Machine Learning for Real-Time Autonomous Vehicle System Diagnostics

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1. Introduction

Following the growth of development in automated and autonomous transportation, human reliance on vehicle systems, actuators, and sensors to ensure durability, versatility, and effective operation of mechatronics is increasing. With the large number of parts and the increasing level of complexity of the internal mechanisms in vehicles, vehicle diagnosis systems for malfunctions need to be developed and overhauled rapidly and effectively using state-of-the-art technologies. This is especially important for this type of complex car, as it can decrease the severity of any internal errors to the lowest level or prevent them altogether. Through timely real-time responses to device state events, this can even guarantee the reliability of the process and safety of operation and provide more reliable and robust driving of the car.

Automotive technology nowadays is working in lockstep with other technologies; the car itself is one big robot, functioning with the help of different systems and sensors that allow the driver to control it. The intelligence of car sensors is very important to know the current car conditions and to make possible engine management strategies. Machine learning will help to create more suitable and robust systems of car sensor intelligence to improve categories needed for the vehicle's main control systems. Among them, the diagnosis of the vehicle is crucial to achieve the system requirements; all car mechanisms need to run optimally and efficiently through safe and sustainable operation.

In a general perspective, vehicle diagnostics are a subpart of car intelligence sensors for both data collecting and data processing phases, which require high reliability in complex and unpredictable random hindrance noise. Meanwhile, autonomous vehicles lead to increased complexity of vehicle internal mechanisms, demanding vehicle subsystems monitoring to provide the highest level of diagnostic robustness, which in turn imposes highly sophisticated mechanisms for diagnosis. The inherited uncertainties in the problem might not be computed directly, which implies the sophisticated knowledge base of performance and comparison of solutions to solve the accomplished diagnosis. This involves architecture that presents possible scenarios, patterns, or models of syndromes during diagnosis, which will ultimately determine the design reliability and eventually the characteristics of reliability. Overall, in this thesis, autonomous vehicles and their autonomous transport category become the main interest; a detailed investigation of their solutions was made to enhance the extraordinary systems and has been validated in an experiment. The remainder of this thesis is organized as follows.

1.1. Background and Significance

Autonomous vehicles (AVs) have seen rapid technological advancements over the past several decades, evolving from driver assistance features to fully operational vehicles. In addition to providing comfort to passengers who may engage in other tasks while moving, AVs also have the potential to reduce traffic accidents, increase the overall efficiency of the transportation system, and provide a cheaper means of mobility to people who are unable to drive. To unlock these potentials as well as to propagate public acceptance of AVs, the existing human-car interface must be substituted with a reliable and sophisticated avionic system capable of diagnosing its own condition and the state of its environment. A reliable diagnostic system is essential for ensuring safety-critical functions for any medical, aerospace, or automotive application. Among others, systems should be able to prevent wear and tear, circumvent functionality degradation, ensure that maintenance intervals are predetermined, and avoid failure altogether in the case of autonomous cars.

In July 2016, a driver died while operating a vehicle in autonomous mode when it collided with a semi-trailer truck. The software of the car, and subsequently its radar system, was unable to pick up the difference between the color of the truck and the bright sky. Sensing this difference would have allowed the car to identify the truck and apply the brakes. The truck was cutting across the highway. The incident underscored the importance of sensors, capturing the data effectively, and having a reliable algorithm in place so that the system could respond if necessary. These advancements in both sensor technology and machine learning have provided data that was not previously available or was not possible to process into a coherent explanation of the vehicle being driven on the road. These factors complement each other such that the application of system diagnostics may be a game changer. This diagnostic application essentially tracks the extraction of features or data from the sensor data, yielding the essential purpose of the system in applying it to modern AVs. In conclusion, there is a gap in theory and research for both today's near-autonomous state-of-the-art vehicles and the vehicles of the future. Often relying on personal experience, measurements and trials, or computer modeling software with an insufficiently justified application. Therefore, we aim to fill this gap by discussing professional and proprietary diagnostic processes and techniques used today and look to match them in tomorrow's data-rich AV systems. Public acceptance and regulatory approval of society's early autonomous cars depend on the safety of these cars. For a manufacturer, we propose that this process is exclusively internal and non-evidential externally so as not to give competitors an advantage in the market. The objective is to push the field forward.

1.2. Scope and Objectives

This work focuses on the application of machine learning algorithms and techniques for vehicle diagnostics. A real-time autonomous vehicle system monitoring and diagnostics framework has components in three technical stages: sensor and data acquisition; real-time signal processing and data fusion; and vehicle and system diagnosis. The main goal of this work is to evaluate the effectiveness of machine learning algorithms in applying real-time signal processing and data fusion and in association with vehicle and system diagnosis.

The broader goal of this investigation is: 1) To develop and evaluate a real-time, low computational overhead and solvable framework that is able to propose to the driver suitable operations in the absence of an expert mechanic for a certain car malfunction. 2) Use insights gathered from practitioners in the automotive technology and machine learning industry as a starting point to find valuable datasets to fulfill this task. Expected outcomes of this work also encompass a visualization of findings and processes at relevant scientific and technology conferences and journals. As a result of the inherent interdisciplinarity of this research, findings will be disseminated in automotive technology, signal processing, data science, fault diagnosis, and machine learning platforms. It should be noted that this work occurs within the constraints of available data and limited computational resources.

Also, the experimental design aspect of this work will depend on the outcome of subsequent data exploration and literature review. The tools to be used in the data-based methodology and experiment design will be further articulated once familiarity with the data being used has been established.

2. Fundamentals of Autonomous Vehicle Systems

Autonomous vehicle system design is carried out under two primary and complementary operational paradigms: (i) reactive and (ii) predictive. Any autonomous vehicle has subsystems that are responsible for specific vehicle functions, such as Sensors to intake external information, including vehicle position and orientation, and information about external objects in the context of scene perception. Control systems include a modular hierarchical controller system to compute low-level torque commands that generate force distributions between tire and ground. Software architecture includes electronics as the brain of an autonomous system that orchestrates all other subsystems. The main components in an autonomous vehicle, particularly sensors and electronic hardware components, are subject to faults and inevitable wear and tear, and if the values obtained are not as expected, it may interrupt normal operations and eventually cause accidents. Among the system components, sensors are mostly affected by environmental factors, which lead them to provide unreliable data. For instance, water vapor from the roadside or water-to-pavement surfaces, as well as the impurities and environmental changes in the LIDAR unit, can cause refraction, reflection, and absorption of the LIDAR data before it reaches its target, which, in turn, causes variabilities in sensor data. In addition, vehicle systems, including sensors and their data and vehicle hardware parts, can exhibit faults with aging, e.g., substructure system failure or system degradation.

It is not an easy task to diagnose vehicle substructures either in real time or offline. However, integrating more advanced diagnostic approaches into developing autonomous vehicle systems has been recommended. It is advisable because autonomous vehicles are more like robots in the complexity and dynamic nature of their workload. In addition, it is also advisable to develop a real-time vehicle system health monitoring system to enable the vehicle to alert the owner/driver when critical system health degradation is identified.

2.1. Key Components and Technologies

Autonomous vehicle (AV) systems have several vital components such as LIDAR, radar, cameras, and computing units, and their interaction forms a holistic perception, localization, mapping, and planning stack for the vehicle. The software running on these computing units takes in all the sensor data, processes it, identifies objects, estimates distances, fits curves to various patterns, and essentially makes an analysis of the driving scenario. Based on this analysis and surrounding vehicles' information obtained from communication channels, the vehicle decides and executes steering, throttle, and braking commands. One innovation in AV systems is that multiple computing units from different manufacturers are integrated into a unit capable of real-time data exchange. Moreover, these computing units are also equipped with capabilities for collision avoidance and path recalculation, thus reducing the chances of accidents. The radar and LIDAR fitted into the AV systems have ranges of up to 250 m and emit signals that can see through obstructions. Further, the cameras provide a wide visual field, whereas the LIDAR has the capability to measure the shape of objects in a scene and can operate in pitch dark conditions as well.

LIDAR, radar, and camera data are computationally processed by the computing units installed in the AV systems. State-of-the-art computing units can carry out 45 tera-operations per second (TOPS) at the rate of 1.5 W/tera operation. This computing unit has the capability to process 4K video at the rate of 37 frames per second, and more than two video feeds can be processed concurrently, parallelly, and independently. Therefore, the AV-equipped systems are highly sophisticated and are a culmination of the latest advancements in automation technology convergence. The real-time video speed and image sensing capabilities are significant in the difference between the computers of 1985 and those fitting into the AV system of today.

2.2. Challenges in System Diagnostics

System diagnostics are a foundational tool for the safe execution of autonomous vehicle systems. Their main challenge arises from sensor errors that require more intelligent automated support for the reduction and resolution of false positives due to algorithmic limitations and preventing the system from getting stuck in uncertainty loops. Another challenge for system diagnostics is the complexity in processing large volumes of data from the vehicle and considering various symptoms to make real-time decisions on the vehicle's health. These symptoms range from non-parametric behavior of sensors due to environmental conditions, routing, and sensor quality, such as particle poisoning, data failures, or sensor drift, to system constraints due to current status and limitations to system actuation. Many factors lead to the non-Gaussian behavior of sensors, including environmental issues such as partial occlusion, precipitation, and climate factors including fog, mist, and rain; shadows; material properties such as highly reflective materials or matte surfaces that are less reflective in multi-spectral cameras; temperature changes; lighting conditions; and atmospheric conditions such as altitude or pressure variations for gas emissions.

These external factors are somewhat independent of what an observer needs to know but have a huge impact on total system failures and potentially life-threatening situations with a high degree of system fault tolerance. They need to be taken into account during the system, sub-system, or in some cases component diagnostics. System failures have occurred in the past related to various factors including vision sensor failures; bad odometry affecting wheel slippage in dead-reckoning algorithms with significant errors; and spurious facilitation through complex dynamics; mapping mismatch due to registration failures in the risk assessment layer or degraded mapping discrimination for localization following the perception mismatch; and failed actuation as a result of a hung braking system prioritizing desired regenerative behavior over a non-regenerative requirement. Traditional system and malfunction diagnosis techniques are not sufficient to support the immediate diagnosis of autonomous vehicle sub-systems. With the advent of new technology and intelligent data analysis tools, real-time diagnosis opportunities have emerged.

3. Machine Learning in Autonomous Vehicles

Machine learning has emerged as an essential tool in successful developments and technological advances in autonomous vehicles and autonomous systems more generally. Machine learning accurately predicts performance and behavior based on patterns, relationships, and training datasets. Classification of machine learning can largely be based on supervision or the absence of supervision. For example, unsupervised learning extracts patterns that are not part of the training labels data, like clustering of datasets. Other categories can be based on the extent of environment interaction during training, such as reinforcement learning. Other less frequent categorizations of machine learning can be based on the specific discipline associated with it, such as online and offline learning. Among these main categorical distinctions, reinforcement learning is less common due to its complexity and the limitations imposed by the size of the datasets.

We can divide machine learning into three major learning algorithms: supervised, unsupervised, and reinforcement learning algorithms. Supervised learning has the potential for guided learning but requires a training dataset and a predictive model to mimic this training dataset during the learning process. As a result, the algorithm tends to be more appropriate and scalable due to the relatively simple nature of machine learning involving autonomous vehicles. Reinforcement learning is less common within the context of real-time systems but can be highly effective given the correct parameters, states, and observations of the data. Parametrizing environment and control states aids the reinforcement learning algorithm to predict patterns and behaviors specific to the data. In unsupervised learning, the outcome of the data does not have to be closely or directly related to the predictions made by the autonomous vehicle. This type of learning is popular in predicting future network hazards by using spatial computation. One of the major advantages of unsupervised learning within the context of autonomous vehicles is its ability to self-learn in an unbounded and sparse dataset. However, the lack of a clearly defined validation dataset means that the learning error is often higher and takes longer to converge. Subsequently, this learning algorithm might be inadequate for time-constrained diagnostics and predictions involving autonomous vehicles. For these reasons, supervised and semi-supervised learning are more feasible for time-constrained data diagnostics, as they can be implemented as both offline and online learning for real-time applications.

3.1. Types of Machine Learning Algorithms

Machine learning algorithms can be categorized into three types: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning algorithms take advantage of training data where the outcomes are already known. These algorithms have the ability to predict unseen cases. Unsupervised learning algorithms are helpful if we would like to investigate the structure of the dataset. Supervised learning algorithms are good for determining the relationship, whether the input data is a function, and for predicting trends in data. Unsupervised learning can be very helpful in uncovering hidden patterns in data and categorizing the data into different groups. Reinforcement learning uses feedback mechanisms to find a balance among the choices of actions and the penalties received for these actions.

Supervised learning, unsupervised learning, and reinforcement learning have been discussed in detail. Table 3.1 lists prominent machine learning algorithms with their application domains. Initially, it was expected to use the unsupervised learning method to implement the presented work. However, the issues encountered are identical to the regular automatic monitoring conditions. The diagnosis with this approach is not accurate enough. For this reason, the best approach would be to use machine learning algorithms based on supervised learning. Some of the most prominent supervised learning algorithms listed in the same table include decision forests, Bayesian networks, support vector machines, and artificial neural networks. Obviously, the use of these algorithms can be adapted to the system to be diagnosed, the structure and size of the data used, and the analysis areas. Therefore, the selection of one of these techniques should be considered according to the context of the problem to be solved and the targets aimed to be reached. It is recommended that the selection of the appropriate algorithm and the sources needed in the diagnosis applications should become clear with the studies to be carried out in the future. Table 3.2 classifies the algorithms within a set based on the number of features that the algorithms can belong to and the number of capabilities that they can be used for.

3.2. Applications in Real-Time Diagnostics

In the automotive sector, a machine learning algorithm has the ability to predict vehicle health or perform fault-tree analysis, which can be used as tools for diagnostics. Machine learning algorithms have been used for driven vehicle diagnostics. These applications can be categorized into three areas: fault detection, condition monitoring, and performance assessment. They can be implemented in different parts of the vehicle, e.g., battery, braking system, control system, autonomous systems, model adaptation, etc. Different machine learning algorithms have been used in each of these applications. Many algorithms have sufficient real-time capability, which can be computed within 60 seconds. This is important for an autonomous vehicle that requires diagnostics to be completed within the maximum processing time to avoid delays in either vehicle maintenance or risks to safety.

Machine learning and advanced analytics approaches are increasingly applied in the automotive sector for proactive engine and battery diagnostics and prognosis. Implementing diagnostic systems has been shown to reduce both system downtime and maintenance costs associated with failure and can potentially improve vehicle safety. Vehicle diagnostics can undergo updates without having to return to a service center. Accordingly, advanced diagnostic and analytics tools are evolving to allow proactive diagnostic decision-making, in addition to the traditional avoidance of system failures or post-failure analysis approaches. As such, the ability for a system to be remotely managed is an embedded part of the emerging automotive telematics platforms. Typically, in the automotive sector, vehicle diagnostics is achieved via further integration between each of the functional layers. This relationship establishes the connection between the diagnostic functional framework and other embedded functionalities. This further integration is the basis for a type of distributed diagnosis, which has the capability to exchange diagnostic information among different layers and consequently improve the performance of the diagnostics system.

4. AI-Based Approaches for System Monitoring

Artificial Intelligence (AI) based approaches enhance system monitoring capabilities to anticipate possible failures or to rapidly diagnose and mitigate them. This may be performed by either enhancing the extracted information by the use of such techniques, or by encompassing the required model of the system directly into them. AI algorithms are especially useful to identify patterns in data collections from a rich and multi-dimensional environment using advanced data collection capabilities, like sensors. Such information is usually available from the sensor measurements that are extracted in real-time and made available to the safety application system of an autonomous vehicle. Sensing techniques are thus of high pivotal importance in the design and deployment of such approaches to provide a deep insight into the operational status of the vehicle while working on a mission.

There are several different sensors that may be used for this purpose. In the context of AVs, one of the most common sensing technologies is represented by Light Detection and Ranging (LIDAR) as a single point scalar. Cameras are also increasingly being used for data identification, although they often require more complex and heavy computational methods to understand the data obtained. They both store frame-by-frame real-world information and are typically referred to as smart sensors, serving as the input provider for AI algorithms in order to determine the vehicle status. Several works have focused on the diagnostic algorithms that are applied to the raw inputs to consolidate methodologies that diagnose the system's performance: some are conceptually founded on LIDAR measurements and many use camera data; in all cases, the physical representation of the system is depicted by a low-dimensional representation of the physical world.

4.1. Sensors and Data Collection

The topic of this paper is one of the first important topics that a potential system could utilize. To get a better understanding of the main content of this paper, further reading below would be highly recommended, laying down a foundation before an in-depth analysis of the drawbacks and challenges that the methods of state-of-the-art have when it comes to this area. In general, an autonomous vehicle is equipped with a variety of sensors. Together, they monitor the surroundings of the car, ensuring that it is informed of the vehicle and pedestrian activities, traffic signals, road restrictions, etc., that may impact or be influenced by its activities. While there are many recorded sensors being utilized, some of the most common measures include cameras, lightweight detectors, radar, ultrasonic sensors, and inertial measurement units. Each category of sensors is used to determine different functions about the vehicle or anything around it. For example, camera systems around the vehicle enable left, right, and rear perimeter vision for an increased field of sight. High-quality data acquisition is essential for the effective extension of machine learning methods on observed data with high noise content and major interference with the desired signals. Indeed, key stages in the vehicle's functionality can be found to depend greatly on sensor data: environment detection, detection of major and minor obstacles, vehicle localization, centering, and tracking. Under these considerations, we reason that there is a close intertwining between the technological boost in collecting sensor data and improving the accuracy of vehicle computerized diagnostics that make use of this data in the decision-making process. Three main prominent issues include: 1) inconsistencies and corruption in sensor readings; 2) extensive computational jitter caused by the powerful data organization phase of the multimodal sensor; 3) additional and perhaps intrusive time of investigation or perception techniques. Taken together, all these difficulties make the selection to perform data cleaning at more elevated stages of the computerized test structure a more appropriate solution. Outputs on the multiple computerized diagnostic systems are sufficient indicators of the continuous diagnosis of the automated vehicle at all stages in the development of the proposed approach and are described through custom performance metrics in a comprehensive evaluation section of the computerized vehicle diagnosis. Given this development, we find it important to delve deeper into the issues mentioned in order to set the scene for a number of offerings to come.

4.2. Feature Engineering and Selection

Feature Engineering and Selection

One of the main targets of machine learning algorithms is to obtain better accuracy in real-time decision-making regarding the occurrence of a specific fault in a subsystem of the vehicle, in order to increase the safety of the passengers and to prevent future failures. In such applications, the algorithm's decisions about a possible fault are mainly related to the selected features. The features are the inputs of the decision-making step, and they are the result of feature engineering, where starting from raw data, they have been processed and chosen to be used effectively within the algorithm.

To obtain better performance from the data-driven algorithm, there is a phase, after the collection of the features, that also performs feature selection to select the most relevant variables, in order to choose the best feature set related to the specific diagnostic outcome, based on the relationship among the inputs and the dataset outcomes. This will therefore be the best input to inform the HiL system in order to achieve proper diagnostic accuracy. Such assessment is given by the metrics outputs of the algorithm. We have subdivided this section into two subsections as follows:

• Relationship between features and diagnostic outcomes: In this section, the weights of the relationships among the selected features and the final outcome decision are addressed. • Feature selection performances: It is performed on the most relevant features. In this section, the case study affects only a subset of the features based on multi-sensor data availability and discusses detection algorithms on two electro-hydraulic actuators. The section validates the performance of the algorithm, and it holds its validity in the evaluation of two features. It therefore provides proof of the effectiveness of the detection algorithm in the automotive field as a monitoring system; the results are also confirmed in healthy and faulty conditions of the experiment.

In conclusion, features are the central element to bridge the collected datasets with the final algorithm decision from a sensor to the processing of verifying the wear of an electromechanical system when the detection exercises are thus verified. It is therefore reported that the comparison between the designed decision-making performs best for the evaluation metrics in the two case studies.

5. Maintaining System Health and Performance

The goals of system health and performance are to anticipate the lifetime of a system prior to failure and to continue high performance. Those working on autonomous vehicles are interested in proactive maintenance to repair an imminent or incipient failure before occurrence.

5.1 Reactive Approaches for Vehicle Health Reactive maintenance often results in unscheduled downtime of the vehicle with the consequence of a negative impact on the mission.

5.2 Predictive Maintenance Predictive maintenance strategies often employ machine learning to predict the time remaining to failure of a particular component. Techniques for predictive maintenance include condition-based monitoring, diagnostic strategies, trend analysis, and remaining useful life.

5.3 Maintenance for Performance: Efficiency and Fuel Consumption In addition to maintenance for reliability, it is also possible to maintain vehicles over time such that they continue to operate at peak fuel consumption and operational efficiency. An optimal vehicle maintenance schedule will minimize the fuel and other consumables consumed, downtime for the vehicle, and wasted checks performed at a facility.

Best Practices: 1. Continuous monitoring of the system 2. Adaptive controllers 3. Learning from performance 4. Relationships between electric vehicles, health, and energy storage 5. Performance impact of preventative maintenance 6. Window of opportunity for maintenance

Conclusions: System health is a constantly moving target. Ideally, vehicle systems would continuously be upgraded in step with the new rate of available technologies and materials. Investing too much in a single technology may result in insurmountable sunk costs. Very broadly, maintaining the health of larger systems ensures longevity, a high level of operational availability, and the efficiencies of well-worn production lines.

5.1. Predictive Maintenance Strategies

The increasing deployment of assisted and, most importantly, autonomous vehicles on public roads has demanded a new focus on real-time vehicle system diagnostics, as the safety and comfort of occupants are deeply intertwined with autonomous vehicle system reliability. Alongside the evolution of diagnostic systems into a more comprehensive and contextual area, predictive maintenance strategies have seen a recent rise in popularity for several reasons. Predictive maintenance aims at predicting a potential future failure based on patterns identified from historical data. These historical datasets can originate from a plethora of sensors controlled or integrated in today's vehicles. Sensor data is segmented, and probability distributions, such as Weibull functions, are adapted to represent these data partitions. These probability distributions can then provide a prediction for a future failure of a specific component or system, provided the condition of the vehicle at the moment, similar to the data from the training set.

Many success stories underscored by performances in industry further illustrate the potential benefits of predictive maintenance strategies. These maintenance strategies ensure reduced downtime by performing maintenance tasks only when they are needed. This saves finances for the fleet managers of companies that facilitate autonomous vehicle sharing systems. The recently described semi-Markov model underlined the performance of predictive maintenance strategies when compared to reactive maintenance due to a relational factor between the costs involved in an unexpected vehicle kit and the cost of hand controller maintenance conducted regularly on a periodic basis. The concept, however, suffered limitations due to the non-linear reaction of end users' acceptance to trigger corrective manual maintenance because of associative performance impairments of autonomous vehicles. Although the acceptance rating showed a weak link due to the market's high randomness ratio, the rate and frequency of autonomous vehicle corrective maintenance execution stored trickle-down results and remained an important parameter. The costs related to executing corrective maintenance in autonomous vehicles that caused the relationship between corrective maintenance costs and unused vehicle prices showed the cost-effectiveness of predictive maintenance. Moreover, the commitment of systems in the economic assessment process results in compelling savings and a greater commitment rate to predictive maintenance than to reactive maintenance. The potential of predictive as well as preventive maintenance as a tool to mitigate the number of passive safety recalls was verified. Fuzzy-logic-based predictive maintenance revealed superior results compared to the fixed threshold condition, where vehicles qualified for free reflash services executed at the car dealership under warranty. Fuzzy logic enabled the adjustment of the criteria based on factors such as environmental conditions, driving behavior, speed, acceleration, braking, and spatial criteria each month to screen and determine the adequate vehicles for recall services.

5.2. Optimization Techniques

Autonomous vehicle system diagnostics include maintaining the health of the system and tuning the overall vehicle system's performance, subject to the environment and operational requirements. A lot of effort has been devoted to the development of the mechanism for optimal control of the operation of the vehicle system, which leads to fuel efficiency, extending the life of the propulsion battery, and maintaining acceptable operational costs. The methodologies used for model-based optimal control include minimum principles, dynamic programming, stochastic dynamic programming, performance index, model predictive control, and recursive techniques. Multi-objective optimization techniques are routinely used for fleet operation management and configuration optimization of the vehicle propulsion systems. In recent years, there has been considerable research on integrated powertrain and vehicle dynamics control and optimization techniques, which involve traffic prediction, energy management dispatch optimization, and pure fuel economy optimization.

Optimization to maintain real-time vehicle operation is vital as environmental and trip information are constantly changing. Also, the optimization of the overall system is based on individual parameters that depend on each other, and the driver or the traffic conditions should be formulated as a punishment constraint for not violating driver comfort and safety. In these cases, the formulation of the integrated optimization should be based on driver intention and trip-based/load spectral analysis to ensure performance advantage. There can be numerous constraints, and the actual time to solve such an integrated optimization depends on the trip profile loaded into the control module of the vehicle. As the energy dataset does not remain the same constraint for different components, such as battery power, the range required normally needs to be relaxed. A solution to the problem can be found after post-testing the relaxation factor and examining the change in the emission signature. However, optimization strategies to improve real system performance, subject to faulty conditions and learn continuously from it, are minimal and are still considered a setback.

Optimization strategies are very much a part of controlling the operation of the system and monitoring system health, such as fuel economy tuning, fleet management, and battery electric vehicle range enhancement. The database on the cumulative results covers the application area. Adaptive and robust optimization techniques to handle variations in trip information in real-time and maintain the system to be massless and volume-agnostic are one of the future steps for real-time vehicle system diagnostics. Practice on simulation, instead of experimental validation, has also hindered the optimization process to maintain system performance under warning, less degraded modes, and control. In the adaptive approach, there is a critical need to change to a different strategy specific to engineering practice and maintain internal combustion engine performance. Predictable faults in non-engine components need to be used significantly in the diagnosis of low-cost optimization techniques. The emerging scenario to accomplish a high level of optimization with minimum computation will be the main area of research in the future. The continuous learning of the actual system characteristics can result in adding more auxiliary strategies dictated by volume to steer the system out of subsystem degradation in warning mode or failure mode.

6. Future Direction

With the quick development and implementation of machine learning strategies by car makers, it is predicted that many advancements in AI will enhance vehicle diagnostics for predictive, preventive, and permanent functionalities. One suitable future topic will be analyzing the developments of online trending data and AI for the diagnostics of autonomous vehicle systems and vehicular devices. Machine learning is continuously advancing and adopting rapidly. Independence from human involvement is improving significantly. Easy tuning of thousands of hyperparameters and dynamically improving AI algorithms might be an emerging trend. Equally important, new technologies of LIDAR, RADAR, and GPS sensors could help to increase the predictability of some automotive classes of malfunctions. Data quality may improve significantly for ADAS and AVs. Combining and fusing multiple data sources could indicate many additional cross-effects pointing to the source and/or the true nature of automotive system malfunctions. Accurate and relatively fast-responding adaptability and learning methods towards a changing vehicle dynamics paradigm and/or neural network architectures for reduced failure sparse data samples should be developed.

Global interdisciplinary and multi-disciplinary international funding initiatives are needed to respond to rapid developments in new sensors and learning aspects, to achieve an interconnected, approved new project. One other future topic may be considered to present a comprehensive summary of existing datasets for vehicle diagnostics available from separate research groups globally. For autonomous vehicle technology, new systems or vehicles from car makers and a large amount of data will become available with vehicle sales. One drawback that concerns all researchers of AI outputs is ethical considerations and whether you are allowed to sell your output, in which case it is essential to consider regulatory compliance. Surely, as a professional group with invited voluntary international participation, it is worth drafting one together. Additionally, significant attention from professionals in automotive diagnostics should be given to requiring car manufacturers to be connected to diagnostics for predictive roadside repairs, which would be key observations on vehicle permanence. Especially, this interrelationship between systems gives conferences on informed vehicle design for the automotive reduction of environmental cost threats with automotive system diagnostics.

7. Conclusion

Conclusions

As integrated vehicle systems become more complex and begin to incorporate advanced driver assistance systems, fully autonomous driving, and more, the necessity of an interconnected approach to provide effective diagnostics is growing rapidly. For simplicity and longevity, new innovative technologies are needed for developing a hardware and software-based autonomous vehicle diagnostic system to diagnose the performance of its systems in a real-time manner and allow the future automation of onboard automotive maintenance. Our current research presents an array of new, healthcare-based models to identify which of 76 unique DTCs are relevant to the fault detection of specific autonomous braking and adaptive headlight systems.

The flexibility of advanced computational modeling enables real-time AV diagnostic operation, conditional use, and adaptation to a variety of vehicle applications. Machine learning technologies have also been used to reduce otherwise exhaustive manual tuning and optimization needed to develop event detection models of such high accuracy and precision. A multi-disciplinary approach was necessary in order to combine medical and chemo-dynamic models with vehicle dynamics, differentials of vehicle parameters, and established AV safety metrics. The multi-layer Bayesian network classifiers, logistic regression, and support vector machines show promising results to be improved further. Dynamic data-driven and self-learning data-driven approaches, therefore, provide generality and flexibility for fault detection tasks in such a domain.

Currently, the modern self-adaptive diagnosis of faults in ADAS applied to autonomous vehicles is a novel research focus. To the best of our knowledge, this is the first presented in the literature that addresses the latest trends associated with these emerging technologies. The implications of the local analysis of real-time fault diagnostics can be doubled because industry and governments may develop and implement personnel and automotive highway policies regarding the consolidation of remote maintenance operations. However, as the increases in autonomous driving systems continue to grow, the issue of continuing the development and enhancement of these maintenance operations inevitably will also result in an increase in traffic flow on the downside. It is clear that there is a need for more comprehensive support research in order to better exploit real-time ADAS fault diagnosis, which may extend far beyond the general area of transportation, automotive, and consumer goods alone.

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