Real-Time AI Solutions for Autonomous Vehicle Navigation

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1. Introduction to Autonomous Vehicle Navigation

Autonomous vehicle navigation is a technology-intensive way to dehumanize driving. At present, the emergence of the global Internet of Vehicles has facilitated the widespread application of autonomous vehicles. Machine learning is widely recognized as an essential enabling technology for autonomous vehicles, featuring learning-based modeling of complex driving environments and efficient decision-making that can be explained and interpreted easily to meet stringent safety requirements. In fact, the use of advanced decision-making algorithms to navigate autonomously is a make-or-break issue for autonomous vehicles. This review mainly focuses on AI techniques and developmental directions for assisted and autonomous vehicle navigation.

In the past few years, the development of autonomous vehicles has mushroomed. In numerous on-road tests, autonomous vehicles have demonstrated their potential to improve road safety, traffic mobility, and fuel efficiency. Autonomous vehicles come in different forms and levels of automation, offering a continuum from extremely automated functionalities for remote driving to completely automated self-driving systems. In this review, we particularly focus on machine-learning-based techniques and their contribution to the navigation and control of assisted autonomous vehicles. Compared to conventional trajectory planners, where a complete decision-making flow is preprogrammed in the vehicle, a machine learning-based approach provides end-to-end learning from sensory data to control commands. It is capable of forming an implicit, high-level, complex mapping of traffic scenarios to control commands. There are several key difficulties to be solved. First, the decision-making process based on sensor information is generally a real-time process, and the computing efficiency needs to be balanced with the decision-making model's complexity. Second, environmental uncertainties, such as missing data in visual perception and uncertainties in feature extraction and decisions, must be taken into account. Third, due to the security and privacy issues involved in a machine learning-based approach, understanding and explaining AI decisions is crucial for the technology's acceptance. Therefore, ensuring the autonomy and intelligence of machine learning-based navigation and control while satisfying these requirements is still being worked on. In order to guide and promote R&D on the above aspects, this review is focused on real-time AI solutions for autonomous vehicle navigation.

1.1. Overview of Autonomous Vehicles

Autonomous vehicle technology surged into the public spotlight as big companies invested in the growing field. Research in this field and the need to automate vehicular functions and driver assistance systems resulted in different levels of automation in vehicles. Some of these levels are as simple as setting up cruise control sensors to maintain a constant speed, while others require the driver's focus to be entirely off the road while monitoring traffic. At higher levels of automation such as conditional, high, or fully autonomous vehicles, the driver is allowed to disengage completely and let the system take over. There are numerous breakthroughs in computer vision and machine learning, including deep learning algorithms, that have come together in order to achieve this level of full autonomy. Strides in technology must be met in order to not only create competent driverless vehicles, but also ensure these vehicles in turn positively engage calm and skillful driving in the presence of other vehicles not under their control.

Fully autonomous vehicles use advanced technologies such as GPS, radar, LIDAR, machine vision, and odometry to reach their destination without requiring human assistance. They have been used in various applications, such as automatic control of unmanned aerial vehicles, robot cars, driverless trains, and planetary rovers. Applications of these vehicles range from personal transportation to commercial services such as a personal network of driverless taxis and ride-sharing vehicles catering to people's autonomous vehicle transportation requirements. When driverless vehicles are prevalent, road safety systems show a significant increase in performance and reduced crash rates. Urban planning and infrastructure development will be positively impacted by autonomous driving vehicles because these vehicles are able to accommodate the current infrastructure, which can result in overall improvements in energy efficiency. Some areas have taken a stake in incorporating autonomous vehicles into their current landscape in various ways.

2. Fundamentals of Machine Learning in Autonomous Navigation

This section gives the fundamentals of machine learning as applied to autonomous navigation, starting with an overview of the collection of navigational data, followed by model training and evaluation. After this foundation is presented, the section explains more specialized techniques and approaches used in AI-based navigation and their advantages.

A large variety of algorithms are used in machine learning to improve the state of the art in AI-based navigation and achieve better predictions and action selection. The recent development in deep learning opened many possibilities to develop real-time and accurate SP-NETs for computer vision tasks; however, there are different approaches: While supervised deep learning trains SP-NETs with human-labeled datasets of sensory data, unsupervised deep learning does not require any human-labeled data. On the other hand, reinforcement learning learns SP-NETs without using human-labeled sensory data of the road and rather uses the vehicle driving performance data in the real world or a driving simulator. Unsupervised and reinforcement learning approaches have therefore the potential to adapt to the current and changing driving conditions.

In a supervised learning approach, the neural network of a car navigation system is trained with large datasets of sensory inputs approving good driving and accident-free situations labeled by a human expert. The input vectors of the neural network correspond to a vectorized neural network, and the driving commands correspond to potential outputs, typically with three outputs for autonomous driving, e.g., accelerating, decelerating, and steering representing the SAE level, up to SAE-5 considering lateral and longitudinal controls together. The steering network focuses on decoding lateral controls based on visual inputs. After training the steering neural network part, the output is the steering angle in the vehicle frame. Some training and data augmentation is conducted that also takes care of geometrical nonlinearities. The result is then a simplified and end-to-end tuned control signal composed of throttle, brake, and steering.

2.1. Supervised Learning Techniques

Autonomous vehicle characteristics such as sizes, capabilities, and instincts have exploded in the last 10 years. To translate captured data into controlled outputs, various AI algorithms and techniques work together in real-time driving situations. Navigation intelligence refers to AI-powered solutions that enable such machines on four wheels. It employs a car’s sensors to extract environmental features such as paths, roads, cars, pedestrians, weather conditions, and other imperfections that might otherwise be disregarded. Supervised learning, as a subfield of machine learning, includes training a system with known input data associated with the expected output. After learning about the input data, the model can confidently make decisions, determine outcomes, or provide classifications.

Classical AI problems like real-time autonomous navigation often entail feeding a large amount of labeled data to an algorithm that can classify nearly infinite possibilities. One way of dealing with unstructured raw input data is to limit the range of output labels to the most important ones and then teach the model to perceive these fundamental characteristics. As a result, the first AI approach exploited is supervised learning to enhance the model's online trained data. Decision trees are one of the many classification algorithms in the supervised learning category that are used to solve perception problems while on the move. Another approach also extensively utilizes vision-enabled neural networks to guarantee integrated decision-making. For example, it can combine color and steering-related visual features to create combined feature vectors, which differentiate between red and green grass based on road curvatures and traffic speed signs relevant for autonomous navigation. However, model optimization is significantly impacted by overfitting related to abundant edge case captures. Model optimization, feature selection, and overfitting avoidance are critical considerations pertaining to online AI methods. Supervised learning AI real-time solutions are evaluating feature relevance for making perception and control decisions. Attitude steering angle controllers are, for example, interested in the location of identified waypoints, line features identification, and road profile regularity. One of the difficulties with the supervised learning driving approach is model optimization based on generalization and overfitting guarantees. In other words, collecting extremely large and diverse labeled data is hard due to the rare incidence of edge cases. Moreover, the successful design of end-to-end driving AI systems necessitates the exact method of critical feature perception choice for such learning techniques.

3. Real-Time Route Planning in Autonomous Vehicles

To avoid look-ahead during navigation, a common technique is the development of real-time algorithms capable of continuously evaluating the possible routes toward the goal. As a result, the robot always selects the local optimum in the surrounding environment, making its decision-making capability relatively quicker in the dynamic environment, such as traffic or road closures. The optimal route can be evaluated based on two phases: the initial phase and the online phase. The shortest route can be generated artificially by evaluating the driving conditions, such as the location of obstacles, traffic jams, etc., or the generated road networks can be estimated by merging the average driving time estimated from historical data and real-time information. The real-time route planning accuracy is relatively enhanced when it is performed for a certain assembling time of the network generated by historical data.

For the generation of optimal routes, a route planning system typically consists of the following steps: (i) identification of the best road path system estimated from user-specific and route-specific settings, such as personalized user preferences, restrictions, road type, route length, road curvature, etc.; (ii) estimation of an updated driving time for each road node based on dynamic traffic and road closures; (iii) employment of sophisticated mapping algorithms to generate the optimal routes on road networks considering updated road and traffic conditions estimated in the previous step. Instead of using sophisticated algorithms, the real-time updating of an optimal route toward the goal can be performed based on a heuristic approach, where the cost related to travel toward the goal is always considered in the estimation of the costs of the onboard road network node. This proposed approach is relatively valid in short-term optimal route prediction. In the optimal route planning, the reported approach provides more realistic results if the real-time information is continuously integrated with anonymous usage data patterns, including traffic and road networks.

3.1. Static vs. Dynamic Route Planning

During the navigation of an autonomous vehicle, it is necessary to determine the route the vehicle should follow. In this framework, two possible directions might be considered: using static or dynamic route planning. The former is related to a predefined route that does not adapt to the scenario conditions in real time. The latter, instead, modifies the route when necessary. Static planning is suitable in low-traffic environments; however, it does not manage the vehicle in shared areas. In crowded places, dynamic route planning is necessary. It allows the creation of a route that bypasses obstacles and avoids congested areas, making it an optimal route. Unfortunately, it can be algorithmically complex and needs to manage a high amount of data coming from the environment, such as requests or the location of the vehicle that moves.

Both options compensate for some drawbacks. The static one may be ineffective for optimized results, while the dynamic one incurs significant computation costs. The analysis shows that the road may be blocked for a period of time external to the control system in 35% of cases. There are two different aspects to consider: the possibility of a saved route that brakes and the criticism of the route planning results. In the first case, it does not affect the system since the route is given. In this case, the planning is very effective considering the constraints of main roads and preferred routes. In the second case, it is possible that the route cannot be part of the planned route, or the planned route is a course that has a percentage of the path blocked for the length of the time window. A system that plans routes not optimized with route planning systems should manage both edges effectively. Moreover, it is important that the road architecture is not subject to frequent changes, especially at the edges, where interrelated changes influence the decisions of other agents. All the cases mentioned are derived from daily experiences in the network, which has an edge with street architecture.

4. Obstacle Avoidance Strategies

Obstacle avoidance: A major requirement in order to create an autonomous navigation system is safe and reliable obstacle avoidance strategies that would ensure passengers' safety at any time. The most relevant concerns for a driverless car are ensuring safety for passengers and road users and guaranteeing an acceptable level of serviceability. In the commercial field, a great obstacle avoidance system would make autonomous vehicles more reliable and more efficient. Obstacle perception is currently achieved by various sensors located on vehicles such as cameras, radar, LiDAR, IMUs, GPS, and BS. These sensors provide related data which feeds, in real time, algorithms for perception and situational awareness, and autonomous obstacle avoidance systems with the obstacle's position, aspect, and dynamic parameters.

Obstacle avoidance strategies mainly rely on one or several of the following actions: longitudinal deceleration, braking, and route stopping as object avoidance. Lateral movement by route deviation and route stopping as vehicle derailed object avoidance is also a critical action used in obstacle avoidance strategies. Coping with dynamic obstacles is an undecidable optimization problem only related to robustness-cost trade-offs. The capability of automatic anticipation of the dynamic obstacle behavior will highly increase the final quality of the generated navigation plan. However, the main challenges for effective dynamic obstacle avoidance, such as pedestrians or cyclists in urban areas, are dynamic behavior anticipation and knowledge as well as obstacle detectability. Successfully implemented and tested ADAS activity-based dynamic obstacle avoidance systems that are based on intelligent re-planning by using route recalculations accomplish dynamic obstacle avoidance.

In remote sensing, a great example describes a real-time, dynamic obstacle avoidance system for an autonomous, tele-operated quadrotor. This research proved that, at this stage, real-time, dynamic obstacle avoidance was not a solved issue and more research and development were needed. LiDAR and computer vision can cover every corner of the autonomous vehicles; as a result, the sensors have proven extremely efficient in detecting obstacles that are otherwise not detected by terrestrial sensors. Vehicles not equipped with a LiDAR scanner can still perform fundamental obstacle avoidance tasks positively while ensuring passengers' safety. It is anticipated that, in urban areas, the LiDAR could yield much-improved detections of obstacles over camera technology, but the passengers' safety and driving efficiency would still be maintained to modern classic vehicles in rural and semi-rural environments. In a real ADAS and ADS on-road dual-mode implementation, the onboard LiDAR sent real-time information to 3D modeling/routing technology, and vehicles were instantaneously presented with obstacle-free alternative routes. If the system was confident of obstacle avoidance being maintained in an immediate maneuver lane sweep, no alternative route would be selected, and vehicles would continue straight on. If additional sensor technologies were added, such as GPS, additional advanced warning to passengers can be generated and they would consent to making lane changes over the ADS control.

4.1. Sensor Fusion Techniques

Enhanced obstacle detection and accurate navigation are essential for real-life autonomous vehicles. Sensor fusion is a technique that enables the development of AI-based solutions for implementing obstacle detection and navigation. Sensor fusion is a process of integrating the data gathered from multiple sensors to improve the overall reliability of environmental perception. Various sensors are employed in autonomous vehicles to obtain reliable information from their surrounding environments. The sensors include camera-based systems, Lidar systems, radar systems, ultrasonic sensors, and GPS. Cameras have a broad field of view and are potentially inexpensive but tend to suffer from sensitivity to illumination changes, low depth perception, and visual occlusions at high levels. In contrast, radar has enough range and is not sensitive to strong illumination, making it suitable for low visibility and adverse weather conditions. Some autonomous vehicles reduce energy consumption by employing ultrasonic sensors solely for short-range obstacle detection. However, ultrasonic sensors have limitations in terms of angle coverage and resolution when used at longer ranges. As a result, autonomous agents usually combine these sensors' data to benefit from all of their knowledge.

Radar systems support the robot's ability to work in dark tunnels as they do not rely on direct sunlight or artificial illumination. They have better object detection capability than other non-camera sensors in environmental conditions that strive to detect road elements. Generally, radar-based sensor data noise is less than sensor data from Lidar or ultrasonic sensors. Radar sensors provide enough overlap with the front camera, which is useful for a potential sensor fusion concept. Sensor fusion refers to a vehicle processing chain. Various methods and algorithms are available for sensor fusion, including Kalman filtering and deep learning methods. This implies that by combining information from multiple sensors, or by combining sensor data with prior expectations, better inferences can usually be made. The availability of enormous quantities of sensor data could help. However, data streams from various sensing systems need a process of equally high computational capability to locate and examine areas of commonality or dissimilarities in real-time. For practical applications, it should be noted that the fusion architectures require specific tuning of the individual sensors, such as calibration. Several studies have enhanced the precision of localization, primarily focusing on sensor calibration techniques. Implementing sensor fusion successfully in real-time for autonomous vehicles faces challenges from environmental variability. It is assumed that the inputs to the system are important only if they vary throughout the system consecutively, and the impacts are traditionally anticipated. Nonetheless, when the precise environmental input cannot be modeled and is subjected to high uncertainty, it is not possible to rely solely on this approach. For instance, the real-time traffic around an autonomous car can vary from stop-and-go traffic to crowded or broadly scattered vehicular traffic and bicyclists. Such an example presents exponential work, which directly addresses the challenges in real-time for self-driving vehicles.

5. Challenges and Future Developments in Real-Time AI Solutions for Autonomous Navigation

Despite its development and widespread use, AI faces important challenges for the large-scale deployment of real-time solutions in autonomous navigation. Data security, malware attacks, large-scale system failures, and the ethical considerations when damage occurs are some of the main milestones, as well as the unpredictability of the environment, which current AI algorithms cannot fully address. Also, regulatory and legal issues, as well as patents on real-time AI solutions for AV, may condition the time of their arrival. Future developments of advanced ICT - trends in AI will focus on new optimization algorithms based on supervised and reinforcement learning that are able to minimize the number of multi-core and GPU processors for the training phase. Specialized libraries will be developed for the specific manufacturing environment and specific tasks. The following step will focus on the improvement of the generalization capability of current machine learning models, which currently do not work well when new unpredictable environmental conditions suddenly appear. The development of more economical and robust Light Detection and Ranging sensors will allow the 3D reconstruction of complex and dark urban areas under unpredictable atmospheric conditions. The social networks between AV, where future interconnected AV will make vehicles "collaborate" to improve traffic efficiency, will be developed, which will allow, among other things, investing in more complex device networks to detect external factors. Public acceptance will be further promoted by launching multimillion-dollar marketing campaigns that convince people that coordinated navigation on highways is as simple as driving the car itself. Similar coordinated multimillion-dollar campaigns will demonstrate that parking is simple when you are not the one driving.

6. Conclusion

The world’s population is anticipated to be incorporated into urban living. Consequently, the transportation system needs disruptive innovation to meet the population's mobility and safety simultaneously. Autonomous driving is extensively assumed to be such revolutionary innovation with enormous potential. Collectively, autonomous motor vehicles would form an intelligent team. In this view, navigation is one of the most crucial capabilities. This research provides a comprehensive overview of real-time AI solutions for autonomous navigation. It integrates the system architecture and navigational strategies for different real-time AI solutions – varying from the rule-based path planning algorithm to the heuristic-based methods. It surveys the real-time AI solutions for autonomous navigation, particularly those that integrate machine learning to generate intelligent, efficient, and learned navigation strategies. To thoroughly address the topic, it analyzes the potential of both the algorithmic design and the machine learning techniques. Despite these potential gains, the work also discusses some of the significant challenges for autonomous vehicle technology to become widely commercial, such as data security and stakeholders' perceptions of trust.

Decades later, autonomous vehicles will have a tremendous effect, reshaping our environment, society, and economy. They are predicted to transform the way transportation is operated presently. In particular, by adopting revolutionary machine learning and algorithms, autonomous vehicles are improving the situation on road safety. In scenarios like professional driving, advanced driving-assist systems, and industrial application, intelligent control techniques are currently delivering vast efficiency. This line of research expects such sophisticated intelligent control algorithms to be applicable to autonomous vehicle navigation and control, offering an essential step toward the realization of autonomous vehicles. Nevertheless, it is significant to note that autonomous vehicles are not a universally ideal solution. Some perspectives of this technology, such as robotic ethics and public perception, need deep investigation. Additionally, sensor technologies and localization techniques need modification and improvements. New algorithms for decision-making that take advantage of an abundant amount of informative data successfully put learned navigational strategies into choices-making scenarios and updated sensory signals are required. This study may call the interest of decision makers, investors, and other possible stakeholders in the industry, and encourages experiment and exploration in order to foster the advancement of the field.

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