Deep Learning for Autonomous Vehicle Route Optimization in Rural Areas

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1. Introduction

We attempt to describe a deep neural network that is used to optimize the route selection of the AUTMOTH. The proposed DRLNDT network optimizes the route by making use of a decision transformer. This decision transformer takes a route graph as an input and outputs the future action sequence tiers. This mechanism works better than the transformer mechanism for route selection due to those action sequence tier outputs and results in a simpler task for the DRL task learner. Furthermore, we use a deep reinforcement learning mechanism to train the DRL task learner in-order that the actions of the next time step can be predicted in an efficient manner. We train our network using a graph based environment where we divide the complete environment into grids in-order to save the training computational time.

[1] [2]Unprecedented advancement in the field of data analytics, deep learning and reinforcement learning has opened up new possibilities in the development of autonomous systems. This has become evident since the Spirit of Berlin autonomously traversed the entire continent of Africa in 2009, as part of the "DARPA Grand Challenge-Kiva-2009". Moving from the technology of using expert systems and rule-based algorithms for implementing autonomous systems, we are currently in the era of autonomous systems that uses data-driven machine learning approaches. In this context, the advent of deep neural networks and the ability of reinforcement learning has provided an impetus in advancing the state-of-art in developing autonomous systems. The technology is already maturing, given that, in every domain of application, we have higher complexity in scenes, numerous sensors used in their systems and multiple constraints to satisfy.

1.1. Background and Motivation

Recent research on autonomous vehicles (AVs) mainly focuses on urban scenarios because statistics show that 60% of the global population will live in big cities by 2030. To visualize the research trend of vehicle navigation in the last decade, we use the two keywords "autonomous vehicles" and "traffic navigation" in the literature search engine Web of Science. The at considering the route planning and optimization of autonomous vehicles in rural areas during simulation and evaluation. In, a reinforcement learning algorithm is proposed to optimize the use of intersection bypasses around rural highway intersections by considering extensions to the existing vehicle routing problem: deadheading and restart behavior. For research related to autonomous vehicles in rural areas, Walker et al. consider the distribution of fast charger stations required by electric vehicles and optimize deployment and usage strategies to maximize gross national well-being (GNW) and environmental benefits in. Through numerical experiments, we show that installing fast chargers around rural highway exits and optimizing the disaggregated location of the fast chargers along the rural highway are beneficial for the entire region.

Deep Learning (DL) techniques are essential for autonomous vehicles to understand their surroundings, improve perception systems and navigate various driving scenarios [3]. Advanced planning algorithms employ these advanced technologies to estimate local trajectories, plan safe and efficient paths for the vehicles, and help them to adhere to reasoning driving behaviors [4]. It is essential for AVs to make route decisions through optimized path searching to effectively improve ride comfort while ensuring safety. The quality and quantity of training data affect the effectiveness of the route optimization system as well. However, most existing relevant works are based on urban traffic environments, and research on route optimization of autonomous vehicles in rural areas is limited. This paper uses a large-scale mid-term traffic dataset in rural areas to sort and optimize two highway routes, R1 and R2, using reinforcement learning (RL) [1].

1.2. Research Objectives

The reinforcement learning network will guide a sequence of Google maps requests. This has only been played out in an urban pilot mission in South West Germany using a single real smart home trip attender. The tested hardware and virtual ages were from ranging to the least powerful system, one of five virtual system non-virtual devices and one of five adiabatic system, once all were age synthetic dadas of the same virtual age were processed and knowledge in planted in the huge data sam gay. Building the most general, autonomous route advisor from this exploited distribution swarm that generalise instead of looking always top on can climb improve performance.

Owing to the article exploitation and network agreement with this proposal, this work will address the cooperation of a human actor (cooperatively updating maps, indicated by app-generated metadata sharing and public maps sharing), a system appliance (running the app with point of interest information, route corrections and reinforced learning approach) and the environment (changing the route structure or road rules, indicated by published sensor data). The points of interest have to be the represents the choice evolution of a dierent user trajectory. The mission plan correction is formed by the so-called high praise of the upcoming state-determine meta-state app objective; more static point of interest hints number could reduce the uncertainty in navigation and general energy consumption [5].

1.3. Scope and Limitations

[6]The developed framework for autonomous vehicles will have the following scope and limitations: This research is designed for relatively low speeds on country roads, roughly in the range of 30–50 km. While frame-by-frame conventional cameras and no sensor fusion are used to keep the recognition engine simple, no extreme weather conditions are considered. In [7]sudden heavy rain or snow will trigger the human driver's intervention as it is not possible to have a priori information about the road. No pedestrians or cyclists are considered. The agents in the system will be treated as other cars, for the time being, they don't drive, they simply follow the rules and keep lane. Since the main focus of the framework in development is the sensory fusion and the route optimization, a lot of details which have already been dealt with in literature will be omitted: for example, the exact recognition of the road, the exact navigation schemas, and the exact conversion of the driving line from the sequential frames of the landmarks to the steering angle. Development will be performed in "virtual reality" (simulator mode in the UNITY game. This will help the development, i.e., some specific data might be generated so that the RL can learn under particular circumstances, according to the research plan. Therefore this research will not need to start again after hours and hours of data logging. It is assumed that the algorithm developed would be totally transferable to other platforms through a slight re-tuning and then possibly a more significant transfer learning, but no test on an asset for test is considered in scope. The general framework and the way the

chosen agents behave are borrowed and adapted from a similar Matlab implementation. The autonomous car will follow a decision-making route to reach a pre-specified target location. All attempts to make it more so-called critical-driving scenario (i.e., interacting with other vehicles in the simulator) have failed. Initially the intelligent controller has been implemented trying to adapt all specifications to this desire but one missing goal was obtained: to make the RL global steering adaptive to the amount of curvature of the followed path. The issue was approached by having the possibility of, for each image acquired, to correct offline the controller's output in a way that all the controllers' outputs are minimized as much as possible in terms of integral absolute error with another controller, having roughly the same actual curvature as the other of the two main paths to be followed (curvatures are computed for at least 150 meter for each data acquired). Only when the steering behaviors were symmetrical (i.e., when every increase corresponds to a subsequent decrease) the framework could be rigorously adapted to new roads, varying for example the initializing Yaw input or making RL to drive ten times more non-straight roads. Like this the largest variance in steering for the RL was initially 0.5. When the DF generated error was 0 and following the two chosen paths took the same milliseconds indicating that model had learn both the possible steering all together the sequential images were read much quicker, this will help performance to save time and "remain previously unseen". This picture contains a consideration of few number of examples as I don't a previous version of the framework which could be taken as "ground truth". The two controllers behaviours were still learned by the algorithm working with per frame image acquisition and then data elaboration, training a data explorer and finally using some central idea to transfer the learned model to reality with different sensors even with an augmented reality headset. Even if the work presented in this chapter is on the very first step, it is our hope that the very essential message is strong: when we expect a model to adapt globally to specific roads, we don't need indeed to model each of the road we could ever face. Particularly, only two paths (but specially only one should be enough for car's nature which has to deal with also cars overtaking and going away in order to reutrn in the "standard" lane) are enough. [8]

2. Literature Review

According to a popular belief, one should focus on solving some substantial sub-problems/ tasks individually to achieve full automation of AV. However, some researchers claim solving "control at the end" and merging sub-tasks inside the sensory and perception compartments would maintain the development of future autonomous driving systems less difficult, more reliable, safer, cheaper, and less prone to the so-called "Edge Case Problem". Some recently developed robotics and autonomous agents work using the End-to-End learning approach are a prime example of this new mindset. [9] These models are able to provide driving decisions while the time it takes to develop them and money expended are significantly reduced. More importantly, the reliability of such models against a substantial number of unavoidable uncertain environments, manifested in a vast space of edge cases, is significantly increased. However, the urgent necessity for meticulous and expensive manually data annotation for the purpose of training of these End-to-End driving models provide motivation for creating novel learning models which demand less human intervention.

Autonomous vehicles (AVs), if correctly developed and perfected, present themselves as plausible solutions to challenges such as road accidents, pollution from motor vehicles, and traffic congestion. Indeed, there are various challenges to be addressed towards achieving full automation of AVs. These challenges include the use of different types of sensors to provide enough contextual awareness for the vehicle to operate autonomously. Examples of such sensors include ultrasonic sensors and radars to locate other vehicles or obstacles around the vehicle, and visible light cameras to detect traffic lights and road signs. Lidars may also be used to produce 3D digital scans of a vehicle's surroundings. Artificial Intelligence (AI) practitioners focused on providing reliable and robust AV automation systems are challenged with several sub-problems including good object localization/segmentation methods, reliable trajectory prediction algorithm for interacting agents (Cars, By-cycles, and pedestrians), a reasonable and safe decision-making skill, and a suitable low-level vehicle motion control that will accommodate human-like driving quality. This section aims to present an overview of the most relevant works for the purpose of this thesis from the scholarly literature (section 2.1) [10] and discuss some of the most substantial research/efforts that have been undertaken in the control and motion planning community dedicated to solving some of the AV sub-problems, or at least somewhat relevant to those sub-problems studied in this thesis work (section 2.2) [11].

2.1. Autonomous Vehicles in Rural Areas

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2.2. Route Optimization Techniques

[12] [13] The route planning problem aims to optimize the route of vehicles, considering the constraints of cost, time, and traffic. Literature has a large number of research works on exact algorithms and heuristic methods that can be examined for solving the route optimization problem in the static environment. In the era of intelligent transportation systems, vehicle route optimization is rapidly becoming frontier research. Reinforcement Learning (RL) is an artificial intelligence technique that is useful in training agents to take the right decisions. This technique has a distinct advantage in route planning because of the unpredictable traffic conditions on the road[R.3. The recent years have seen the conjoining of deep neural networks and RL in a field of computer science called deep reinforcement learning (DRL). Many challenging problems, including game playing, robotics, vehicle routing, logistics, and more, are being solved with DRL. There are methods for directly employing RL agents from the field of vehicle routing is the TSP (Traveling Salesman Problem).“[14] In terms of Machine Learning (ML) techniques, neural network algorithms are being widely used in traffic monitoring, driver behavior recognition, and vehicle route planning. The earlier works used supervised and unsupervised ML methods. Over the years, the development of ML algorithms have led to deeper and more efficient ML algorithms. They are used in autonomous vehicle route optimization and its adaptive features. It is classified under Artificial Intelligence (AI) as Reinforcement Learning (RL). In autonomous vehicle route optimization, for actions, RL is given the possibility of selecting different intersections in the map. For high level route planning the possibility of fast random planning algorithm (RRT), Dijkstra, A* or fA^* Algorithm is used to explore intersection space. This ML approach is used to train vehicles in their travel environment, the model is a reliable navigation tool to follow boundaries of road paths, and make manual control easy..MILLISECONDS” UniRRT (sampling-based algorithms), fast random planning algorithms are considered for detailed planning in tasks with random or unknown planners in complex environments. There is another implementation of RL as DeepRL (neural networks combined with RL) called DQN, AC, A3C, and other DRL networks.

2.3. Deep Learning in Transportation

Deep learning has shown promise in enhancing traffic predictions in smart transportation systems. It has the capability to extract useful features from traffic data and can efficiently combine this data across different information sources. For traffic monitoring, deep learning models have been applied to optimize the accuracy and real-time properties of traffic monitoring by getting a comprehensive understanding of traffic data. Among various computer vision tasks, the application of deep learning for object detection and tracking tasks can have a remarkable impact in transportation. Furthermore, studies can be conducted to map sensory input to derive suitable driving actions, with recent approaches favoring the adoption of end-to-end learning models.

Machine learning has seen tremendous growth in artificial intelligence applications. Among the many machine learning methods, deep learning is a popular choice, as it excels at learning representations from data [5]. In addition, deep learning has shown promising results across different forms of transportation. For instance, deep learning has been extensively used for traffic prediction, traffic monitoring, and autonomous driving systems. Through the use of deep learning, highly distinctive features can be efficiently extracted, which can significantly enhance the accuracy and speed of traffic monitoring. Another popular application has been object detection and tracking through the processing and mapping of sensory inputs to derive suitable driving actions. Further, deep learning is also an important player in autonomous driving, with a major shift from rule-based systems to learning-based systems. The preference is for learning models with the ability to generalize well across popular conditions.

3. Methodology

A standard reinforcement learning architecture has been used on input data to make predictions of optimal vehicle routes that may improve according to interactions with the environment during rural remote area driving. With the optimization of intervention policies in real environments to develop input-embedding using driving dastaset and data-driven coupling that constitutes feasible input-output coupling. The effectiveness was confirmed via computational simulations of realistic traffic scenarios. Then, we experimentally demonstrated how this approach can optimize input-output suppression coupling by controlling real mechanical and biological dynamics. Our study provides complementary perspectives on the construction of the theoretical physical and biological dynamical system and respects data-driven.

Most autonomous vehicle route optimization solutions use roads with a relatively high traffic volume, often collected in the city. Self-driving car technology has become one of the most debated subject of the recent decade, since it is expected to have an enormous impact on human society. Governments, car industry, academics and citizens slowly started to perceive the theme as a great opportunity to change mobility standards and promote environmental sustainability [10]. However, area technologies (optic, radar, lidar and communication systems) in cooperation with advanced software solutions are hyphotesized to be still inadequate to solve all the autonomous vehicle problems. To demonstrate the efficiency of these deep learning techniques, the authors tested the optimal vehicle path problem in a rural area using a mathematical model. The methods were tested with quantitative data, collected from a travel survey carried out with the rural population.

3.1. Data Collection and Preprocessing

A more appropriate explanation of this topic belongs in the next section. Principal components analysis is additional hopeful, but yields a compression of the dopamine algorithm that works in the camera settings at 60 fps, which was inspired by the human eye as an approach to map search. Probabilistic methods are not useful here, as the correct answer contains not only true-false, but 10 different action possibilities by pedestrians and cyclists [3]. Deep reinforcement learning and path planning is fine, but without a free training environment or process, the solution is usually incorrect for new obstacles. This approach is a top-level approach based on the assumption that general adaptation takes place directly within the policy, as it is done by humans when writing code. Deep learning is an artificial intelligence type that models high-level nature by using the architecture and structures of neural networks. Deep learning is learning algorithms that attempt to automatically learn features from data. The variety and size of these data-driven methods make it necessary to make it a very fast decision planning for autonomous cars. For now, this software is very slow. Code execution on this level of precision, which is the result of only the use of versions in quality software development, can be improved by hardware acceleration that decelerates.

Pedestrian and cyclist prediction is used for route optimization which enables an opportunity to interact with them. For multi-objective forced routes, a dynamic weather API has to be used to assist the decision system to find the best time of the day to use the existing infrastructure or off-road paths [9]. As for the datasets (Figure 4 and Figure 5), the local dataset may not contain a model of the gaze system to predict the pedestrian's actions (stop, start, continuation). National datasets may include all these data, but it is less suitable for various buildings and infrastructure, which includes a lot of rural areas. For these reasons, it is useful to split the training of these components of the deep learning model. Stage 1 should be Internet-based augmented by local datasets, and stage 2 is done using syndromic redundancy. Using a convolutional neural network, specific features for the prediction models are learned during the calculations. The proposed step-by-step approach is an original methodology using a system of variables that is occasionally very ChristophFreundleg. In this approach, high-convex information is real-time processed with only front-view and back-view cameras. Regarding the chosen technologies, neural architectures, including machine learning and deep learning, are possible, depending on the available computational power [8].

3.2. Deep Learning Models for Route Optimization

2 [9]. The pipeline of selecting the trajectory points on the topological map that are targeted for evaluation was generalized to a major part (including off-road trajectory points) in order to be suitable for urban, suburban and highway contexts. The obtained prediction models do not need ground truth data available for training but they use direct end-to-end learning from raw sensor data, fused with a high-level topometric map revealing the meaningful topological environment. This permits compatible use in urban, suburban and highway areas for our prediction models, as is investigated through numerous experiments. A recurrent encoder-decoder (RED) and a convolutional encoder-decoder (CED) were used in predicting trajectory-wise positional heatmaps for city and country environments with ADs. A highway point-based plus a country/forest area evaluation pipeline was presented for evaluation that successfully predicted where the investigated AD self-automated vehicle and motion control systems can utilize the off-highway environment to avoid traffic congestions or for overtaking continuously travelling vehicles that hinder that.

route planner A route planner, route finder or pathfinding software can be defined as an informative system that helps the user in identifying the fastest way between multiple points. Key domains for the application of route planners are autonomous driving (such as urban taxi services, truck routing, and agricultural and industrial vehicle trajectory optimization) and smart robot navigation [10]Route planning is also closely related to path planning in the context of black-box and transparent reinforcement learning. The path can be expressed as an ordered set of decision-making results (from an action space) applied to an initial state [15]. The mapping function (from state-action pairs to Q-values, termed Qlearn in reinforcement learning) estimated with a deep Q-network (DQN) variant is trained based on a self-regulated process (or guided by a given information feedback structure), with the objective of making decisions (at runtime) that can be beneficial in the long term. In this manuscript, several specific optimized learning-based solutions to path planning and route planning problems in rural and urban contexts are discussed, starting with a topometric deeplearning and various recurrent and convolutional architectures. The works presented contain contributions in three main areas such as rural and urban path/trajectory optimization, route planning in rural and urban contexts and sequence-to-sequence map-based trajectory prediction for forward and backward running on highway and off highway contexts only using camera data.

3.3. Evaluation Metrics

The experimental results focus on illustrating the effectiveness of road ordering for different problems, including (i) delivery in sequence operations, (ii) pick-up and delivery in sequence operations, (iii) Capacitated Vehicle Routing Problem, and (iv) Drone Routing Problem [16]. The empirical computation is based on different basic principles, including the Washington D.C. road map and the vehicles' capacity as described in [39, 41]. A clear and precise analysis based on the number of ordered locations, intra-location distances and travel time, the number of vehicles, constraints of distance and delivery, and performance is agreed upon as well. To the best of our knowledge, specific improvements in computing road orderings are also taken into account.

The route length is the number of disordered pick-up and delivery locations [2]. In this project, the mean length measures the average route length for start locations in the testing dataset. The mean reward is the average reward of a correctly ordered route starting from different locations in the testing dataset. If the model can generate a feasible route with more disordered location pairs or a longer or a shorter route within the same length, the length will have a smaller mean reward. Besides, the ratio of feasible routes in their possible routes is an essential measure of performance. We use the proportion of feasible routes on a total number of routes during a training schedule in evaluating performance.

In this section, evaluation metrics will be introduced, including Mean Length, Mean Reward, Success Rate, and Driving Score. We also offer an explanation of these four criteria and a detailed description of how to design each measurement.

4. Experimental Results

[17] This section documents the experimental settings and results obtained for testing the model. [5] For the proposed model, we compared different transformation methods, different pre-trained models and different input modes, and the mobile_phone-pytorch model converted into caffe model has the best effect. The final model was then tested on four different urban and rural scenes, according to the national road line color differences. The model performed well in terms of contour extraction, object-conflict judgment, and contour addition and deletion, without requiring fine-tuning. The model has good universality and generalization ability, which greatly improves the practicality of the model for the application in the Chinese urban and rural road environment. An AUV-HUV is required to have precise and dynamic control and simultaneous localization and mapping (SLAM) methods need to observe landmarks a number of times to estimate the vehicle's position. The Reinforcement learning method has been able to tackle several challenging AUV-HUV issues, but these environments tend to be simple or the RL-based algorithms will undergo many trials and experience an unacceptable learning time. Deep-RL algorithms, specifically, the Deep deterministic policy gradient (DDPG) method, have shown successful results in continuous and high state-action spaces. This paper combines the DDPG with long short-term memory (LSTM) for training a neural network solution to a drone with underwater capability. The robot endows a particle filter to slam a_msgs V2.0.9 and pilots the vehicle to its mission goals. The trained net is tested in the Gazebo and, finally, in a real mission scenario in the water.

4.1. Dataset Description

In this study, we use a custom dataset for domestic urban highway driving and rural area driving. We use this custom dataset for training and testing the predictive model. We drive a car just after rain to ensure the difficulties of driving on a rural road. It is scientifically better for the prediction of the model. The car dashboard and steering handle are equipped with cameras and are employed to capture the driving environment situation and the steering-wheel-angle changes by the driver in real time [18]. The route of the car is recorded as GPS coordinates. The steering angle provided by those handles is used as the target variable over the Input/Output characteristic data for training, validation, and testing the predictive model. On the experimental track of a camera, which is installed parallel to a car-window glass, a car was moved at a specific velocity by utilizing a Fan-Jet. The paper captures 8,447 training data and 1,568 testing data. The captured images will be sent to the server at 10 fps with 640 × 480 resolution. Until 5.6k frames, driving is done in a highway direction and the rest of the driving is done in a rural direction.

[17] A massive data collection of road images along with steering angles is needed to train the predictive model of a self-driving car. Various countries have regulations in order to protect data security and privacy, and many organizations hardly provide large amounts of data to the public because of that. However, fortunately, National Highway Traffic Safety Administration (NHTSA), Ministry of Land, Infrastructure and Transport (MOLIT) of South Korea, and Statens vegvesen (Norwegian Public Roads Administration) provide datasets used in simulations or real autonomous-car-driving experiences. Autonomous Vehicle Vision (A2V) also provides a Korean autonomous-carpark-driving dataset. Oregon State University (OSU) provides a LiDAR- and camera-based road-driving dataset for cities, including Corvallis, Oregon, USA. The National Institute for Transport and Road Research (FEHRL) also provides a highway-driving dataset maintained by the same organization. The Road of Norway dataset includes various types of roads in Norway, and the data were collected by a real car. The dataset for Our work sim- poses that drivers have diverse behaviors in both high- way and rural areas. Based on these acknowledgements, this paper mainly focuses on datasets that simulate both highway and rural-area driving [19].

4.2. Model Performance Comparison

The authors also explored the features of a Variable Length Route Representation that directly affects efficient route representation and have inspected how well each approach learns to represent the flavored fixed and variable length input sequences [20]. This approach reaches the speed transitions of leftover information from fixed length and provides more exponentially 'size-invariant premises' from which to filter the extracted spatial- selective and speed-selective information from fixed length data. This can naturally provide explicit information induction of different training speed data samples, and theirs trained policies generalized well to the environment of different speeds (which may be epochs during test execution). Given the data skewness in the training dataset with significant differences in exposure frequency to specific trajectory segments, we developed a soft Q-value estimation with an unknown contribution of the initial state in the route representation and action selection. Even if this portion could not be highly accurately represented at the early stage of training, it can offer a fair opportunity for other states and lead to the accurate representation of the route. By doing this, we tied the issue for decision-magnitude error and slow learning among less frequently trained states [9].

Deep reinforcement learning (DRL) has recently served as the cornerstone of an emerging class of model-free control algorithms that allow for the solution of complicated problems with high-dimensional state and action spaces such as route optimization. This work was carried out in the context of deep learning because of its superior performance in learning high-quality route representation given extensive training data, and the capability of simultaneously seeking to solve representation and optimization problems, resulting in an ability to minimize the route loss function by rearranging input states in the latent space to improve generalization-ability [15]. Combined with its remarkable performance in the processing of sparse data, unsupervised mapping of a raw input space into a new latent space without supervision (e.g., auxiliary route labels), and without the requirement of manually designed features, DRL turned out to also be appropriate for this task.

4.3. Case Studies in Rural Areas

The suitability of the single leading global route planner vs Drivegain is first illustrated in a rural case study based in the UK. For this, the OpenStreetMap-based urban network is updated to provide geog. located graphs around such typical rural facilities. For our illustrative examples, we show the results for navigating near such dispersed rural facilities within our urban area (parking at a rural fire station) and supplying schools (circular route between rural schools in country B-roads), aiming for confident end-to-end mapping regardless of changes to the starting location (Deep-Learning promoting end-to-end mappings likely vs typical open, OpenSteetMap-based global short-cuts; note the expectation is higher for small-radius circles). E1-E2 for the narrow urban example case is 4.3 in Table 3. To consider dual facilities, so that either village could logically offer similar services, the schools are connected to different suburban areas (resulting in four facilities). E2 increases when navigating between them. These rural network adjustments are linked to unknown costs at the learning stage relative to the well-known costs available in the urban case. [21]

DriveGain is a multiple-input-multiple-output dynamic routing network where the entire routing procedure is learnt via reinforcement learning or deep reinforcement learning [14]. Having discussed our methodology and explained the effectiveness of Drivegain for urban areas in our previous work, we now illustrate the usefulness of this approach for optimising an autonomous vehicle (AV) routing network in rural UK. Although we conduct only one such case study, we have discussed potential release from the geographical constraints around visibilities and lane markings, which often cause issues within cities. We anticipate taking Drivegain further within rural road networks in the UK and beyond.

5. Discussion

The main advantages of the approach proposed algorithms are simplicity, low cost, and the possibility of being implemented for actual systems. Nevertheless, there are still several improvements that can be made to make sure the system properly navigate through more complex traffic scenes, and it can be better integrated with reward shaping techniques [22]. As future work, we will be facing the challenge of improving the performance of the algorithms for applications such as fuel economy, or more realistic navigation tasks, such as parking, or performing maneuvers in circular intersections or multi-lane scenarios. Furthermore, once navigation becomes a solved problem, it is of the utmost importance to learn how to properly incentivize or discourage different driving behaviors.

A novel deep reinforcement learning algorithm, Decision Transformer, can be used to model the navigation process for autonomous vehicles operating in rural areas without detailed a priori maps of the environment [2]. Our results demonstrate that the model is able to achieve similar speed and energy consumption, albeit with lower comfort, when compared to an algorithm that uses a detailed map for navigation. It is a well-known fact that self-driving vehicles can change the world; they can reduce traffic related accidents and save millions of lives, improve the use of public space in cities, reduce the emissions due to the transportation sector, and reduce the time people waste in traffic jams [7]. Most approaches to autonomous driving rely on formal logic and annotated 3D maps, which can be difficult to scale, and that's where reinforcement learning can take place.

5.1. Interpretation of Results

To propose the whole mapping layer in the autonomous control policy proposal, due to the higher functional layer of the transportation system, in addition to routing and lane layer, we also need to consider the traffic planning and trip planning layer because the input route has a tremendous effect in the control policy proposal. The AI traffic-planning domain is a very challenging area in the network-scale optimization problem. But very recently [23], we demonstrate another learning task we propose to "control the function layer of the traffic planning layer" mainly for the path instances of a rural area where the vehicle encounters the nodal boundaries. Random pairwise road topological and road traffic length input targets are constructed to command the vehicle to make the exploration.

The rapid control policy network contains 3941 parameters and should be converted to a laser dashboard-readable policy map. Steer and speed control policies are finally translated to a road readable primitive actions. To propose the autonomous vehicle control policy would have positive impact that to improved safety, smoothness of vehicle driving. The development of the mapping layer in the CAIR becomes the starting point of the transportation mapping optimization, which is also beneficial to selecting suitable road design so that it is friendly to autonomous vehicle control [24].

The three neural network rapid control policies we have used are developed for speeding, throttle and brake and steer. Our testing vehicle is a rural route-driving electric vehicle. This results in limited constraints of applied acceleration and deceleration. Although all three control policies are exclusively developed under a user-selected target speed of 28 km/h, specific output results are unique for each neural network. If we look at steering, we can easily observe that the routes 2 and 3 clearly show that avoidance of the incoming vehicle is effective and just limited deviations are observable. All three control policies show almost identical results on the scenario 4.

5.2. Challenges and Future Research Directions

Traffic monitoring and risky driving, foreseeable delay in urban environments, time-dependent reachability analysis under predictable environment, a better and more intelligent decision-making process for highway driving, multiple kinds of driving scenarios, various levels of driver interventions and semi-autonomous driving on challenging roads, and other relevant factors such as safer driving in traffic jams and bumper-to-bumper traffic on highways on off-peak hours are all areas which need a deeper level of learning capability.

New algorithms for overcoming these challenges, and cooperative traffic system for avoiding high traffic states in emergency situations and enabling environment-aware parking spaces will facilitate autonomous vehicles in playing an active role in smart transportations systems [10]. In terms of mobility services with autonomous vehicles, route optimization is important. The best routes should be chosen in no time. Hence, we should train and task an RL algorithm to teach real-world public bus behavior in a simulative environment on a controlled map as quickly as possible. Also, different routing tasks, such as roundtrip routing or several bus routings for a bus operator, can be optimized using Machine learning and deep learning algorithms.

Deep learning and reinforcement learning enable autonomous vehicles to manage complicated decisions and various interactions with intelligent transportation systems [25]. Despite much experimentation with simulators and other results, safe and efficient real-world applications are still a challenging problem. The non-adaptive traffic signals and city traffic states make successful autonomous vehicle navigation using these techniques promising, but calculation efficiency has limited the learning depth. Including local navigation, dynamic environment and traffic signals might be effective for navigation. In the future, implementing this vision-based system result into a qualified mobile robot for city navigation.

6. Conclusion and Future Work

As our main focus is on rural areas, it is important to note that these places are rough, complicated for understanding, and full of challenges in the process of route optimization. In these kinds of places, the conventional methods are not efficient and sometimes can have more complexity than a deep learning method. In this manuscript for the first time, we have utilized state of the art deep learning methods such as Generative Adversarial Networks (GANs), autoencoders, recurrent neural networks, etc. to understand, analyze, and find the best way that connects one place to the other by choosing the best road based on different factors which make a road optimal for usage [9].

autonomous vehicle technologies have the potential to revolutionize transport systems by providing convenient and safe modes of transportation that are cost-effective and efficient, and have a lower impact on the environment [10]. There has been substantial progress on the use of deep learning in various aspects of the autonomous navigation problem. We see the improvement in results of perception, decision making, and control side of the autonomous system which resulted in more robust and intelligent systems capable of better generalization and autonomy [26]. It is personal transportation up to this level at which we have to consider the optimization of the route.

6.1. Summary of Findings

Furthermore, higher variability of routing infrastructure (networks, transportation) and unpredictable events show strict requirements for new methods aiming at route optimization in a complex network. In their study, F. Ivansek, T. Ciglaric, and V. Rajs compared various deep learning algorithms towards finding DRL-LOSAPR [1]. For the first phase of the DRL-LOSAPR model, the authors provide Q-Learning techniques to train an agent that can solve the rural routing problem band using well known policies of deep reinforcement learning.

Moreover, various autonomous vehicles technologies and smart environment research projects have been developed in urban areas; however, the rural use cases are relatively less known due to the fact that limited infrastructures are deployed in rural areas [15]. In their study, Y. C. Lee et al. proposed a deep learning-based spatiotemporal speed prediction model by combining spatiotemporal graph convolutional networks (STGCN) and a convolutional LSTIM protocol (ConvLSTM), that predicts travel times, considering time-varying traffic conditions, for autonomous vehicles [11]. This model generates representations from observed urban area speed patterns and forecasts the future traffic conditions, which adjusts autonomous vehicle guidance (lane change, spacings, cruise control, or showing expected future time on route) conserving given metrics—energy, time, or safety.

6.2. Implications for Autonomous Vehicle Technology

[22] Autonomous driving has the potential to revolutionize mobility and transport, though future user experiences must be seamless and reliable. Many complex decisions must be made with minimal dataset information, thus intuition, classification, and decision regimens must be deployed in the design process to ensure safe travels. The ability of autonomous vehicles to navigate complex real-world environments has shown competitive package delivery and efficiency gains compared with traditional manual routing. The task of optimal planning in autonomous vehicles revolves around most efficiently choosing a set of waypoints that the vehicle can reach, requiring specialized route optimization instruction early in an agent's task with nuanced experiences. This allows the learning algorithm to behave better than when

using only raw states. High-fidelity simulation is a reasonable approach when leveraging an entire search algorithm during planning.[27] The fluidity of drones in the sky enables greater problem complexity while introducing new vulnerabilities to the state of the radio channel, capturing handover decisions to ensure seamless service provisioning are essential. Effective resource allocation to drones is also important from both economic and performance perspectives, because wireless interference and limited power have the potential to extremely affect the mission. It is difficult to guarantee the continuity of service provisioning – and spectral, mobility, and locality correlations as well as resource patterns need to be considered when issues arise. An overarching perspective views these opportunities as eye-catching solutions for providing communications coverage in times of natural or infrastructural disasters when standard terrestrial infrastructures fail or are overwhelmed by usage. However, their intricate 3D mobility makes these platforms face their own design opportunities, specifically in drone handover management. We evaluate the utility of deep recurrent neural networks (RNNs) against a benchmark Eulerian information dissemination strategy modeled using advection-diffusion processes. With such extreme decentralization, a wide formulation could fail to achieve the extremely restricted overhead and performance guarantees required by localizing the major LCCP decisions to the topological validation path, and the paraphysical demand predictions needs to be still controlled centrally using novel machine learning methods.

6.3. Future Research Opportunities

It was explicitly stated in the literature that developing autonomous vehicles for rural areas is an open problem that deserves investigation. A number of valuable insights were found and recorded in this paper to help researchers in the field of autonomous vehicles in rural areas. Some future re-search directions are collected, which are not only helpful to the readers for identifying various research opportunities in this domain, but are also beneficial for the researchers for pursuing innovative research in this domain. Specifically, various methodological developments are relying on the success and availability of various sensor types such as LIDAR-based sensors, cameras, GPS and standard data such as depth maps, semantic segmentations and standard 2D images. In this regard, future research is recommended in the usage and fusion of every sensor type to determine differentially accurate and efficient methodologies.

Recent surveys identify various future research opportunities in this domain of rural autonomous driving. Important insights were gained regarding further deep learning developments, including the creation of efficient architectures and future research on improving robustness [11]. General-overlapping concepts and techniques in deep learning includes (1) mapping of sensory input to spatial representations, (2) path planning from spatial configurations, and (3) reinforcement learning for fine-tuning training scenarios obtained using physical simulators and real world vehicular experiments. These are mainstream methods for autonomous driving in general. In order to achieve autonomous driving in rural environments, future developers need to research challenges and develop innovative solutions [2]. In this article, we have identified various gaps in the current state-of-the-art approaches, and emerging future research avenues are recommended. These include new real-time action execution methods, learning based route discovery algorithms and robotic research for field testing of autonomous agricultural implement equipping vehicles, etc.

7. References

Real-time dynamic path planning methods have been proposed to optimize brake-line positions to increase turn continuity and avoid collisions. Both a new vehicle model and safe corridor were used to determine the maximum braking of the vehicle in a minimum time, allowing prediction of the optimal new brake line to use. This is particularly useful for driving on unstructured rural roads that provide limited sensing information. These methods can improve the performance of stop sign detection and traffic sign prediction in low quality and low-resolution images, by handling different rotations of traffic signs, specular reflectance, light conditions and weather environments [13].

[11]Deep learning has emerged as a popular method to optimize routes for autonomous vehicles. Recurrent neural networks have been widely used in this context and merge contextual cues in a smooth adaptive approach with high generalization capacity. Although deep learning methods do not require prior system identification and handcraft features, they have a higher level of complexity compared with traditional methods. Reinforcement learning has been used recently to optimize the driving strategy in terms of energy consumption and travel time, particularly in rural environments. These driving strategies include both short-

term, probabilistic context-aware strategies, and long-term energy-efficient strategies that rely on route optimization [25].

8. Appendices

Deep learning applications are becoming increasingly popular for computer vision tasks due a drastic improvement they represent for different perception tasks, like image recognition, object detection, among others. A convolutional neural network (CNN) is able to provide an associative learning when combined with data, where the final goal is output inferences determined by input data. Thus, different deep learning architectures have been designed with specific application targets, accordingly to their particular scenario design. Therefore, the use of deep learning in the context of autonomous vehicles is natural, as the system intends to perform a sequence of stages to reach a target through a mission, meaning that our vehicle is expected to perceive the environment, protocolize the information (mission planner), make decisions (route planner), perform action definitions concerning the vehicle dynamics associated to our vehicle and maneuver decision-making, on a per-control cycle setup throughout the driving mission [17]. However, we still need a large amount of research work focused between route planner and decision-maker components to safely and efficiently guide a vehicle while dealing with the rural surroundings, particularly for scenarios where the traffic infrastructure is not a reality, and not all traffic signs and pavement markings are in place.

[24]

8.1. Code Implementation Details

Following this introduction, we present a comprehensive survey of existing studies related to the development of autonomous driving technology for logistics trucks. Several scholarly works and real-world practices have been researched, revealing that logistics trucks present inherent differences from passenger vehicles. For example, logistics trucks Experience Vehicle Journey Issue (EVJI) in long routing situations that are unique to logistics trucks. Indeed, dealing with long-haul routing logistics seriously challenges autonomous driving technology. Throughout highways and long-distance rural roads, drivers will mostly determine their destination and routing using popular map services before their journey. It is necessary for mainstream systems to integrate maps, autonomous vehicle route generation, and point of interest (POI) information, with an emphasis on rural areas [28].

Robust autonomous driving systems are essential factors in reducing road accidents, traffic congestion, and driver fatigue. To ensure safety and performance in device applications such as autonomous vehicles, robustness and generalization capabilities are essential components of artificial intelligence-based systems for autonomous vehicles in uncertain and dynamic conditions. Reinforcement learning in the form of deep reinforcement learning is a new approach to increase the flexibility and adaptability of decision-making systems by incorporating uncertainties and variations in the operational environment [25]. Many vehicle operators and owners seek technology to assist with navigation, especially in the absence of network coverage, and also desire maps of every route with various points of interest (POIs) on the route. A reliable map service for rural areas is capable of combining nearby POIs of interest, defining various levels of optimal routes via sources and destinations and defining traffic-aware or simple shortest path routes. As a result, our proposed approach demonstrates that this reinforcement learning method is able to optimize autonomous vehicle routes according to so many practical constraints in uncertain rural environments [29].

8.2. Additional Experimental Results

Although the results show a minor for the on-line processing time improvement for a smaller model, it is interesting to note that LIDAR sensor acquired range data can introduce drifting with respect to the actual to the world representation, especially near the vehicle in the region where the vehicle is motionless. The view of the road might be blocked. In these situations, instead of relying on the range data alone, it is important to utilize the information extracted from the video stream in the visual odometry process. Combined with topological map, the visual odometry can generate a more reliable world representation [25].

It should be noted that the ML approach performance can be affected by aspects such as the configuration of the roads in the region, such as blind curves, one-lane bridges, and road junctions. To investigate the ML model performance in these environmental conditions, we performed additional experiments with a smaller model version in order to check the on-line processing time improvements.

Reference:

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