Design and Realization of Autonomous Cars using Deep Q Learning

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***Abstract* - Self driving cars are one of the most acclaimed technologies of the 21st century after the internet, but they have become a bone of contention amongst orthodox drivers. With the evolution of advances in software such as reinforcement learning algorithms and Q-learning, the world of artificial intelligence has taken a big leap forward. These algorithms are nature inspired to categorize actions through a system of reward points and negative points. Our research reported here focusses on implementation techniques of such reinforcement algorithms in scenarios such as the self-driving car. In this work we refer to the Bellman equation to give rewards for certain actions and the Markov decision processes for decision-making which includes a certain degree of randomness in the self-driving car and make compromises to reach its destination.**

Keywords - Self-driving cars; reinforcement learning; artificial intelligence; Bellman equation; Markov decision processes.

I. INTRODUCTION

Self-driving cars, no matter how ambiguous at first, are the breakthrough that the world wants in the current scenario. Considering the fact that the average American is bound to spend an average of 82 hours stuck in traffic every year costing them up to $1800 each year and this number increases drastically in developing nations such as China and India. Major car manufacturers come up every year with new variants of their products with increased vehicle intelligence but only few of them have actually succeeded in that line of invention. Tesla for an instance is the closest the world has to autonomous driving vehicles, though it still requires you to sit on the driver's seat and place both your hands on the driving seat, ready to assume control whenever necessary. The world needs to come up with even better solutions wherein all the cars can become driverless taxis, the user puts in the location, sitting on the back seat and the car takes you that specific location and you can relax meanwhile. Major tech giants are arduously working to achieve this level of safe autonomy in self driving cars [1].

Despite the adaptiveness of human beings, there are numerous critical problems related to HVA (Human-Vehicle automation) that have become noticeable with advancements in the technological field. For instance, the term "self-driving" or autonomous can calmly mislead anybody into thinking that the driver's role in vehicle operation will render minuscule with the arrival of advanced self-driving cars. Actually, the role of a person in driving is shifting from orthodox manual control to assisted control with an increase in the level of vehicle automation. Many problems applicable to HAV are gathering research consideration and autonomous vehicles are far from an exception.

In aviation, studies on automation and mode choice have centered in the main on issues in pilot– autopilot interaction, like mode awareness or mode confusion [2, 3]. within the past decade, the military equally, we are able to benchmark human–automation problems in ground transportation. Aerial and ground transportations are similar in that vehicles are operated in each these domains. However, these domains have many key variations. As an example, road traffic encompasses a comparatively high hazard density and likelihood of two-dimensional collisions, whereas aerial traffic encompasses a low hazard density and likelihood of three-dimensional collisions. The threat response times for road and aerial transportations are on the order of seconds and minutes, respectively. Once extremely machine- driven systems like UAVs are introduced into the aviation domain, the operators will most likely be active military officers with ample experience in terms of flight hours, instructor experience, and authorized training. in the case of ground vehicles, the senior can very likely to encounter the foremost advanced functionalities of autonomous vehicles, considering their buying power [4,5]; in alternative words, they will afford top-of-the-line and valuable vehicles, which is able to have the foremost advanced functionality.

Generally, the self-driving automobile [6-13], conjointly termed as the wheeled mobile robot, is a kind of intelligent automobile, that arrives at a destination based on the data obtained from automotive sensors, as well as the perception of the trail surroundings, data of the route and car management. The main characteristic of self-driving car is transporting individuals or objects to a planned target without humans driving the automobile.

II. AVAILABLE TECHNOLOGIES FOR AUTONOMOUS CARS

The automatic management, design, AI (Artificial Intelligence), computer vision and plenty of different technologies are integrated into the self-driving car that could be a product of the highly developed computer science, pattern recognition and intelligent control technology. From a distinct viewpoint, the technology of self-driving car represents the amount of research and industrial strength of a country. However, due to the complexity very few papers have surveyed the technological methods of a self-driving car. The core technology of self-driving car can be categorized into four key components that are referred to as: car navigation system, path planning, environment perception and car control [14].

A. Car Navigation System

During self-driving, two issues, that are the current location of the car and how to travel from the placement to the destination, must be resolved. Certainly, the above 2 problems may be solved by a human's own data in human driving. However, in self-driving, the car must be able to automatically and intelligently find its position and perform the trail planning to destination. For this objective, the on-board car navigation system is deployed on the self-driving car.

Within the car navigation system, geographic information system and global positioning system (GPS) are equipped to receive the placement information like longitude and latitude from the satellite. This information, together with the road info generated by location system and Digital map information, function the supply knowledge inputted into the map-matching model, wherever the intelligent path planning algorithms (i.e. Dijkstra algorithmic program, Bellman-Ford algorithm) are utilized to alter the trail planning calculation. after calculation, the self-driving car can find itself. With the data of the self-driving car's location and also the destination, the driving route also can be programmed and calculated by the path planning model.

B. Location System

The main purpose of the location system is to determine the vehicle location that typically may be classified into: relative location, absolute location and hybrid location. For relative location, this position of self-driving car is obtained by adding the moving distance and direction to the previous position. As an example, inertial guidance system (INS) [15] is a common relative location system.

The absolute location technique is employed to find the vehicle's position consistent with the data obtained from positioning system. A standard positioning system is the satellite-based system, like GPS, GLONASS, Galileo, Beidou so on.

The hybrid location, which mixes the characteristics of the higher than 2 locating ways, is that the commonest technique employed in getting the position of a self-driving car. as an example, the self-driving car of Shaihai Jiaotong University involves a typical hybrid location implementation system, which implements the Gmouse UB-353 USB GPS model and Analog Device ADIS16300 INS [16] to get information of the placement. GPS/INS cannot be solely used for navigation, however conjointly for location applications, like turning. As an example, [17] projected a brand-new vehicle cross-road turning technique supported the GPS/INS information. consistent with this technique, the vehicle turning may be achieved by adopting a predefined map, which is generated by the road curve-fitting and predicting methodology supported the placement and road condition given by GPS/INS. Carnegie financier University [18] made use of distributed GPS knowledge combined with the aerial mental imagery to find the self-diving car within the road, that was named Boss.

C. Electronic Map (EM)

EM is employed for digital map information storage, that principally includes geographical characteristics, traffic information, building info, traffic signs, road facilities, etc. Nowadays, most of the EMs that are employed in a self-driving automotive square measure the EMs designed for humans. it's expected that special EMs for self-driving, like automatic road sign recognition, car's driving information interacting among self-driving cars, are developed within the future.

Now, the EM for self-driving car named HD map has already shown up. Compared with the normal map, on the one hand, the accuracy of absolute coordinates of associate HD map is higher. for instance, it's declared that its next generation of drawing applications are correct in centimeters and, on the opposite hand, the road traffic information parts are richer and a lot of elaborated.

D. Map Matching

Map matching, that is the foundation of the trail planning, calculates out the car's location by using the geographical information from GPS/INS and also the map information from EM. Throughout the calculation, the advanced fusing technique is used to fuse the longitude and attitude or alternative coordinates information into the EM. From the sensible viewpoint, the output of car location should be correct and time economical. In this regard, it's a very important issue to search out a decent methodology to fuse the knowledge from GPS and INS. In fact, typically the satellite signal in GPS or the INS might be lost, therefore, a decent information fusion methodology that may integrate the data from the present location and route situation will greatly enhance the accuracy, hardiness and reliability.

Therefore, it's the analysis hotspot to make use of vehicle running characteristics in map matching, for instance, those literatures planned a novel methodology to resolve map matching [19- 21]. Besides, hidden Markov model (HMM) and heuristic algorithms are some competitive algorithms in those strategies, for instance, the literature [22] presents a brand-new methodology named SnapNet, that provides correct time period map matching for a cellular-based trajectory trace and employs a completely unique progressive HMM algorithmic program to resolve the matter. In the paper of Jagadeesh and [23], a completely unique map-matching solution is planned which mixes the widely used approach of HMM with the idea of drivers' route selection. Similar articles using HMM include: [24-26] and numerous techniques based on heuristic algorithms for map matching, for instance Gong et al in [27] which develops a completely unique map-matching system.

E. Global Path Planning

Global Path planning is used to see the best driving path between the beginning point and finish point. Generally, the everyday path planning algorithms, like Dijkstra algorithmic program, Bellman-Ford algorithm, Floyd algorithm and heuristic algorithm [28] are used to fuse the EM information and calculate the optimum path.

F. The Next Step of Navigation System

In path planning, the module of location is needed to integrate the knowledge from EM. Although the key technology of location (i.e. location system and also the EM) in self-driving car has matured and enforced at the business level, there are still several challenges that have to be faced in the future.

G. Laser Perception

Strictly speaking, laser perception system may be a kind of radar system. In laser perception, never-ending laser or laser pulse is launched to the target, and a mirrored signal is received at the transmitter. By measuring the reflection time, reflection signal strength and also the shift of the operation frequency, the cloud information of target purpose will be generated, then the testing object information, like location (distance and angle), form (size) and state (velocity and attitude) will be calculated out.

H. Radar Perception

Radar perception is mostly used for distance detection that is achieved by calculative the return time of millimeter wave transmitted by the radar detector

I. Visual Perception

Visual perception is critical for a self-driving automobile, i.e. it's necessary to spot the traffic signals. Nowadays, most traffic signals are designed for the human vision; so, it's necessary to recognize the light. Besides, the machine vision is also used for location, navigation, to evaluate the motion so on. However, it's complicated that environment perception use vision thanks to the large quantity of information and inefficient algorithms. Specifically, the most complicated visual perception is how to make sure the reliability and hardiness of the algorithmic program [29]. It includes two parts, i.e., electronic control unit (ECU) and communication bus. ECU primarily implements the management algorithm, whereas the communication bus realizes the communication operation between ECU and mechanical elements.

III. PROPOSED MODEL AND CONCEPTS USED

The proposed design of the autonomous car is an AI based application developed in Python by using the concept of Deep Q-Learning.

Deep Q-Learning: this uses the concept of Q-Learning and Artificial Neural Network. Vectors are used to encode the various states of the environment and are the input to the Neural Network. Various transitions from the present state are possible and the Neural Network predicts which of them will take place. A Q- value is returned for every possible action and the decision is taken based on it.

Markov Decision Processes: The basic principle behind decision making in this project is "Markov Decision Processes". These processes are those in which the current state does not depend upon the previous state and when the car goes from one state to another state then there is a slight probability that the car may make a wrong decision and does not go in the right decision. This also helps the car in learning and it records the last step with a negative reward and does not do the same mistake again in the same manner.

The Bellman Equation: This is a dynamic programming technique used as the necessary condition for optimality of reinforcement learning situations. Since all the situations that are faced in reinforcement learning require to have profits, losses, weights or other quantitative rewards this equation gives the most optimal condition the value of 1 and the one before it slightly less and so on. Thus, the virtual assistant uses this equation to find the most optimal route to gain rewards. The bellman equation is:

$$V(x0) = \max_{a0}\{F(x0, a0) + \beta V(x1)\}$$

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Where V(x) is the optimal value, F (x, a) is the function which represents the state (x) and the action (a), β is the discount factor and V(x1) refers to the next state.

Reinforcement Learning: Reinforcement learning is a technique in which the artificial intelligence is not trained beforehand rather it is put in actual surroundings and the optimal solution for the particular conundrum is found through minimizing the cost or the weight or maximizing the rewards step by step. Particular rewards or weights are given to the artificial intelligence and the agent refers to them while making the best decision.

Q-Learning: It is a reinforcement learning technique used to make the artificial intelligence agent learn the best way to perform a particular technique. This is very important to reinforcement learning since it does not require a particular environment or predefined values. It finds its way through subsequent transitions.

IV. IMPLEMENTATION DETAILS AND CONCLUSION

Some of the previously existing equations and learning techniques have been used in this work (WHERE, THERE IS ONLY EQUATION!!) to enhance the decision making of the self-driving car. Reinforcement learning has been used with other technologies to achieve the basic idea of near human behavior in a self-driving car.

This car uses reinforcement learning and Q-learning which is a technique of reinforcement learning. The car has been given a set of reward points based on which the car decides on which way it should move. It is used to make the car learn from its previous decisions. The reward points are stored in a batch and the car refers to them while making a decision. The guidance systems uses neural networks to replicate the processes of biological decision making systems which includes input variables to give output as the decision taken. The hidden layers define what steps to take and refers to them as rectifier functions (Softmax function) to carry forward the variables onto the output layer. Then the actual working file takes in the inputs as the current position of the car and the sensors and their orientation and catches the output that comes from the AI file and shows it in the GUI. This file also has the cars velocity vector and the reward points for the movements.

In this simulation a track is designed and the source and destination for the car are given as input. When the car goes off the track or hits any obstacle it gets a negative reward of -1 and when it gets away from the goal instead of getting closer to it then it gets a slightly less negative reward that is -0.1. When the car gets closer to the goal then only it gets a positive reward which is +0.1.

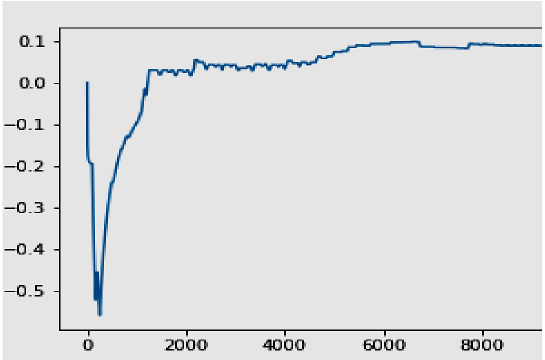

Figure1: Rewards at various time steps

Figure 1 above shows an example of the rewards given at various time steps based on its proximity to the obstacle, track and destination. It can be seen from that during the initial phase of training there is a large deviation, but after some 1500 to 1700 steps the graph becomes more or less stable. This means that the system gets trained at this point of time.

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