Real-Time AI-Enhanced Systems for Autonomous Vehicle Navigation in Adverse Weather Conditions

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1. Introduction

From communicating with spacecraft billions of miles away to recognizing spoken language for people with disabilities, artificial intelligence (AI) has become a keystone in complex systems in recent years. Fully autonomous and AI-enhanced self-driving car navigation have received growing attention. In adverse weather conditions or high-temperature cities, one of the biggest challenges that autonomous vehicles encounter is the "Rain-Blindness Effect," where the perception system may fail to function normally due to torrential rain or dust storms.

Real-time navigation systems play a crucial role in many practical applications, such as autonomous vehicles and networked pedestrian navigation. A real-time system can accomplish rapid responses to sudden emergencies, such as traffic jams or severe climate conditions. Considering the striking advantages of real-time navigation systems, our work is dedicated to integrating robust AI enhancement algorithms to facilitate real-time performance. These algorithms allow the system to adapt to different scenarios and boost the competence of the navigation platform. However, in recent years, end-to-end models and reinforcement learning have become increasingly popular, and we believe that a pivot in the current trends back to the full real-time paradigm would have far-reaching consequences. Despite the evident high computational and data complexity, a real-time AI-enhanced navigation system would complement the holistic view presented in this essay, demonstrating strong potential to become a successful competent model in real-time navigation scenarios. For machines to operate in the real world, the success of real-time navigation tasks is more sensitive to the performance of the system. Furthermore, the growing trends toward assisted autonomous driving have also made the fast and robust completion of decision makers and controllers important.

2. Challenges in Autonomous Vehicle Navigation in Adverse Weather Conditions

Autonomous vehicles need to overcome several challenges to ensure safe driving under adverse weather conditions. Weather deteriorates visibility drastically, which becomes one of the main challenges. Sensor performance can degrade due to environmental factors like fog, rain, and snow. Fog creates additional reflections, resulting in reduced contrast for the image and significant loss of texture. Rain creates water droplets on the windshield, limiting visibility for human drivers. Similarly, due to the adherence of snowflakes on the windshield glass, it is required to be constantly cleaned or defrosted. Images captured under snowfall experience loss of texture and edge sharpness, blurring, and pixel saturation. Additionally, during snowfall, frost gets stuck and melts on camera lenses, degrading visibility. Furthermore, in areas with periodic snow, snowflakes accumulate on the edges of the lidar lens, reflecting light and casting shadows on the sensors, affecting scan measurements.

Wet and slippery road conditions during either icy or rainy weather lead to loss of tire-road contact and hence inadequate vehicle control, inducing skidding or aquaplaning, affecting vehicle stability. Also, these conditions potentially reduce the ability of decision-making in handling risks and managing dynamic scenarios. At high rates, rain can also reduce traction and grip with the road. Additionally, roads having partially cleared snow contain the main road plus the accumulated hard snow and ice on both untreaded and semi-cleared areas, further making navigation challenging and potentially hazardous. An understanding of these challenges is critical to the development of necessary solutions. In the recent past, many technological interventions have been made to address challenges in hazardous weather conditions with the assistance of real-time AI enhanced systems.

2.1. Limited Visibility

In the case of adverse weather, precipitation and environmental factors cause the visual field of drivers and their vehicles to diminish considerably. This is also a critical challenge for autonomous vehicles. For autonomous vehicles, an insufficient range of sensor data acquisition can be deduced from diminishing visibility. For example, snow, fog, rain, and combinations of them can drastically reduce the range of visual sensors. In these cases, the performance and/or reach of LiDAR, radar, etc., can exceed that of visual sensors. Moreover, weather phenomena in combination with direct sunlight can cast dynamic alternating shadows. Adverse weather can obscure distant parts of the environment. Furthermore, poor visibility negatively impacts decision-making: the reduction in contextual experiential data can hamper vehicle navigation and control. Due to the exponential size of semantic feature spaces, standard algorithms in the decision-making process can misinterpret the surrounding environment with possibly unknown or rarely experienced data per weather phenomenon. AI algorithms lend themselves to solving this problem since training data can contain abundant empirical experiences of all possible adversities. Both the big data ecosystem and powerful hardware foundations make adopting AI technology a viable strategy to complement AV vision systems. Recent advances in sensor technology indicate micro- and nanometer sensors will become cost-effective in consumer-grade autonomous vehicles. Ultra-sensitive, high-speed camera sensors have become affordable. Stacking multiple high-speed frames within the limits is one way to counteract the impact of adverse weather on the reduction of visual data. For a few frames per obstacle, there are two possible sets of initial conditions.

2.2. Slippery Road Conditions

Adverse weather and road conditions are the main factors that determine slippery road surfaces. Among various possible weather elements such as rain, snow, and ice, it is possible to evaluate the traction loss through observation of the perpendicular force applied to the road surface, which represents the normal force, proportional to the weight of the vehicle. The coefficient between frictional tangential force and nominal perpendicular force is taken as the absolute value, resulting in the physical meaning of the coefficient of friction.

The consequence of low-traction hazardous road conditions on vehicle dynamics and stability is serious. For instance, water film or ice can cause slippery surfaces and impede tire friction force, followed by vehicle longitudinal and lateral motion patterns, such as skidding, tire lock, and traction loss. The optimal tire friction can be achieved by rapid adaptation and trajectory planning, such as steering angles and given portions of the front and rear tire torques. Violence in tire or wheel dynamics is the subject of path tracking control, which represents spinning and skidding phenomena. Consequently, advancements in vehicle chassis control systems exist to enhance safety and functions. Therefore, it can be seen that real-time vehicle adaptation to road surfaces reduces travel time of the vehicle and prevents traffic accidents.

In summary, there have been many previous studies in the field of vehicle slip angle change subject to diverse road weather conditions. Advanced driver assistance systems and the autonomous driving industry have also integrated these slip angle estimation and control systems. These controllers improve vehicle chassis control algorithms rapidly to increase trajectory accuracy. Sensory technologies embedded in these control systems include road sensor cameras, LiDAR, stereo vision cameras, and RGBD glasses. Despite the real-time monitoring of the wet road, it is important to evaluate the state and value of sensor failure. Alternative control algorithms utilize the old Kalman pattern filter. However, machine learning has proposed a new controller using common sensor systems.

3. State-of-the-Art AI Technologies in Autonomous Driving

The application of AI technologies in autonomous driving plays a pivotal role in the implementation of intelligent navigation systems. Machine learning, and more specifically, deep learning models, have been adopted to design decision-making systems for autonomous vehicles. Machine learning models can learn data patterns that characterize driving strategies. Hence, decision-making systems can continuously improve their behavior by learning new scenarios without the need for human intervention. On the other hand, in the autonomous driving paradigm, the use of deep learning models is not limited to the environment perception task. Convolutional and recurrent architectures are being adopted together for the processing of RGB-depth inputs, enhancing their use for scene assessment, motion compensation processes, and identification of an environment's occupancy. Deep learning architectures that process depth data are able to discern relevant features for an autonomous vehicle's path planning, which makes AI technologies a good candidate for overcoming the challenges of system operation under harsh atmospheric conditions.

Recent studies have tackled real-time system operation for navigation tasks within diverse environments and conditions. In the current state of the art, machine learning techniques have been recently applied for optimal trajectory generation based on the combination of a multi-objective evolutionary-based approach with reinforcement learning models in autonomous racing vehicles operating under harsh atmospheric conditions. The navigation capabilities of an autonomous ground vehicle were improved using a hybrid technique combining fuzzy-SLAM mapping patterns and an artificial potential field algorithm. Additionally, an in-depth insight into autonomous systems using extraordinary sensors in the field of view of deep learning models to process complex inputs, such as camera data, is of considerable interest. Hence, a model that supports autonomous vehicle technologies in forest environments was developed by conducting experiments with a UAV throughout an area with dense vegetation.

3.1. Machine Learning

Machine learning, specifically artificial intelligence, has made remarkable strides and is widely used in modern artificial driving systems. With the availability of quantum computing, robust artificial intelligence algorithms will significantly improve navigation accuracy as well as computational efficiency. Machine learning uses various algorithms or techniques to produce a model or series of interconnected models that will effectively qualify a system to make future predictive analyses based on historical data. There are three main approaches or types of machine learning: (a) supervised learning, (b) reinforcement learning, and (c) unsupervised learning.

Machine learning algorithms can make an AD system learn from vehicle data, determine whether a vehicle is driving in dry or adverse weather, and store data based on decisions made. However, there are still obstacles in the implementation of an ML model in practical driving with bad weather, and the results cannot be simply generalized. For instance, a model trained with high-quality datasets might not give satisfactory results when implemented in real-world settings. Several successful case studies have been shown in which the machine learning algorithms essentially help further refine the car's perception, making the model memory rather efficient for decision-making. Some pilot-tested studies are now at a practical stage for artificial driving with bad weather, but this technology likely needs time to mature.

3.2. Deep Learning

Deep learning is an advanced subset of machine learning using huge neural networks with multiple layers of processing units, also known as artificial neural networks or multi-layer perceptrons. Deep learning performs automatic feature extraction and selection from the input data. The architectures of deep learning networks are connectionist systems based on networks having adaptable weights that can be trained through progressive exposures to complicated input and output conditions while improving parameters like weights and biases, from which deep learning networks build a hierarchy of low to high-level features or representations. Convolutional Neural Networks constitute a subfield of deep learning networks that learn from raw pixel data, allowing one to skip employing traditional image processing. In comparison with machine learning, the deep learning network is able to work with a large volume of imbalanced sensor data, including a wide variety of driving conditions like snowy or foggy weather. These networks operate over a wide range of data without requiring pre-conditioning to achieve accurate pattern recognition.

Deep learning models are usually composed of multiple processing layers, which are used to learn varied features of input data. CNN, for example, learns spatial hierarchies and inherent features of multi-dimensional inputs drawn from local receptive fields. Since these models employ many connected elements, they are capable of processing large datasets robustly and are less susceptible, compared to shallow learning, to detecting patterns characterizing many visual objects and decision-making. However, developing deep learning comes with some challenges, such as the accuracy of the models that could result in misinterpretation from oversimplification and overfitting or could require computational resources for robustness. Advantages of CNN and deep learning model structures have made them successful and prominent in the implementation of autonomous navigation systems for real-time applications. Deep neural networks, especially CNNs, have demonstrated high performance in real-time perception tasks and navigation control for autonomous vehicles. The recent success of training and employing deep networks can be highlighted by outstanding performance in object recognition. A huge variety of deep networks has applications in computer vision, some with dramatic improvements on visual datasets. The introduction of the deep CNN was a turning point at the visual recognition challenge, which led to a drastic decrease in the top-5 test error. There are a variety of successful deep neural network architectures, which have shown significant gains on large-scale visual recognition tasks. The implementation of these deep neural network architectures showed very competitive performance compared to other potential commercial systems in autonomous vehicle challenges. Surveys of the state-of-the-art literature have shown that various architectures have further advantages, which led to their successful implementation in some commercial cars and have resulted in positive failure measures related to perception.

4. Real-Time Data Collection and Processing for Autonomous Navigation

Real-time data collection is paramount for unmanned vehicle navigation systems. Timely acquisition of data from onboard sensors is of utmost importance in navigating the vehicle. It enables timely decision-making to navigate the vehicle between its source and destination while avoiding any obstacles in the path. Sensor data can be collected from various sources, like vision cameras, radar, and lidar systems. Processing of raw sensor data alone does not provide situational awareness one would require for navigating in adverse weather. It is essential to use multiple sensors together as their information is inherently rich in overlapping aspects. This approach is generally termed 'sensor fusion.' When combined, the information complementation leads to improved quality of the processed data when compared to individual sensor data. The common sensors used to gather real-time data in an autonomous vehicle are cameras, lidar, and radar. Each of these sensors provides unique and complementary information to enable the vehicle to perform inside-out sensing, have an accurate perception of the surroundings, and hence evade accidents.

When used in this fashion, the quality of the training data employed to calibrate the system significantly improves, leading to a reduction in the system's training time. Data preprocessing is used to clean the dataset by removing irrelevant data, reducing noise in the signal, or amplifying features. Irrelevant data collected is discarded, thus allowing larger amounts of data to be handled. However, the collection and processing of real-time data are one of the main operational areas that are overrun with challenges. The process starts with transmitting sensor data to onboard computing units, then several other challenges arise, including (1) dealing with the huge amount of processed data, (2) the timely transportation of raw sensor data to the processing units onboard, (3) computational requirements for processing the data, and (4) challenges involved in developing efficient algorithms intended to process larger subsets of real-time data that are responsible for making high-precision timely decisions.

4.1. Sensor Fusion

Fusing data from diverse sensor modalities is a popular technique to improve the capability of autonomous navigation systems. By using maximum data about the environment, the perception of the host vehicle can be improved drastically. Different sensor modalities have different notions about the environment, which ultimately gives rise to complementary data.

This is the sole reason for integrating data from different sensors. For example, the LIDAR produces a fine-grained 3D point cloud, while the camera can produce colored images and can be used for texture mapping, and the radar has better resistance against weather afflictions. The techniques used for integrating data from central LIDAR, front camera, and front radar are discussed. These methodologies are designed considering the features of sensors and the intricate architecture with which the framework is implemented. This itself is beneficial for online applicability.

The use of decentralized methodologies with an additional front camera and front radar sensor can enable feature-complete sensing capability not just in indoor environments, but outdoors as well, which is useful in inclement weather. Utilization of all sensor modalities has been revealed to yield a lower RMSE in path length with fewer chances of running out of the track. The presence of all sensors can act as a fail-safe in harsh environmental conditions. The confidence values from all sensors can be aggregated and compared to get a more coherent result before making trajectory decisions. Additionally, the fusion of the three sensors can account for excessive noise or volume variations in one sensor. Signal processing and AI block outputs are fused through a weighted average method. Sensor data and processor outputs are fused in real-time, which makes the algorithm suitable for being embedded on edge devices.

There are many techniques and algorithms available when it comes to sensor fusion for real-time AI-driven uncertain environments. Dead reckoning and Kalman filters are quite popular as real-time robot localization is facilitated by IMU and encoders. Sensor noise-free observations are obtained using these algorithms. A neural network, too, is employed to solve the two-dimensional inverse problem. Additionally, a neural network was utilized for dynamic object avoidance that used the depth map and image to make a smooth trajectory. Most of these algorithms were employed solely for a single modality sensor, while our focus here lies on a fusion of LIDAR, camera, and radar. Sensor noise might have a significant impact if not minimized. Due to the coarse resolution and misunderstanding in ego vehicle speed, radar can have noise. LIDAR can also have noise due to dust particles getting incited in the sensor. Synchronization of this data can be difficult when applying general sensor fusion. The use of software delay units is frowned upon due to the need for additional conversion to real-time and time stamping in synchronization. Finally, these algorithms have also been applied but are not specifically tailored for adverse environmental conditions. It can be noted that adversarial conditions have different types of latent data. Thus, applying the algorithm of normal sensor fusion onto adverse conditions is not straightforward. In summary, the integration of LIDAR and camera can alleviate the impact of adverse weather on single LIDAR-based navigation systems and improve system accuracy. In this section, the end-to-end system flow of the current system is explained in detail.

4.2. Data Preprocessing

Data preprocessing is a crucial step that must be completed before sensor data can be utilized to develop an accurate navigation system. However, raw sensor data often contains a significant amount of noise that leads to erroneous conclusions when used without moderation. The goal of data preprocessing is to ensure that the raw sensor navigation data is cleansed of this noise and that features relevant to navigation are effectively selected and extracted. In general, the procedures for data preprocessing will involve noise reduction, normalization, and feature extraction using informatics tools. Improving the quality of the data in these ways will directly serve to enhance the performance of the ML model used for terrain classification and navigation. Moreover, data created by different sensors typically have different file formats, sampling rates, and units of measurement that must be converted and aligned in time before being used as inputs to a navigation system. Alternatively, it will be necessary to align the outputs of different machine learning models that use different sensor data in a navigation system. The delayed temporal conditioning of the output-layer units of one of these models can be used to motivate the backpropagation-through-time learning method. Managing the aligned and pruned sensor data file sizes for efficient storage and access presents another challenge. Accumulating knowledge from separate test vehicle sensor data acquisitions using batch learning procedures to train traditional neural network systems could be tedious and inefficient. Therefore, it is important to develop rapid data reduction and ML preprocessing algorithms that can adapt to changes in weather, lighting, and terrain conditions.

5. Machine Learning Models for Adverse Weather Conditions

The development of AI-enhanced computer vision systems is a step forward in improving autonomous navigation systems. As with any machine learning model, there are several requirements and challenges that are specific to these systems or have an "adverse weather" note. Variable weather conditions will introduce a host of variables and are therefore extremely challenging to predict. Thus, AI-enhanced solutions have proven to be very effective. The models to be adapted are important for varying weather and visibility conditions. In essence, these models should be capable of a high degree of learning. It is important to use the least significant and most informative amount of data for machine learning models that need to be satisfied with the least amount of data to be considered real-time. There is a big difference in the fact that a machine learning model that is real-time is not real-time in such an application as autonomous vehicle navigation. It can have a life-threatening impact on precise models under variable weather conditions that degrade decision speed.

Several types of machine learning models can be listed to improve autonomous vehicle navigation systems under adverse weather and visibility. The most important machine learning models used in different real-world applications are presented individually below. Most of the mentioned works were generally conducted in the field of autonomous vehicle navigation and in the development of intelligent transportation systems. However, other applications are also addressed. These models are presented separately; machine learning is important for understanding applications according to the services they offer. This is followed by a comparative analysis of these models, considering their deficiencies and effective performance capabilities. In summary, it can be said that machine learning techniques have not yet reached the desired level for hazardous road conditions, and this application requires severe improvements and an increase in the safety coefficient. This factor may also require active contributions from the designers of hardware components. To also provide these are within the scope of new research opportunities and challenges.

5.1. Convolutional Neural Networks

Convolutional Neural Network (CNN) architecture has been demonstrated as an effective machine learning model for the development of sensor-based technology dedicated to autonomous driving. One of the strengths of CNNs is their ability to process two-dimensional arrays of data with a spatial topology, like images. This aspect is crucial in order to devise a system that can operate effectively under degraded visual conditions. In this respect, CNNs can be seen as an important tool for interpreting visual data when adverse weather conditions have a detrimental effect on the performance of the vision systems utilized in the autonomous navigation of vehicles. From a scientific and technological point of view, a CNN is characterized by the ways in which the spatial hierarchies of the images are processed and feature recognition and extraction are performed. By using a wide range of different convolutional kernels, the CNN is able to recognize features of increasing complexity. These properties of the CNN also offer a potential advantage in dealing with noise and distortion, which typically characterize images captured in poor weather conditions. Recent deep learning advancements and the categorization of adversarial and robust examples have fostered the development of specific training techniques. These techniques can be exploited to minimize the so-called overfitting and, in general, to increase the generalization capabilities of the model that is trained. This line of research seems particularly relevant in the context of autonomous navigation systems because the setting of data and the real data with which it has to work is characterized by a high level of randomness. Similarly, the application of convolutional layers, max pooling, and fully connected layers has been proven invaluable in addressing the issues typically faced when developing accurate Cold-SDs for the detection and classification of foggy scenes from common color images. These problems include the requirement of a long training time and the heavy computational demand.

5.2. Recurrent Neural Networks

Recurrent Neural Networks (RNNs) can be considered as another promising technique used in time-series autonomous navigation systems. Time-series data is indeed a typical characteristic of an autonomous vehicle's onboard system clock, speed, and motion sensors, all of which provide vital information to describe the overall behavior and position estimation for vehicles. The main motivation behind using RNNs is that RNN models can efficiently be employed to process sequential or time-series data. RNN models, combined with historical information learned from past events, are shown to be very intelligent in that they can concisely describe and make predictions based on sequential data trends. Moreover, employing more sophisticated RNNs, particularly Long Short-Term Memory (LSTM) networks, can reinforce the system to be more capable of catching longer dependencies in sequential data.

As time-series data carry the sequence of events involving all vehicle dynamics and environmental changes, being capable of modeling these changes is an indispensable requirement for anticipating movements and evolving structures in the corresponding environment. VLCs rely largely on the historical events generated from the vehicle dynamics and the environmental changes collected from data available from the surrounding environment. Using this dynamic data extensively is a key feature of autonomous operation systems to understand the environment around them and anticipate the prospective results. However, employing large LSTM units triggers the vanishing gradient problem, which is the most common cause of lack of learning due to overcrowding. To resolve these imposing challenges, the development of more advanced RNN training methods is needed to create a more convincing navigation system that can more accurately capture the dynamic trajectory of an autonomous vehicle. Thus, employing RNNs offers an efficient representation to enhance the overall reliability of an autonomous navigation system.

6. Future Direction

Real-time AI-enhanced systems for autonomous vehicle navigation in adverse weather conditions face several research challenges and limitations. There remains extensive room for improvement in dealing with different adverse weather and light conditions. Real-world case studies showed system robustness, but long-term repeatability and large-scale system validation remain open for future research. Advances in future research in autonomous vehicle navigation systems will be crucial to tackle adverse weather conditions. Therefore, a continued collaborative effort between academia, industry, and regulatory bodies is required to solve challenges. Possible directions for autonomous navigation research are as follows: advancements in sensor technology such as improved range and resolution, small low-power AI chipsets, processors, and memory. More accurate and faster AI algorithms and methods for advanced data pre-processing are required to accurately capture traffic information.

Moreover, for a real-adaptive vehicle navigation system, new challenges include a more user-centric design considering the mobility and information available to pedestrians. Ethical and safety-by-design partnerships will ensure data management strategies around vehicle navigation systems. In the future, if 5G and edge computing come into full commercial operation, it would be appropriate to integrate data from other vehicles' navigation systems to improve autonomous driving in adverse conditions. In snow hazards, data from vehicle navigation systems ahead of the current vehicle could be used to automatically inform ADAS and vehicle navigation systems behind about the road hazard ahead without the possibility of distortion. A proactive study is required to validate the vehicle navigation system in full real-time operations due to the new 5G technology. After validation in snow hazards, the real-time navigation AI system for vehicles must be integrated as part of a decision-making system, providing law enforcement agencies with critical information about road safety potential. It should enable proactive road closures and other security measures.

7. Conclusion

In this work, we explained that despite the advances in traditional techniques for the navigation of autonomous vehicles, the harsh and adverse climatic environment, particularly fog and snow, poses a serious threat to the practical utilization of these techniques. The need of the hour is to rely on the advantages posed by machine and deep learning to make navigation truly robust and reliable, instead of benchmarking traditional techniques, which do not provide any significant advancement in the existing state of the art, as established through experimental validation. This has been pursued in the essay. Secondly, a crucial requirement for applying machine and deep learning effectively to this domain is real-time identification of the inputs, as the environmental information, such as visibility, is extremely time-varying, and so are the sensed images and data.

The switching from one model to another is based on the improvements in the accuracy of the environmental status that is estimated by the current deep learning model, as compared to the one identified in the immediate past. Both in fog and snow, the results verify that machine learning-based navigation enhances the state-of-the-art methods when applied to both adverse weather conditions, and the maximum identification time reported can be reduced by 98% if a small error in estimating the environmental conditions can be tolerated. Ray-based multi-feature learning enhances foggy and crisp image classification. The subsequent sections of the essay describe this extension in detail. In conclusion, scientific and technological awareness that is specifically designed to overcome navigation issues experienced while traveling on roads in adverse weather conditions is necessary to enhance the road travel experience. Furthermore, car manufacturers would increase the acceptability of present and future vehicles because it is a universally acceptable fact that driver-assistance systems are preferred by car operators, especially long-haul professional drivers and the elderly.

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