we choose to use deep learning to train a vehicle detection model to detect targets in video. In the end, we use trained data set to control the speed and navigate the vehicle in crises situations. Conversely, not much research is going on of usage such networks for elaborating of real time data. The goal of this work is exploring, experimenting and providing new approaches of classification non-stationery data using neural network.

Keywords: *Autonomous, Object Detection, Deep Learning, Vehicle Detection, crises, Neural Network*

I. INTRODUCTION

Autonomous Driving has been said to be the next big disruptive innovation in the years to come. Considered as being predominantly technology driven, it is supposed to have massive societal impact in all kinds of fields. Having a closer look at the history of Autonomous Driving, as explained in the IEEE Spectrum it can be observed that the technological development and main milestones of the autonomous driving field started already a few decades ago. Leading to a vast analysis of some semi-autonomous features, development of present technologies and understanding on the future problematic while focusing the near future in the connected car. Full automated car is not accepted by many countries and doesn't show high accuracy in real life. It doesn't mean humans are better drivers, human drivers face many situations where they lose their human ability e.g. drunk and drive, drowsiness etc. For improving the safety and a new method has been proposed. The method includes the combination of deep-learning object detection and human activity monitoring to make self -driving more reliable.

II. RELATED WORKS

The application of reinforcement learning on control and decision-making has been investigated in several works. Pyeatt and Howe [10] applied reinforcement learning to learning racing behaviours in Robot Auto Racing Simulator, precursor of the TORCS platform, both are open source racing simulators. Daniele et al. [11] used the tabular Q learning model to learn the overtaking strategies on TORCS. Riedmiller [3] proposed a neural reinforcement learning method, namely neural fitted Q-iteration (NFQ), to generate control strategy for the pole balancing and mountain car task with least interactions. In above work, both the state and action spaces are low dimensional. NFQ used the MultiLayer Perceptron (MLP) model as the value function for Q iteration in which the traditional three-layer neural network is employed under normal circumstances. It may fail to find a feasible solution with the increased status and action spaces. In recent years, the deep reinforcement learning has seen an exciting development. One of the representative works is published in Nature 2015 by the researchers of Google DeepMind, in which the authors developed a novel artificial agent of a deep Q-network, based on convolutional neural network (CNN) and Q-learning. The artificial agent learned policies directly from high-dimensional sensor inputs and achieved human-level control on the challenging domain of classic Atari 2600 games [8]. Another exciting work by Google DeepMind is more convincing. AlphaGo defeated the world chess champion Lee Se-dol by 4:1 [12]. The technology behind it was a combination reinforcement learning, and Monte Carlo tree search technique, supplemented with extensive training set.

III. Proposed System

The proposed system developed to drive cars in an efficient and safer way. This system does not support for fully automated self-drive car. Instead, we are likely to present the semi-automatic car for some CRISES situation. The semi-automatic car can be easily interacted with human beings in emergency. [(Ex) In Drunk and Driving situation, car would have 85% of the control, the driver can still drive the car but within a limited speed. During turning or Heavy Traffic, the car will detect the traffic signal using pre-trained model and make decisions according to the situation]. The four phases involve mainly a sensor phase, an image processing phase, an object detection and an automated phase.

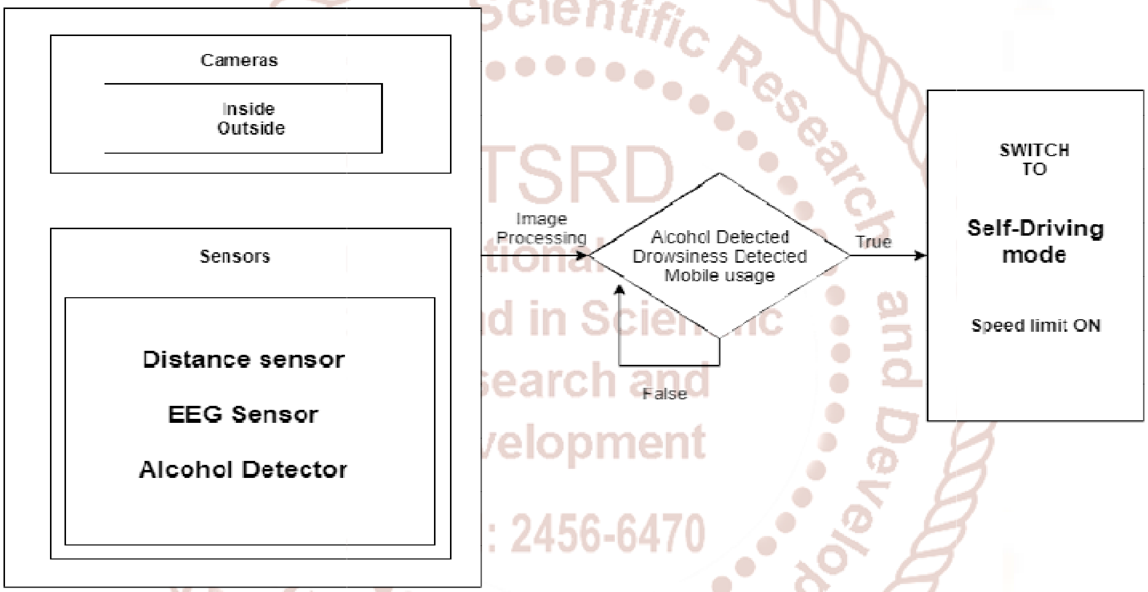

Fig. 1 Architecture of semi-automated system

A. Sensor phase

Multiple sensors and cameras are attached with the car. This provides input data to the system. Data are divided in two types of data, Camera data and sensor data.

i. Camera data:

Data from camera is used for image processing. Data from the camera is high in resolution, so it is reduced to low resolution. Four cameras are used, three cameras are inserted outside the cars which used control the steering angle, and another camera is used to collect images inside the car to detect drowsiness and mobile usage.

ii. Sensor data:

Three types of sensors are used Distance sensor used to calculate distance, EEG Sensors is used to detect drowsiness and Alcohol detector (MQ-3) used detect the level of alcohol in the driver’s breath.

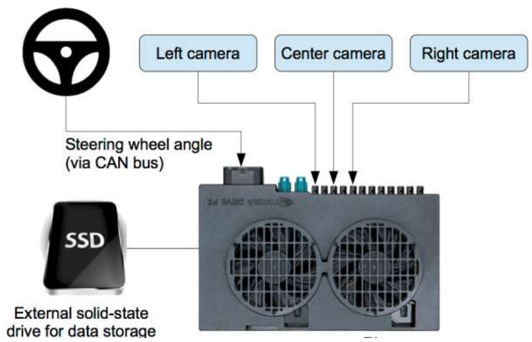

Fig. 2 Camera data

Fig. 3 MQ-3 Alcohol detector

B. *Image Processing Phase*

For image processing neural networks is used. One advantage of using neural network is that once the network is trained, it only needs to load trained parameters afterwards, thus prediction can be very fast. An end-to-end learning approach is used for self-driving. The end-to-end learning takes the raw image as input and outputs the control signal automatically.

The model is self-optimized based on the training data and there is no manually defined rules. These become the two major advantages of end-to-end learning: better performance and less manual effort. Because the model is self-optimized based on the data to give maximum overall performance, the intermediate parameters are self-adjusted to be optimal.

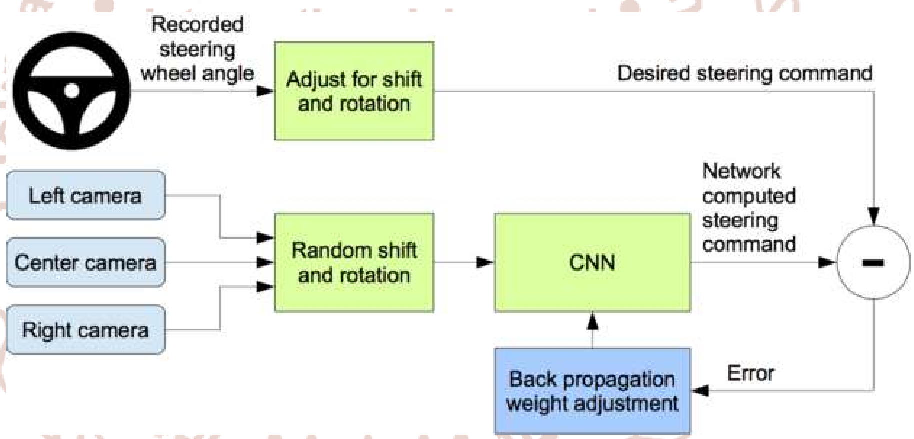

Fig. 4 End-to-End Deep Learning

C. Object Detection Phase

For object detection TensorFlow object detection API is used. In order to use this API, a Images are collected in TFRecords for the training and testing data, two options are available. Pre-trained model is used, and then transfer learning to learn a new object, or learn new objects entirely from scratch. The benefit of transfer learning is that training can be much quicker, and the required data that you might need is much less. For this reason, we're going to be doing transfer learning here. Pre trained ssd_mobilenet_v1_coco model was used to train the Traffic signals dataset, which produced high accuracy and faster detection.

Fig. 5 Traffic sign detection

D. Automated Phase

In this phase data from sensors used for controlling the car i.e., each sensor is set to a threshold value, a driver should satisfy this in order to control the car. Distance sensor is used to calculate the distance between the object in front of the car, for an example minimum distance can be set to 20 meters which helps the car to avoid collision. EEG sensor is used to detect drowsiness and the alcohol detector detects the alcohol level of the driver if the level is high, the car is switched to automatic mode and speed of car is reduced. Since the human driver is not is his control so he/she lost is human ability, so the automatic car can perform better than the human driver.

E. Conclusions

Deep learning is a new breed of Machine Intelligence technique, which is gaining much popularity and wide use in various computer science fields, such as object recognition, speech recognition, signal processing, robotics, AI gaming, and so forth. The semi-automated designed system uses low power consumption and only used in crises situations. The proposed system is mainly useful in reducing the highway accidents. In future it is very useful for disabled person, senior citizens and reduces the number of road accidents. Since semi automation system is used, manufacturing cost will be reduced, and it can be used for commercial purpose.

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