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Research on On-Demand Autonomous Vehicle Automation Systems Using AI-Powered Smart Cities

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Abstract

Intelligent cities and transportation could benefit greatly from automated vehicles (AVs). AV technology may help vehicle platooning, which involves one car moving quickly behind another by reducing the gap between them. But effective AVs have the potential to make a much bigger difference [27]. The growing popularity of autonomous vehicles (AVs) will require modifications to currently designed roads and highways [14]. To fully utilize AVs' potential in intelligent transportation networks, we must begin planning as soon as possible. Exploring and utilizing the unique characteristics of AVs has enormous potential to progress technology and develop AV systems with a host of extra benefits. This is because research topics fall into "the following three major categories: traffic information management, which includes road infrastructure and driverless cars [15]. Use cases for autonomous vehicles from the vehicle to the grid (V2G). An AV's usual energy source is a battery. Prices for producing electricity may increase in a smart grid when supply and demand are out of balance [16]. Utilizing AVs' massive battery capacity to maintain and balance the power grid is one way to find a solution. We might use the excess energy to charge the AVs if more energy is generated than is required. In a similar vein, if demand outpaces supply, we could release the AVs to provide the grid with additional power [26]. AVs were able to access parking garages with vehicle-to-grid services by means of a central scheduling system. In order to resolve the ILP variant of Given the coordinated parking problem [17], a decentralized strategy will be used. However, because AVs are restricted to a single parking spot, the flexibility of V2G services is limited. V2G services can only be identified by counting cars, but this problem also needs to take into consideration the power that these cars exchange and the voltage effect they produce. As a result, when planning charging times, the actual power flow of AVs needs to be taken into account. Finding parking spaces for autonomous cars is therefore essential for "rebalancing" vehicle-to-vehicle and vehicle-to-pedestrian interactions, and it's a vital area of study [18].

Keywords: Smart Transportation Network, Automated Vehicles, Autonomous Cars

INTRODUCTION

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The provision of social advantages and a wide range of human activities depend on an efficient intelligent transportation system in a modern "smart city." In the future, autonomous vehicles (AVs) are predicted to completely change the transportation network. Modern Artificial Intelligence (AI) technology and fully automated AV navigation make it possible to integrate many AV systems in transportation and smart grids [1]. We'll start by examining and evaluating the current transit choices. Then, we'll get right to the point: an AI-powered autonomous vehicle (AV) "on-demand transportation" system [2].
While individual "AVs create and execute fully automated control, group control has additional advantages and possibilities. Autonomous Mobile Deployment, or AmoD, has been touted as a new mode of transportation that provides a greater range of services and employs autonomous vehicles as the carriers of transportation services. This year, "Waymo One," a real-world AMoD, was established to offer commercial autonomous vehicle service in Phoenix, AZ, USA. Customers can use a smartphone app to request pickup. "One public transportation system that makes use of AVs to enable ridesharing in order to save money is the Autonomous Vehicle Public Transportation System (AVPTS)[3]. A control center" manages a fleet of AVs and decides on the optimal routes and schedules for clients. Another advantage of this system is profit maximization [4].

REVIEW OF LITERATURE

Since the beginning of time, humans have "innovated in the field of transportation, from animal-powered vehicles to modern trains and automobiles [5]." There has always been a focus on reducing travel time and cost while simultaneously increasing safety and efficiency in transportation. The most common forms of public transportation available today are taxis, buses, and subways. Individuals select various forms of transportation according to their own needs, and each has advantages and disadvantages of its own. On the other hand, public transportation, such as buses and subways, can carry a lot of people for not a lot of money and are nearly always on time [6]. If there are a lot of clients, it might be necessary to crowd, and the service provider might only stop at" well-known locations, which might not be a single passenger's true origin or destination. On the other hand, taxis might offer a comfortable point-to-point service that saves the traveler from having to share space with strangers. At the start and finish of their trip, passengers are free to get on and off without taking a detour. Customers may "have to wait a long time to acquire a taxi" in heavily populated areas, and taxi fares are frequently more expensive than those of the bus and metro. There might not be enough taxis in the area, which would worsen traffic congestion. In recent years, mobility on demand (MoD) services like Uber and Lyft have emerged, enabling users to actively by May 2017, having effectively proven in 2015 that their autonomous vehicles (AVs) were capable of operating on public roads. Business cars that are equipped with Tesla's most advanced version of self-driving technology can now operate on autopilot. The aforementioned examples make it abundantly evident that AV is a technology that will soon spread [11].

DESCRIPTION OF THE ISSUE

Our goal is to predict travel demand for a "certain area A and a specific time period T, where m n grid cells divide the time period T into equal halves. The microseconds between each interval are measured, typically with a value of τ g. A single travel request is counted for all requests from a grid cell (i, j) ∈ A within the time interval t ∈ T. The forecast of future travel demand may be influenced by additional metadata, such as day, time, and weather, in addition to historical data. For instance, demand is probably going to be higher during weekday business peak hours. They might be considered in this manner. to improve the prediction if needed. Predicting each grid cell's (i, j) ∈A demand for the "future τ≥1 interval" is the goal. Assume that we are within the Tc interval. Based on his topical travel demand \={θt,∀ (i, j)∈A,t∈1,2,...,Tc} and other optional" metadata, we predict the travel demands, ˆ= {θ Tc+1, θ Tc+τ, ∀ (I, j) ∈A} [12, 13].

STUDY GOAL:

to investigate the "Dynamic Lane Reversal-Traffic Scheduling Management Scheme" for autonomous vehicles (AVs)

RESEARCH QUESTIONS

The "procedure for AVs to avail dynamic lane reversal-traffic" scheduling management is described.

METHODS OF RESEARCH

The problem-solving algorithm is described in this section. The three components are solvers, GA, and MPC. The flow of the algorithm is shown in Figure 1. We optimise a finite time horizon based on MPC and iteratively improve the solution with new information that becomes available in the ensuing time interval [19]. Under this MPC paradigm, travel demand forecasters can obtain more accurate forecasts by incorporating the most recent data available in each time period. Every time a time interval t begins, we first update the requested data, R and R. The updated data is sent to the GA and solver sections.

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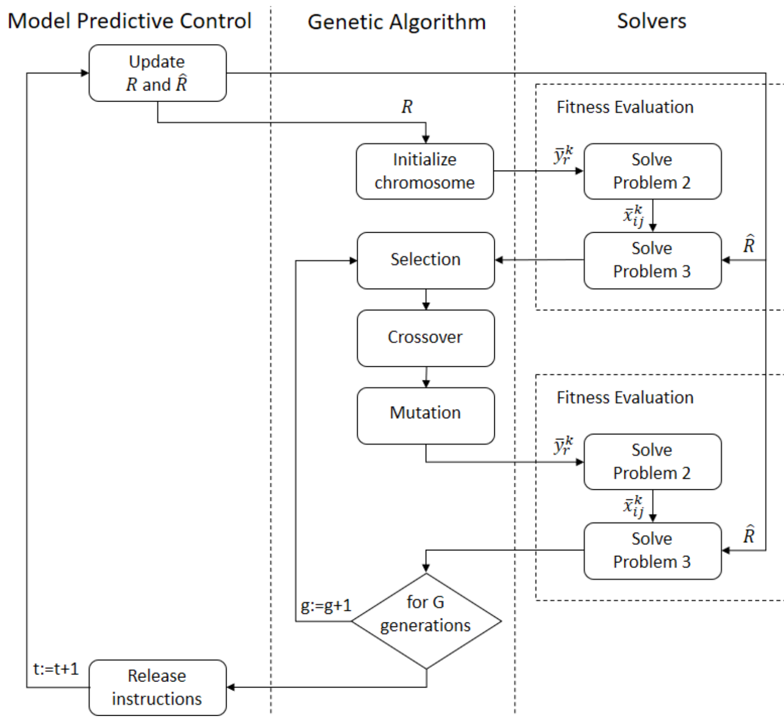

Figure 1 Algorithm Flow Chart

Research design

New "York City" Data from Open Data yellow taxi trips will be used to evaluate the effectiveness of the proposed approach and the system. A pool of transportation requests will be created using the information acquired from trips. Given its abundance of vertices and edges, Fig. 2's New York City is selected to symbolize the road network. Four by six vertices are used to symbolize connecting road segments of the same length. For every edge with the same distance between them, cij equals one time slot if every vehicle travel at the same speed. It should take the same amount of time to run across each edge. Furthermore, we ignore traffic control signals such as stop signs.

Figure 2 The selected road network

EXAMINATION OF DATA

Regarding "Our suggested TSC method requires a significant amount of training time in order to update the Q-parameters. During the training phase, a critical concern for the network is its rate of convergence [22]. Python and TensorFlow are two programming languages that are used to implement TSC's deep reinforcement learning algorithms. SUMO and Sumo-web3d are the two virtual environments available in the Open AI Gym. All of the testing is done for us by the GeForce GTX 1080 Ti.

CONCLUSION

"In this thesis, we propose a novel autonomous vehicle (AV) system, named AVoD, for the future generation of smart cities. AVoD primarily focuses on AI-based transportation systems that incorporate autonomous vehicles. Autonomous vehicles (AVs) have the potential to improve society and transportation by better utilizing their independence. The management of autonomous vehicles, the adaptation of road infrastructure, and traffic data forecasting are three of the most crucial techniques [23]. The primary goal of this research is to use artificial intelligence (AI) to enhance the AV transportation system. Because autonomous vehicles are completely autonomous and have a fast reaction time, we offer AVoD solutions to make them more useful. estimating the flow of traffic, monitoring the use of self-driving cars, and adapting to changing conditions all necessitate a large volume of data "road network development, upkeep, and extension are three of the most important contributions to transportation networks [24].

LIMITATION

We can turn our "deterministic problem" into a stochastic or resilient optimization problem. Since the stochastic or robust formulation allows for flexibility in the vehicle's speed and location, it may be possible to relax the constant speed assumption. There is a great deal of unpredictability on the roads in the real world, including accidents and traffic jams. This thesis makes extensive use of simulations. It is useless to simulate and adjust the agent's settings in a virtual environment. When it's time to deploy our skilled representatives and put systems into operation, we'll investigate. Additionally, when creating a system for the real world, safety comes first. There should be more safety measures in the system. The problem's wording, for instance, can mandate a safety distance between any two cars.

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