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An analysis on diverse Deep Learning Strategies for Automated Driving

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Abstract

Self-driving cars are one of the hottest areas of research and business for the tech tyrant. What appeared similar to a science-narrative, a few years ago, now give the impression more like something which is presently to turn out to be a part and parcel of life. So much so, that now, with the help of basic deep learning, neural network, we can build our own pipeline for autonomous driving. Deep learning is a subset of machine learning exemplar. Deep learning methods have also shown promise in applications to vehicle Automation. The main intent of this paper is to provide an review sregarding the evaluation of various deep learning control techniques like convolutional neural networks (CNN) and their role in various applications. Also this paper includes the discussion regarding the technological challenges for deep learning based control of autonomous vehicles.

Keywords: autonomous vehicles; self-driving cars; deep learning; sensor ;Actuators: supervised Learning; Reinforcement Learning

Introduction

Increasing urbanization and hottest advances in autonomous technologies, transportation studies move ahead to more intelligent systems, called intelligent transportation systems (ITS). Artificial intelligence is to control systems with modest human interference. Combination of ITS and AI provides effective solutions for the 21st century transportation studies. The main goal of ITS is providing harmless, efficient and consistent transportation systems to participants. Some of the key research areas are optimal traffic signal control, automated vehicle control and traffic flow control. The future transportation systems are expected to include full dominion such as autonomous traffic organization and autonomous driving. However, semi-autonomous vehicles occupy the roads and the level of autonomy is likely to increase in near future. There are several reasons why authorities want autonomy in ITS such as time reduction for drivers, power saving for environment, and safety for all participants. When vehicles use up more times on traffic, fuel expenditure increases, which has environmental and economic impacts. Another reason why human intervention is tried to be minimized is the precipitate nature of human deeds. It is expected that autonomous driving will dwindle traffic accidents and increase the quality of transportation. Experience based learning can substitute human learning. Increasing population is the source of high volume of traffic, an example the annual congestion cost for a driver in the US was 97 hours and $1,348 in 2018. [10]. Hence, controlling traffic lights with adaptive modules is a recent research focus in ITS. Designing an adaptive traffic management system through traffic signals is an effective solution for reducing the traffic congestion. The best approach for optimizing traffic lights is still an open question for researchers, but one promising approach for optimum TSC is to use learning-based AI techniques/ Deep learning is part of a wider family of machine learning methods based on artificial neural networks with learning process such as supervised, semi-supervised or unsupervised. Deep neural networks, deep belief networks, recurrent neural networks and convolutional neural networks are the types of deep learning architecture. These techniques were applied to various fields such as computer vision, machine vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation, bioinformatics, drug design, medical image analysis, material inspection and board game programs, where they have produced results comparable to and in some cases exceed human expert performance. Information processing and distributed communication nodes in biological systems were enthused by artificial neural networks. Deep learning refers to the use of numerous layers in the network. Early work demonstrate that a linear perceptron cannot be a universal classifier, and then that a network with a non polynomial activation function with one hidden layer of unbounded width can on the other hand so be. Deep learning is a contemporary variation which is concerned with an unbounded number of layers of bounded size, which permits practical application and optimized performance, while retaining theoretical universality beneath placid circumstances. In deep learning the layers are also permitted to be assorted and to deviate extensively from biologically informed connectionist models, for the sake of competence, trainability and understandability.

A concise narration of autonomous vehicles & Deep Learning application

The first and foremost effort towards autonomous vehicles came in existence in early 1920s [1] and got impetus in the 1980s when researchers build up automated highway systems [2, 3]. Driverless automated vehicles were largely created in Germany and the U.S. during 1980 to 2000 [4, 5]. Automated vehicles are highly indebted to the extensive research on unmanned equipment made by the defense sector known as (DARPA) the U.S. Defense Advanced Research Projects Agency [6]. Google's driverless car gave huge publicities to the AV and attracted a pool of talent from several disciplines. As recently as July 2015, Google's driverless fleets logged over one million miles during which only 14 minor traffic accidents on public roads were recorded. In all cases, however, the AV was not at fault; rather, it was either being manually driven3 or the other driver was at fault [7]. Nevertheless, the first accident where the Google car was found at fault happened on Valentine's Day 2016, when the car struck the side of a public bus in the Silicon Valley city of Mountain View [8].

The motion control of a vehicle can be broadly divided into two tasks; lateral motion of the vehicle is controlled by the steering of the vehicle, at the same time as longitudinal motion is controlled through manipulating the gas and brake pedals of the vehicle. Lateral control systems aim to control the vehicle's location on the lane, as well as carry out other lateral actions such as lane changes or collision avoidance maneuvers. In the deep learning domain, this is typically achieved by capturing the environment using the images from on-board cameras as the input to the neural network. Longitudinal control administer the acceleration of the vehicle such that it maintains the desirable velocity on the road, maintain a secure distance from the prior vehicle, and evade rear-end collisions. The lateral control is achieved through vision, the longitudinal control depends on measurements of relative velocity and distance to the preceding/following vehicles. The range sensors such as RADAR or LIDAR are more commonly used in longitudinal control systems. The mainstream of the current research projects have chosen to hub on only one of these actions, thereby simplifying the control problem. furthermore, both types of control systems have different confront and differ in terms of performance (e.g. sensor setups, test/use cases)[9]. Figure 2.1 shows the Deep learning process applied in Autonomous Driving Control Systems.

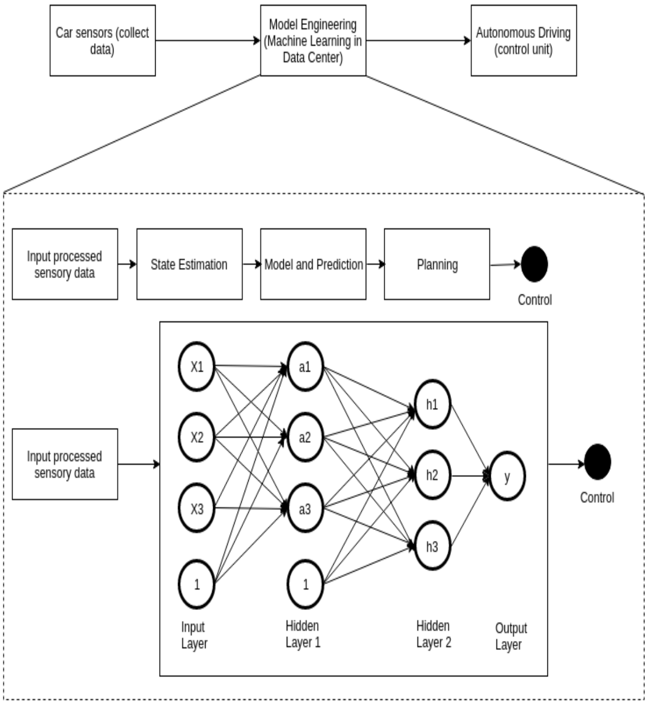

Figure 2.1 Deep learning process used in Autonomous Driving Control Systems

Concepts on Automated Driving – A Review

An automated vehicle driving needs to have the same expert knowledge in driving as a human driver. First, it is able to sense its surroundings. Secondly, it is efficient to perceive, interpret and understand the sensed data. Thirdly, it needs to process the perceived information and decide its driving strategy. This task is handled by the deep learning algorithms. And finally, it requires to use its acceleration, breaking and steering control to move its wheel in such a way that the chosen driving strategy is put into practice. In figure 3.1 shows the general overview of automated driving process using deep learning algorithms.

In this section, the seven significant tasks of sensing information of autonomous driving process were described.

A. **Road Detection** -

It is the process of detecting road boundaries and areas where autonomous vehicle can possibly drive.

B. Lane Detection

It has a major job in ensuring the safety of autonomous vehicles via lane keeping and lane departure control systems, allowing vehicle to be on their specified lane, minimizing the chances of collision.

C. Vehicle Detection

In order to avoid possible road accident, the autonomous vehicle must have to detect and track other vehicles on the road. For this task, it needs to consider different characteristics of surrounding vehicles such as its shape, relative speed, size, and 3-dimensional locations.

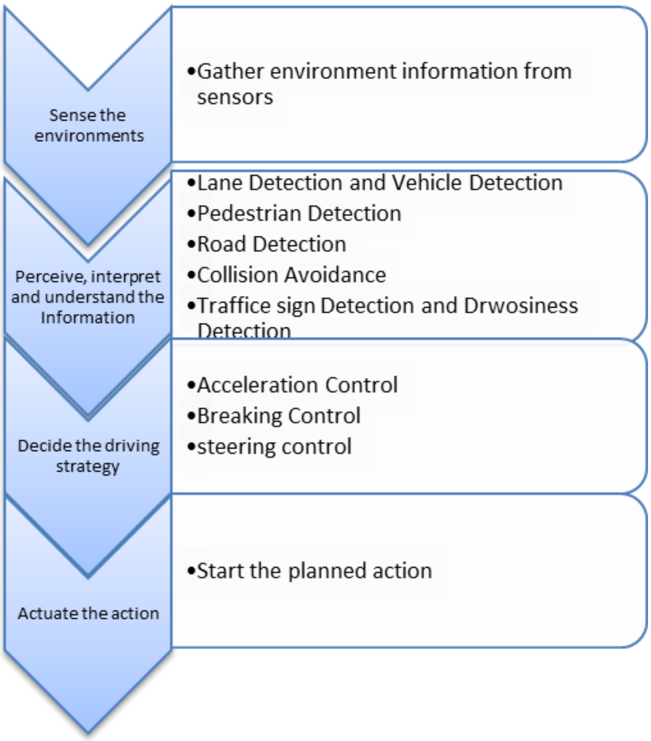

Figure 3.1 An Overview of Autonomous Driving

D. Vehicle Detection

In order to avoid possible road accident, the autonomous vehicle must have to detect and track other vehicles on the road. For this task, it needs to consider different characteristics of surrounding vehicles such as its shape, relative speed, size, and 3-dimensional locations.

E. Pedestrian Detection

It is crucial to discriminate other objects from humans to avoid vehicle to pedestrian accident. Thus, visual cameras are mounted on autonomous vehicle for detection, tracking, and possible recognition of pedestrians for avoiding collision and accidents.

F. Drowsiness Detection

It is one of the key activities in ensuring safety applications as it can automatically take necessary action once driver seems distracted or any drowsy state is detected.

G. Collision Avoidance

It identifies the important objects associated with autonomous vehicles, that can be tracked and detected by them, however, they are not enough to take a decision. The important verdict and feat are taken by collision avoidance system.

H. Traffic Sign Detection

This task is primarily related to the control and safety of the vehicles from collisions at zebra crossing and road junctions, to reduce speed at speed jumps, notify the driver before turns, and suggest about U-turn, etc.

Most of the sensing information are detected, analyzed and implemented by researchers in automated vehicle driving. Recent researchers have used deep learning algorithms for deciding driving plan strategy.

Table 3.1 Synopsis of various application domains in Autonomous Driving

References	**Methodology**	**Application Domain**	**Results**	**Dataset**
[11]	Road pixels are identified by training a **multi-scale convolutional neural network** on a large number of full-scene-labeled night-time road images including adverse weather conditions.	Road Detection	The proposed approach reliably detects roads with and without lane markings and thus increases the robustness and availability of road course estimations and augmented reality navigation.	Ground truth data taken from a differential GPS
[12]	Cascaded end-to-end convolutional neural network (CasNet)	Road Detection and Centerline Extraction	CasNet is much faster than all the comparing methods.	VHR urban road data set
[13]	s-FCN-loc model based on VGGnet for road detection, which is able to learn discriminative features of road boundaries and location priors.	Road Detection	An s-FCN-loc is proposed that learns more discriminative features of road boundaries, Location prior is viewed as a type of feature map and directly appended to the final feature map in s-FCNloc to promote the detection performance effectively and The convergent speed of training s-FCN-loc model is 30% faster than the original.	KITTI Road Detection Benchmark and One-Class Road Detection Dataset
[14]	Deep convolutional neural network	Road and Road Boundary Detection	It detects road boundaries and road areas in a single processing step.	KITTI benchmark
[15]	Convolutional Neural Network (CNN) is trained by using manually labelled Region Of Interest (ROI)	Lane Detection and Collision Avoidance	Experimental results in different scenarios based on two types of dataset proved that our method can realize high accuracy lane detection and classification, even in some challenging situations, such as the night, bumpy road,	KITTI dataset

			shadow, glare, etc	
[16]	Convolution neural network	Vehicle detection and counting	We have achieved the highest true positive rate and the lowest false alarm rate. However the proposed system consumes more time during inference compared with the other systems	Munich and Overhead Imagery Research Data Set
[17]	Long term Multi-granularity Deep Framework to detect driver drowsiness in driving videos containing the frontal faces.	Drowsiness Detection	This method achieves 90.05% accuracy and about 37 fps speed as the state-of-the-art method on driver drowsiness detection.	NTHU-DDD dataset
[18]	Hybrid of convolutional neural network (CNN) and long short-term memory (LSTM).	Drowsiness Detection	It performs with better accuracy and a low computational cost is developed	ACCV drowsy driver dataset
[19]	Deep neural network based collision avoidance policy	Collision Avoidance	Ease of use (no parameter tuning), success rate, and navigation performance.	Collision avoidance data collected by repeatedly running a multi-agent simulator with different parameter settings
[20]	A multiclass classifier with convolutional neural network (CNN) model	Traffic light recognition	Traffic light candidates are robustly detected from low exposure/dark frames and accurately classified using a deep neural network in consecutive high exposure/bright frames.	There is no publically available HDR traffic light benchmark database

Table 3.1 shows the review of some deep learning techniques applied in AD (Automated Driving). The type of methodology, application domain, results and applied dataset parameters are considered for review. Based on this review, deep learning techniques are dominated in most of the AD application domains and provide high accuracy and fast in getting results which can be applied in driving plan strategies.

Evaluation Techniques for Automated Driving

Each task in deep learning is evaluated using multiple evaluation methods including F-measure, precision, recall, overall accuracy, average precision (AP), area under the curve (AUC), and runtime. For instance, majority of the road detection techniques are assessed using the F-measure score. F-measure is also known as F1-score which considers both precision and recall, calculating a harmonic mean of both values and captures the trade-off between them. It can be calculated using the formula

F1 = 2 × Precision × Recall (Precision + Recall) (1)

Similarly, the mainstream techniques for lane detection utilized AP and AUC for its evaluation. AP (also known as mean average precision (mAP)) is a performance evaluation metric for object detectors, which computes the AP value from precision (Eq. 2) for different recall (Eq. 3) levels. More generally, AP is used to find area under the precision-recall curve in the range 0 to 1.

Precision = T rue positive (T rue positive+ False positive) (2)

Recall = T rue positive (T rue positive + False negative) (3)

Overall accuracy= Number of correct predictions /Total number of predictions made (4)

Dataset Contributions

This section introduces the detailed information of the data set used to train the CasNet. It should be noted that few VHR urban road data set is publicly available. Thus, we collected 224 VHR images from Google Earth, and we manually labeled their road segmentation reference maps and corresponding centerline reference maps. KITTI dataset is used for verifying road detection. This data set will be publicly available for further research.

Conclusion

The current materialization of sensing, perception, and signal processing technologies have brought momentous enhancement to the ripeness of AD, thereby sinking human drivers' labors and contributing to the on the whole safety of AD. DL tactic recently solved numerous multifarious problems related to diverse areas in general and AD, This article barbed out the delineate perception regarding deep learning applications in a few domains of AD. Also it is surveyed state-of-the-art for assortment of deep learning methodologies for the execution of AD controlsystems.

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