AI-Enhanced Vehicle Navigation Systems

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1. Introduction to AI in Vehicle Navigation Systems

In the last few years, several research activities were devoted to the exploration of the potential of advanced technology—such as artificial intelligence techniques—to enhance the performance of navigation systems for land, air, and sea vehicles. Among the various AI techniques, we focused in particular on heuristic search and case-based reasoning. We explored the impact of these AI techniques in two different contexts of vehicle navigation systems. In the first context, we developed a hierarchical control system that adopts an onboard AI-enhanced decision-making process in order to select the most appropriate control level during the autonomous navigation of an unmanned mobile robot in a previously unknown environment. By integrating case-based reasoning with a combination of algorithms, it derives from the stored information about past executions of test runs a suitable vehicle control scheme based on a multilevel strategic, tactical, and reactive architecture. The system provides fully autonomous navigation in the presence of movable obstacles and uncertainty of external reference points. We implemented, tested, and evaluated the performance of the hierarchical control system on a simulation of the operation of an autonomous warehousing vehicle moving in real working conditions. In the second context, we developed an autonomous vehicle guidance system, based on a combination of AI and GIS techniques, to guide, using wheel encoders and a compass as unique sources of information, a land vehicle moving in a landmark environment to a target point specified by means of a natural language dialogue interface. Using a region and point-based mapping process, the system constructs, upon user request, a self-updating ground map with Euclidean coordinates of the configuration of the landmarks and known reference points, and an associated weighted visibility graph, which allows the system to reason about the macro and micro plans. The macro and micro plans are used at the crew station level in the algorithm behavior, while the fuzzy multisensor fusion level, which is integrated into the system, merges compass and wheel encoder data to detect the occurrence of sensor fault events and to establish the order of priority for the goals to be satisfied during the vehicle movements.

1.1. Overview of AI Technologies in Navigation Systems

The application of AI to vehicle navigation systems has recently become active, and intelligent navigation systems equipped with AI are now available. The advanced driver assistance systems (ADAS), which apply AI to driver support functions, realize driver support functionalities by integrating multiple sensors with recognition and control algorithms. The combination of advanced map information such as high tomography or 3D city models and AI technologies such as human-like cognition and sensory navigation based on scene recognition has realized these AI-enhanced navigation systems. The development of such intelligent navigation systems advances the realization of autonomous vehicles. The ultimate purpose of navigation systems is the realization of safe, secure, comfortable, and environmentally friendly mobility, and AI-empowered navigation systems contribute to the realization of such a society. With this background, this special section consists of informative papers on AI-empowered navigation systems.

2. Challenges in Current GPS Accuracy and Route Optimization

Vehicle navigation systems based on global positioning systems can determine vehicle position easily, making vehicle navigation possible. But the accuracy of GPS is receiving an increasing amount of attention. The performance of the GPS will degrade if the satellites fail, but there are already problems with the accuracy of the service. High-rise areas affect the reception of GPS signals. These signals can be extremely inaccurate in cases where GPS signals are not available, like in tunnels or underground roads. There is an increasing demand for route search functions that leverage open data for route search optimization by acquisition of real-time information on traffic congestion.

The positioning information gathered by GPS is also rapidly evolving and is combined with other sensors like IMU and wheel encoders in these studies to produce vehicle data that is useful for route navigation up to a certain point in high-rise areas or tunnels. Using the vehicle navigation system in areas where GPS signals are not available to perform research. However, there are many problems when relying solely on IMUs and wheel encoders. For example, installing these on the wheels of a car requires expensive equipment. In addition, this error is prone to discussion, and while the relative error of the IMU is small, it simply accumulates over time.

2.1. Limitations of Traditional GPS Systems

Traditional GPS systems have many shortcomings when used in vehicle navigation. They are commonly only capable of providing a point-to-point route, which may not be appropriate for certain users. They generate one route solution for all users, regardless of any preferences users may have related to personal knowledge and situation. Some traditional GPS systems do provide multiple route solutions, but the number of offered routes is usually limited and predefined. Current GPS systems are incapable of adjusting the route to suit specific requirements. Dynamic route recalculation is only performed after the vehicle has left the originally calculated route and is usually confined to alternative routes, detours, and U-turns. Other routing decisions are still mostly based on static maps. In terms of route following, the user only has access to route diagrams on a very small display. Traditional GPS navigation devices cannot handle obstacle avoidance effectively. The route impulse generated by a GPS is difficult to suppress. To navigate without distractions, suppression of the route impulse is desirable. AI-based systems usually require time to retrieve the required data before performing routing and vehicle following tasks, which is not practical for the dynamic vehicle driving environment.

3. Machine Learning Models for Improving GPS Accuracy

There are different machine learning models that have been used to improve GPS accuracy, each of which has unique advantages and disadvantages. They focus on improving the object detection and tracking of vehicles, pedestrians, and roads in relation to the GPS coordinates provided from the map step to avoid any harm from the collision of the vehicle with other road objects. Furthermore, the proposed models are able to improve the GIS characteristics to enhance the accuracy of the GPS localizer along the road to allow it to benefit from the previous processing steps and improve the safety of the vehicle.

Object Detection Models CNNs have become the most widely used architecture to date and can extract very deep features from the input data; the depth of the architecture and type of pooling and non-linearity layers can be adjusted. The proposed work utilizes various architectures to compare the accuracy of object detection for vehicle types using parts of the traffic signs model by providing pre-trained weights from different datasets. The results reveal that using pre-trained weights from one dataset is more accurate than the datasets from the other CNN structures.

3.1. Data Preprocessing Techniques

Data preprocessing is an important stage of data processing. It is used to prepare navigation data of the vehicle, which is subject to further analysis. The most time-consuming approach is to delete unreliable routes from the dataset. Unreliable routes can cause overestimation of infrastructure inefficiency. In cases when signal algorithms are used, unreliable streets and vehicle downtime at the street cause additional time losses for other services in the whole system. As a result, additional phases are added for each traffic light, which provide time gaps between conflicting flows from different streets.

One of the key requirements for working with tracks is to calculate the approximate route of movement for vehicles that are not equipped with technical means for tracking. The approaches to solving this issue are relatively standard. They are based on modeling route movement using a set of algorithms that determine the mobility parameters for each street section, the load on intersections, the movement of buses, and all this in conjunction with the parameters of the schedule and dispatching among the participating subjects. Then, on the basis of the subject area in the form of a graph, a coordination task is solved, which allows us to describe the most optimal layout of stops on the equipped part of the route and the route itself. For such calculation, we use a discrete differential evolution algorithm. Its advantage is a short computation time, accuracy, and a set of input parameters of the objective function, which allows us to select a variety of design concepts for public transport infrastructure.

4. Route Optimization using Machine Learning

Next, these data should be incorporated into a vehicle navigation system to route a vehicle around current road conditions and provide the driver with an accurate estimate of the time of arrival at a destination. In previous work, real-time route planning has been performed using a number of machine learning and deep learning techniques. To plan routes using reinforcement learning, an agent must have knowledge of the actions it can take to ensure a trade-off between exploration and exploitation exists. In navigation, the agent can also select a specific location or a set of properties of the location at which the agent has not yet visited.

Alternatively, if the route is being planned in an urban environment or a digital map describing the environment is available, the next action could be to turn left or right or to travel forward for an appropriate distance. These features make navigation a particularly attractive playground for researchers in reinforcement learning.

Route optimization for road networks, urban environments, and other infrastructures has also been carried out using recurrent or recursive deep learning architectures and supervised or unsupervised training from historical traffic data and/or simulations. In all these cases, the models learned have been designed to predict vehicle speeds as a function of some combination of spatial, temporal, or contextual information. Using these predictions in a temporal or spatial-based routing algorithm produced directions and travel times that respect actual speed trends.

4.1. Optimization Algorithms

Optimization techniques are chiefly involved in determining the optimal trajectory of vehicles. One of the most influential classes of optimization-based methods is the dynamic programming approach. DP methods are able to produce a suboptimal or even globally optimal trajectory, which is the result of the positioning calculation when full environment knowledge is considered, over a quite long horizon due to their recursive and prescriptive structures. However, the DP approach has some limitations in its convergence to an optimal solution, mainly because of the 'curse of dimensionality' caused by the large state and control spaces of a system, which makes the onboard implementation in real time a quite challenging task, especially for high-dimensional systems and long-horizon routes. Future economy control methods, such as the model predictive control method, are based on a receding control strategy approach, which allows a vehicle to follow moderate predicted horizon references. The first feature of the MPC-based approach was developed using a nonholonomic model, in conjunction with an MP algorithm based on a 'lookahead approach', which calculates a sequence of turning sequences of the vehicle. Finally, the sequences are visualized at the horizon of the vehicle system, after a predefined number of control actions. This approach is implemented in a real-size vehicle, even though the route is not optimal in an environment with deterministic and nonstationary traffic models. Since then, the MPC method has been widely used for wheeled vehicles, flying aircraft, helicopters, and rocket-guided systems.

However, the concept of the programming model and the constraints were converted into continuous form before they could be solvable using the MP approach, which raised the challenge of solving the optimization problem in finite time.

5. Real-Time Traffic Updates with AI

In addition, the real-time information can be incorporated in a collapsible, scrolling list, allowing the user to monitor the road conditions instantly. It is also possible to integrate a voice response to help the visually impaired make their way through the highway network through the voice of cellular telephones, car phones, or handie-talkies. The AI system can supply similar real-time traffic updates to the highway traveler. The updates for the traveler include weather, road conditions, roadwork, or obstructions that could affect the highway traveler's safety and time. Integrating the city AI dispatch with telematics systems and having trained agents supervise the AI systems could result in both decentralized and improved city traffic management. The traffic management AI system can supply real-time traffic updates for highway travelers as well. The search techniques demonstrated during emergency vehicle guidance can be used to provide reporting of traffic conditions during off-peak hour traffic. Due to the reduction of the need for skilled dispatchers, this system could ultimately be managed and maintained by the Department of Motor Vehicles or the Traffic Safety Administration.

5.1. Data Sources for Traffic Updates

One of the reasons for the limited adoption of navigation systems in vehicles is the lack of reliability of regularly updated maps and traffic information, as well as the inconvenience and constraints of enabling these systems on mobile devices using a refresh application. These pertain to how traffic updates are provided to the user; however, they also serve as an essential input to the development of path modification algorithms. Traffic update systems require precise and appropriately detailed information on the delay from weather and road conditions, accidents, crowds, and construction-related lane reductions. This is ideally provided in real time.

There are two types of data resources for providing this traffic information that are generally used. Static data resources comprise information sites and blogs, public and private internet mailing lists, cellular based measurement devices, and media websites that reflect the views of media traffic helicopters. In contrast, dynamic data sources are stationary road point detectors like induction loops and micro detectors that can be installed on existing road infrastructure, as well as mobile fleet telemetry devices that transmit real-time travel information to a central traffic server. No one data type is perfect, and they reflect different underlying assumptions and complexities. Media sources, internet mailing lists, information sites or blogs, and cellular-based device finding are prominent human-based resources for the provision of traffic and road information, where the data is edited to interests. The problem with this data is that the method can register only large congestion, and the delay is only updated periodically. Forecasting is complicated by the fact that the data reflects the crowd behind the traffic source rather than ahead of it. Mobile traffic services have the ultimate goal of developing location-based models and smart tools to provide information on the nearby road infrastructure and predict or avoid future traffic situations tailored to the real-time needs of commuters. The idea of creating road sensors to monitor traffic movement around a regular road network using traffic and cellular mobile phones operating along the highlighted path was proposed.

6. Future DIrection

The direction of our system research includes: 1. More interaction. Currently, the external world and the in-vehicle environment are completely separate. Our system takes the lid off this separated world to observe it. In the coming stage, more feedback and more interaction will be introduced between them to exert the system's sensing ability. For example, a personalized AR environment will be built for drivers when safety hazards are detected, so that the driver receives the warning or conversation in an automatic and interactive manner. Or the system itself regulates the AR environment according to the detected driver's status. 2. More interaction between GPS perception and lane recognition perception. Currently, GPS perception and lane recognition perception are relatively independent, but they can also work together. GPS perception can provide clues to adjust those hard-to-detect situations. For example, the GPS perception results show that the car is turning left and the GPS shows a reserve line curve to the right. Then the lane recognition results could take full advantage of this information. Additionally, the GPS perception results could be available as additional inputs for the nominal model. 3. Robust localization. GPS perception is very far from real autonomous integration, and we are focusing on short-range localization perception fusion in this work. Finally, we move toward fusing GPS information into final lane localization results. By taking full advantage of projections, smaller input sizes, and more accurate perception results, we aim for much higher perception accuracy in future research.

7. Conclusion

In this chapter, we discussed the main considerations that the development of AI-enhanced vehicle navigation systems must bear in mind, including mission planning and goal priors for reliable, efficient navigation. We showed that combining human-generated data uncertainty estimates with model prediction variances results in navigation policies being contaminated with typical prediction errors of the model. We introduced an adaptive rule-based collision-avoidance policy that uses predictions of the u-type bicycle model to respond to vehicle maneuvers during a potential collision. We also presented a multi-agent reinforcement learning framework for incorporating interactions with non-cooperative traffic participants. At last, we opened the discussion of the synergy of natural adversarial training and reinforcement learning, which we find merits future research.

To validate the practicality of our approach, we used real-world data to process and visualize split-second interactions and decision-making in a traditional waypoint trajectory planner versus our proposed model-enhanced planning techniques. We demonstrated that our decision-making approaches respect the geometric stability boundaries of a bicycle model, benefit from uncertainty-aware fusion, and learn robust physical parameter priors to handle task-specific over-detection biases. These findings are the first to suggest that reinforcement learning with sophisticated learned counterfactuals is able to jointly optimize the physical dexterity of the vehicle, its ability to command the traffic environment, and respect the physical capabilities of other traffic participants. This supports shared responsibility when deploying highly automated vehicle systems and places the development of such systems firmly into existing road transportation infrastructures.

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