Evaluating the role of neural networks and cyber security for the development of next generation autonomous vehicles: A Survey

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Abstract: Human drivers are one of the major reasons behind road accidents. By introduction of autonomous vehicles, many accidents can be avoided. To emulate state-of-the-art human drivers, artificial neural networks are proved to be efficient in the design of next generation autonomous vehicles. However, a latest comprehensive survey has been not performed yet, which elucidate the latest state-of-the-art neural networks based autonomous vehicles design in a single literature. Moreover, a general overview of techniques utilizing neural networks for developing autonomous vehicles are discussed in this study. With the emergence of advanced cyber physical systems like autonomous vehicles, new types of security threats have been emerged, which might be a main hurdle in the practical implementation of autonomous vehicles. This paper also covers these security issues along their solutions. In the last some open problems related to the possible role of neural networks and network security has been presented as well.

Keywords: Autonomous vehicles, Cyber security, Neural networks

I. INTRODUCTION

Road accidents are such a phenomenon which cannot be avoided, despite of many efforts in improving road and vehicle interaction. It is noted by different researchers including [1-3] that human drivers are major reason behind road accidents. This may be because of their distraction or inability to perceive 360 degree surrounding environment. It is found by [4-6] that failure to notice vehicles and pedestrians in blind spot and junctions cause several accidents. Solution to this problem is to build either semi-autonomous vehicles [7, 8] providing assistance to human drivers to avoid accidents, or fully autonomous vehicles and making them more secure and reliable as compared to human driven vehicles. To achieve this task, firstly it is needed to emulate state-of-the-art human driving behavior and then making that system more efficient by eliminating causes of human driver's mistakes.

For emulating human driver behavior, the processes of recognition, perception, path planning and decision making should have similar mechanism as in humans. In humans all the cognitive and decision making processes are operating through neural networks. In the literature, many methods have been developed to mimic these processes in autonomous driving.

Like every other cyber physical system, AVs can be hacked [9] therefore while developing AVs, incorporating security is one of the main challenges developers are facing. Acceptability of AVs by humans is dependent on the extent of security and reliability. This paper is aimed to discuss these challenges and their possible solutions.

In section II review of utilizations of artificial neural (ANNs) networks for autonomous vehicles (AVs) is provided. In section III cyber security issues related to AVs and their solutions are discussed. In section IV some open research problems related to this literature are provided. Lastly section V gives the concluding remarks.

II. ARTIFICIAL NEURAL NETWORKS FOR AUTONOMOUS VEHICLES

Driving a vehicle is a complex task because of unpredictable and dynamic environment conditions [2]. Human drivers are able to deal with the complex driving situations because of ample experience gained in diverse circumstances and intelligent perception and decision making of new situations encountered. To simulate human driving expertise in autonomous vehicles, neural networks are being used [10-21]. Because of human brain inspired design and functioning, neural networks are found to present efficient results in many functions of semi-autonomous and fully autonomous vehicles.

ANNs are being used for a variety of tasks related to AV driving, ranging from detection and perception of environment to decisions and control. Various datasets and softwares are being used for each of these tasks. For detection, localization and classification tasks images and videos are used for training ANNs. In this regard, different researchers [15, 19, 20] used human driven cars to collect required dataset, some others like [10, 12, 21] used publicly available datasets (e.g., KITTI, Oxford Robotic car dataset, NYU, Ford Campus vision dataset, TuSimple dataset), while others [22, 23] collected data using video games and simulation softwares (e.g., Unity 3D, TORCS, 3D Max etc). Whereas for training the ANNs for steering, speed control and path planning, different parameters like (steering angles and speed etc.) are obtained through human demonstration during driving. For obtaining this type of dataset there are many methods, most popular among these are to use a simulation software (like CARSIM, CARLA and TORCS)[17, 24-26], or by a human driven vehicle whose actions and decisions are recorded either using video frames obtained through onboard cameras [17] or by specially designed system of sensing actions in vehicles [19].

Purpose of training ANNs is to make the system familiar with various scenarios and appropriate decisions to be taken under different situations. Though aim is to make AVs intelligent to such an extent that they take safe and efficient decisions in all kinds of conditions and environment [27]. To achieve this goal, many methods have been proposed among which overview of most recent technologies and methods are discussed in this section. Fig 1 shows the taxonomy under which the information is presented in this section.

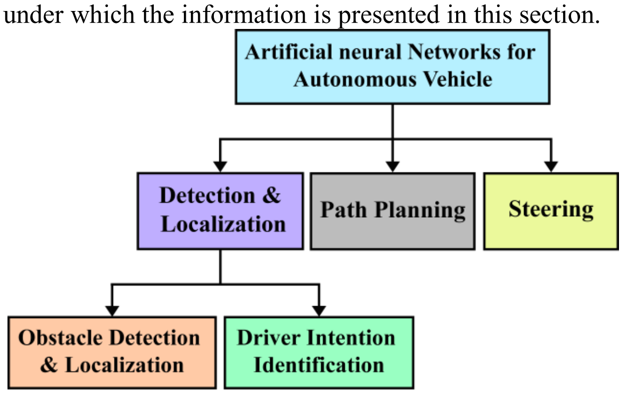

Fig. 1 Taxonomy showing overview of processes in AVs using ANNs

A. Detection and localization

As all the decisions of AVs are dependent on perception and observation of required field of view, therefore it is crucial for AVs to have high accuracy and precision of detection, localization and recognition. In this regard, convolutional neural network (CNN) and its variants (RCNN, fast RCNN, and faster RCNN) are widely used [10, 12, 28-30]. Other latest ANNs used for this purpose include YOLO [31], SOLO and SSD[32].

For the process of detection, recognition and localization, firstly sensors are used to obtain data from environment then this data is processed through some techniques and converted to meaningful information. There are various sensors being used among which cameras, LIDAR and sonars are the common ones. A single camera mounted on AV obtains 2D images whereas, using multiple cameras at different angles can obtain 3D information. Images obtained through cameras can be directly feed into the neural network being used whereas for data captured through other sensor devices need processing before using. Data in the form of point cloud format obtained through LIDAR and other depth sensors is mainly processed through two methods [10]. The first method is to plot this data into RGB space, using the Point Cloud Library, by this method 2D colored representation is obtained. In second method, point cloud data is converted to volumetric encoding and 3D representation is obtained which is then feed to the ANN being used.

i. Obstacle detection and localization

Driving decisions are based on position and speed of obstacles and objects in the environment. These objects and obstacles include animals, other vehicles, road barriers, road boundary and pedestrians. Each one of these are perceived through different features. For example, for detecting road boundary mostly lane markings are used [11].

Among other obstacles the detection, localization and prediction of other vehicle's behavior is a major challenge because most interaction on the road is with vehicles. Yu et al. [12] developed convolutional neural network based model for the detection and localization of neighboring vehicle. For this purpose, data in the form of pointf cloud format obtained through LIDAR sensor is converted to bird's eye view elevation images. For this conversion process, each pixel is encoded using three channels i.e., minimal, median and maximal height estimate of all points within the corresponding grid. As a result of using this three channel representation, RGB image based network can be utilized without modification. A two phase detector is used in their model for detection and localization using Faster R-CNN and trained it on KITTI dataset. In the first phase region proposal network is used, which detects regions likely to contain vehicle and take estimate bounding boxes around those areas, this reduces computational complexity by reducing size of computation for next phase. As the bounding boxes represent the location on x-y plane therefore localization is automatically done in this step. In the second phase, classification network is used which process only areas inside bounding boxes obtained in first phase. At this step orientation and classification of vehicles is done. For this step 16 layered VGG net which is pretrained on Imagenet. For intersection over union value of 0.5, the model achieved precision of 87.9%. Moreover, 75% of identified cars were localized with absolute positioning error of below 0.2m.

Li et al. [10] used abstraction method for detection and recognition process using CNN. They used data from KITTI dataset and open racing car simulator (TORCS). Original raw data obtained in the form of point cloud format from TORCS is converted to 3D representation, and this abstraction is then used for decision making of their model.

ii. Driver intention identification

In semi-autonomous vehicles it is highly useful to predict intention of human driver. This can avoid many accidents by examining attention of human driver in a given situation and taking action by blocking some level of control from human drivers in emergency situations. Vora et al. [13] developed a technique to predict and analyze intention of driver by examining gaze zone of driver using CNN.

Table 1. Review of neural networks usage for Autonomous vehicles

S. No	References	Contribution	Neural networks used	Dataset	Simulation/Practical
1	[10]	Simulated human driver social Intelligence for driving decisions	CNN	KITTI, TORCS	Simulation using TORCS and KITTI vision benchmark suite
2	[19]	Simulated attention mechanism of human brain for path planning strategy of ground AVs	CNN, LSTM, RNN	Human driven collection vehicle	Practical
3	[15]	Steering decisions and actions of ground AVs	RNN	Human driven data collection vehicle/ human demonstration	Practical on Toyota Highlander
4	[20]	End-to-end learning approach i.e., detection, understanding, steering action and speed decisions	CNN	Human driven data collection vehicle	Practical using NVIDIA DRIVE^{TM} PX on real car
5	[18]	Ground as well as flying robot path planning	CNN	NYUv2	Both simulation and practical
6	[17]	Car steering dynamics	CNN	Human demonstration using CARSIM	Simulation using CARSIM
7	[12]	Object detection and localization by utilizing bird's eye view data	Faster R-CNN	Imagenet, KITTI	Simulation using KITTI vision benchmark suite
8	[21]	Reduce time consumption of AV driving decision through sharing encoder in three task	Faster RCNN, VGG, ResNet	KITTI	Simulation

B. Path Planning

Driving path generation in autonomous vehicles is a complex task because of the dynamic and unpredictable nature of real world traffic.

Three kinds of approaches are widely used for path planning of AVs [14]. In the first type of approaches referred as **behavior reflex approaches**, an end-to-end perception and decisions are used. In these kinds of approaches, sensory inputs are directly mapped to driving decision and actions. For example, exploiting image directly to steer an AV [15]. In second type, called **abstraction approaches**, road condition is abstracted to some representation in order to better understand and evaluate the given scenario [10]. While third kind of approach is **direct perception approach** proposed by Chen et al. [14]. In this method only abstraction of specific indicators of the road situation is generated. It is done to reduce computational complexity by ignoring unnecessary data in the environment and focusing on meaningful information required for path planning. Perception of position and direction of own and surrounding vehicles and obstacles is obtained on the basis of which the decisions are taken for position and speed adjustments.

Caltagirone et al. [16] devised driving path generation strategy by integrating GPS-IMU information, LIDAR point clouds and Google driving directions. They used Brain-inspired Cognitive Model consisting Long short term memory neural network (LSTM) and fully Convolutional Neural Network (CNN). The proposed model learned to perform perception and path planning from real-world driving examples gathered through human driving sequences during training phase. Authors reported MaxF score of 88.13% for a region of 60_60 meters. A drawback in this study is that authors attempted to emulate human driver behavior using only 'perception' element of human brain functioning; whereas 'emotions' are also essential part of it which have been ignored in their model.

Li et al. [10] used abstraction of scenes for decision making process, which was a six layered network having 1028 neurons each in the first two layers and 512 neurons each in the following three layers, last layer is the output layer. They used security enforcement method called repulsive potential field for secure and efficient path planning. They used TORCS and KITTI dataset for training of their model. Labeling of images for training was done through algorithm instead of manual labeling which otherwise consume a lot of time.

Chen et al. [14] implemented direct perception approach using CNN and simulated and tested their model using TORCS. The proposed CNN architecture consisted of five convolutional layers followed by four fully connected layers (FC) with output dimensions of

4096, 4096, 256, and 13, respectively. Training was done using KITTI dataset. By comparing results with methods using behavior reflex and abstraction approaches, it was found that direct approach presented more natural driving behavior.

C. Steering AV

Many steering control models have been developed using physics laws but they cannot capture and predict non-physically derived behavior. Traffic behaviors are dynamic which necessitates a need of dynamic system adapting to the needs of decision in different situations; for this purpose neural network governing steering actions is best fit. Garimella et al. [15] used Recurrent Neural Network (RNN) along with physics based module for steering decisions and actions. RNN supplies the system with steering reference trajectory on the basis of which, torque command is generated which governs feed-forward torque. Although this combination of hardware and software of autonomous vehicle is efficient though integrating human emotions factor in steering decisions may handle emergency situations in efficient manner.

Raush et al. [17] developed CNN based autonomous vehicle steering model and simulated it using car simulator (CARSIM). It contained 3 convolutional layers, 1 fully connected layer, 1 input & 1 output layer and a batch size of 128. They used a single camera as a sensor for environment analysis. For training of their model, they gathered frames labeled by steering angles data obtained through human driver demonstration using joystick wheel in CARSIM simulation. They used neural network framework CAFFE. For updating weights and bias they used three solvers Nesterov's accelerated gradient (NAG) solver, SGD solver and Adam solver. Among these Nesterov's accelerated gradient (NAG) solver was found to perform best on their model.

Yang et al. [18] presented a technique of navigation system, which utilized 3D trajectory instead of steering commands being employed in other methods. Process of perception in their method was divided in two steps. In first step, surface normal and depth map was predicted both of which were used in the second step to decide the path trajectory. They used famous Alexnet (which is actually a CNN variant having 8 hidden layers- 5 convolutional layers and 3 fully connected layers.) model with modification by using HHA feature from depth image and fusing depth and normal features obtained with the fourth layer of Alexnet. They trained their model using NYUv2 dataset. Five kinds of trajectories (i.e., left forward, right forward, left turn, right turn and straight forward), generated by maximum dispersion theory developed by Green and Kelly [33], are utilized in their model. They tested their system on flying as well as ground autonomous robots and reported 20% more efficiency of results as compared to existing direct step prediction methods.

III. CYBER SECURITY IN AVs

Safety and security is the main objective of developing AVs [2], therefore it is crucial to find out security issues related to AVs and finding their solutions. In this section security issues and related measures in autonomous vehicles are discussed.

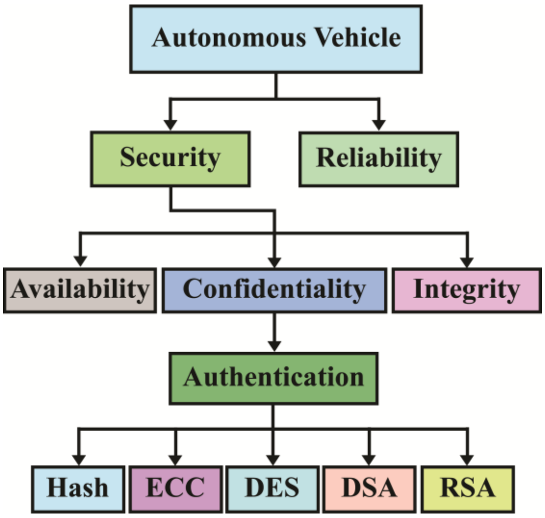

Fig. 2: showing basic security issues in AVs and some algorithms to solve them

A. Authentication

Ho et al. [34] used a cyber-physical security approach to secure sensing inputs. For data transmission and device authentication cyber security protocol was used. RSA signatures was used for the device authentication in their model. For the data transmission phase, AES with session key was used. The implementation and design of a DSRC based road-side beaconing system, called BESAFE was presented in [35], for allowing real-time information sharing with AVs. BESAFE framework supports the dissemination of: (i) traffic light status, (ii) GNSS positioning augmentation, (iii) surrounding traffic information, and (iv) collection of vehicle probe data and node infrastructure status. In BESAFE framework, international standards of DSRC/WAVE, IEEE 1609.x, and SAE J2735 was used, in order to ensure interoperability between infrastructure provider and different AV operators.

Parkinson et al.[36] has identified some main gaps in security for AVs. These gaps are present in Navigation system, sensor, ECU software, cryptographic technique, and Denial of Service attacks. Abueh and Liu [37] presented message authentication scheme to protects cars from bogus message. This scheme protects VANET from Denial Of Service attacks. A hybrid mechanism that use ECDSA with omission techniques and TESLA++ were used.

B. Encryption

Hegde,and Jagadeesha [38] used Optimized Modified Matrix Encoding steganography technique combined with ECC based cryptographic technique to encrypt the user's secret data. for embedding cipher text into H.264 artificial Bee Colony algorithm was used. By comparing their method with conventional FMO and LSB steganography, they obtained improved efficiency by 85%.

Baza [39], a firmware update scheme based on smart contract and blockchain was presented for autonomous vehicles. For incorporating integrity and authenticity, a smart contract was used, and more importantly to manage the reputation values of AVs that transfer the new updates to other AVs. To improve the security of distribution, an aggregate signature scheme was used to allow a distributor to combine multiple proofs to make only one transaction on the blockchain. Evaluation analysis indicates that the cryptography primitives used to secure the firmware update exchange is suitable to the AVs network.

IV. OPEN RESEARCH PROBLEMS

During literature review following open research questions have been found related to the role of neural networks and cyber security in the design of robust AVs.

A. Lack of Affective computing inspired neural networks architectures

During the thorough survey of existing state-of-the-art neural networks-based design of AVs, it has been found that researchers have not explored the role of affective computing or emotions in the design of neural networks. According to Riaz and Niazi [2], emotions play an important role in the design of real human inspired AVs. Hence, researchers can explore emotions to design emotions based neural networks to emulate real decision making of human drivers during threatening situations.

B. Lack of light weight encryption algorithms for autonomous vehicles authentication

In future roads, AVs will be the main actors of smart transportation and will be equipped with different softwares. AVs will communication with different servers to update their auto-pilots. In the same way, AV-AV communication will be very common to exchange their driving credentials for efficient traffic. However, no such research work has been performed, which help to establish a secure and sustainable AVs-Server communication networks. In this regard, existing literature explores existing Symmetric and Asymmetric encryption algorithms, which might be very secure in fixed and delay tolerant architectures. However, for high speed communication networks there will be a need to design light weight efficient encryption and authentication mechanism for the sustainable autonomous vehicles networks.

IV. CONCLUSION

In this paper uses of neural networks in autonomous vehicles are discussed. Furthermore, the different issues in the network security of AVs has been explore using existing literature. In the last the open research questions have been presented. This research paper might help the researchers working in the field of AVs from two different aspects, which are Brain inspired AVs and security issues of AVs explored so far in the literature.

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