AI-Driven Predictive Maintenance for Autonomous Vehicle Sensor Systems

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1. Introduction

In practice, however, failures happen without warning and well before scheduled equipment maintenance was due, suggesting a major missed opportunity in implementing more precise and agile maintenance activities. By adopting artificial intelligence and machine learning techniques, researchers are currently pioneering methods that can diagnose faults and predict equipment failures with significantly greater accuracy. In this article, we provide a high-level overview of potential state-of-the-art methodologies for AI-driven predictive maintenance with a focus on AI-driven predictive maintenance methods developed for autonomous vehicle sensor systems. Properly deployed, the methods present an opportunity to enhance the performance of existing maintenance programs while greatly reducing operating costs. Achieving this level of improvement requires the inclusion of large and disparate sets of sensing data, many of which are unstructured or not sampled regularly. By achieving this data representation in the right way, the sensed parameters can become large and rich enough for machine learning models to recognize the spectrum of factors in formulating the likelihood of failures.

As a foundation of many intelligent and autonomous systems, sensor systems provide critical data to monitor and control devices and predict anomalies. Scientific studies have shown that an overwhelming majority of engineering failures are intermittent and random, preceded by observable changes in the behavior of the machinery. A substantial number of these incidents can be prevented by performing preventive or predictive maintenance routines at a regular schedule. Even with the best predictive methods, there are still limits to the amount of predictive information that can be gained from these methods because of a general lack of understanding the failure modes governing the complete population of systems. Current engineering methods, therefore, rely on a conservative view of the distribution of the dataset.

This includes approximately tracking and scheduling equipment maintenance over the lifetime of the equipment.

1.1. Background and Significance

In this paper, we investigate an AI-driven predictive maintenance framework, which is nonintrusive, model-based, and data-driven. This framework constantly tracks the health of vehicle sensors during the vehicle operation on the road. The proposed framework capitalizes on shared and expected intrinsic characteristics of sensors that lead to common faults that could develop during vehicle on-road operations, which expose the sensors to similar road-going hazards collectively or individually. The framework utilizes state-of-the-art recurrent autoencoder time-series models and learns from the unique fingerprint patterns exhibiting precursor faults from labeled historical large-scale sensor time-series data collected during early vehicle build and field operational service tests.

The large-scale deployment of autonomous vehicles in transportation systems promises tremendous economic, environmental, and safety benefits. Ensuring the roadworthiness of these vehicles is a key societal requirement before these benefits can be fully realized. Current vehicle inspection processes involve checking the vehicle's onboard sensor systems such as Light Detection and Ranging (LiDAR) systems and cameras, fueling and battery charging systems, and mechanical systems such as steering and braking systems to ensure they are functioning within the required specifications. These inspections are prescribed at regular intervals, at mileage- or time-based intervals, without regard to the utilization and the environmental and operational stresses these components have been subjected to. This process increases operational downtime and is not effective in addressing the fact that usage patterns and environmental mode of operation impact component health and wear.

1.2. Research Objectives

We aim to evaluate an economical and effective smart maintenance strategy to diagnose and maintain autonomous vehicle sensor systems as efficiently as possible. Since the output of the predictive maintenance model built by the traditional machine learning model is hard to interpret and not practical for business decision-makers, we take advantage of machine learning explainability and leverage more recent AI and machine learning technologies to improve the inferences in the predictive maintenance model and provide decision-making insights to support the smart maintenance strategy. There are three main objects and four issues we expect to solve in this study. In this research, we recruit the data team and machine learning engineers to leverage the AI technology and build the machine learning model to develop the intelligent maintenance decision-making and prediction algorithm. The sensor system can collect and analyze vehicle statuses and roadway conditions in real-time. The smart sensing device is integrated with advanced technology to provide an auxiliary environment suitable for modern transport vehicles, and the abnormal status of the autonomous vehicle sensor system is detected using the communication service channel.

Future improvements to the transportation infrastructure using the latest technology, such as Intelligent Transportation Systems (ITS), have become necessary. Among the various ITS, we focus on the real-time detection and repair of problems faced by autonomous vehicle sensor systems in smart transportation applications. To protect the communicational reliability of the autonomous vehicle sensor systems' infrastructure, we present a protocol that immediately verifies the vehicular sensing device's abnormal condition and adapts radiation patterns to improve the transmission performance. We evaluate the system's overall performance through analysis and extensive simulations to compare the proposed system with the most recent strategies in terms of average packet drop ratio, average communication distance, and throughput. The results show that the proposed system performs better than the existing strategies and can improve the reliability and real-time performance of the autonomous vehicle sensor systems in the smart transportation applications.

2. Autonomous Vehicle Sensor Systems

In this research, the intelligent driving method aims to control the vehicle smartly to ensure the room and route-safety of the first aid emergency. The basic task is to merge the route information stored in the SDI and the sensed driving condition from Device-1 (LiDAR) and Device-2 (digital camera) to produce a driving strategy to ensure room-safety of the emergency and traveling through the sensible route to the hospital. There are three methods in solving this task: Be controlled by the responsible driver, which implies shifting intelligence level to level one for NHTSA L3 autonomous vehicle; Full automated operation and grab the responsibility of human driver; The intelligent driving at high level (Valet Parking).

LIDAR System As one of the collision warning sensor systems, the laser radar has the characteristics of high directivity, strong directional ability, almost millimeter angular resolution, high peak power, low power consumption, low operating temperature, long life, low cost, good possibility of high integrated with data communication, and high probability of photoelectric conversion. The working range is long and can generally exceed 100 m, the vertical angle is between -3.2° and 16°, the azimuth range exceeds 360°, and the horizontal resolution is 0.0625, providing detailed depth map information. Any target that breaks through the detection range of the video radar can be detected before the lidar detection range is reached.

Wheel Speed Sensors Most vehicle wheel speed sensors are designed specifically to measure wheel motion, not vehicle motion. They are designed to measure the wheel's rotation speed and can directly measure either the angular speed or the linear speed of the one point on the circumference of the wheel. Theoretically, the only information that is available from the wheel's rotation speed is the circular speed of the wheel.

An autonomous sensor system needs to be able to collect data to dynamically understand and respond to an ever-changing, possibly chaotic environment. The architecture and components of a typical autonomous vehicle sensor system are illustrated in Fig. 1. Inertial Measurement Units (IMU) in the Vehicle System Inertial Measurement Units are positioning devices that measure angular rate and acceleration information in the vehicle coordinate system. It can provide heading, orientation, rolling, and acceleration information, which can approximate the position of the vehicle under various conditions. The acceleration information can be used to calculate the acceleration of the vehicle. A typical sensor system includes wheel speed information for the vehicle wheel speed and LIDAR for environmental sensing information.

2.1. Types of Sensors Used

The third sensor modality is the use of ultrasonic sensors, which function on the principles of sonar. They emit sound waves such as ultrasonic sound and utilize the time taken by these waves to hit an object and reflect back to the sensor in order to compute the distance and object. Ultrasonic sensors are usually installed around the robotic vehicle to provide 360-degree coverage of the surrounding environment. Due to the hardware demand of the ultrasonic sensors, the biggest problem is that ultrasonic data streams are expensive and time-consuming to collect, which eventually prevents the automotive industry from making notable progress. The recent advancements in sensor technology and mass expenditure on the data collection processes have made many high-quality sensor systems widely available.

Owing to these advancements, large-scale ultrasonic sensor data is silenced at this very moment, and one of the automotive industry's most ambitious missions is to analyze the ultrasonic sensor data in such a way that massive insights have been collected about automotive vehicles.

Autonomous vehicles utilize a combination of sensors in order to detect and process the components of the autonomous vehicle environment. There are different types of sensor modalities used in autonomous vehicles such as light detection and ranging (LiDAR), camera sensors, and ultrasonic sensors. LiDAR sensors classify as active sensors and can obtain range information of the obstacles in the autonomous vehicle environment. LiDAR determines the distance of objects in its vicinity by illuminating the surroundings with laser light and measuring the time for the light to reflect off these objects and return to the sensor. Camera sensors are passive sensors but still can generate a rich stream of image data for different visual tasks. Cameras can capture different modalities of images focused in either black and white or color. Monochrome cameras generate a grayscale image for the perception of similarity between images, and color or RGB cameras gather images displaying differences in intensity, hue, and light.

2.2. Importance of Sensor Systems in Autonomous Vehicles

The AD personnel tasked with maintaining the AV can expect a variety of challenges associated with the large, geographically dispersed fleet of vehicles and will need to be capable of addressing multiple types of sensors embedded in a dynamic, self-adaptive, multi-domain vehicle architecture. It is preferable to proactively manage sensor resources before remote communication and maintenance becomes necessary and to conserve the time and energy of both vehicle and maintenance personnel. Semiconductor material science research has advanced in the area of self-aware design and sensor reliability, but sensor failure may have to be addressed and mitigated for equipment used in regulated domains in the vehicle industry, including on vehicle platforms such as autonomous driving. Certain long-term involuntary failure mechanisms can be countered through sensor data collector algorithms considering various sensing modalities and data collection and storage policies. The overall maintenance should aim to minimize the number of potentially defective sensors, and the sensor data collected should be managed so as to maximize real-time sensor utility.

Sensors provide the eyes, ears, or any other senses to a computer system. Any computer system, including the most advanced autonomous vehicle (AV) system, depends on sensors to collect input from the surrounding environment. Without generous and reliable input, there would be no output from a computer system, such as an AV system, to control the vehicle. This critical role of sensors in an AV is achieved through gathering real-time data on its surroundings, ensuring safe navigation, combining such data streams for external and internal monitoring and control, and satisfying the regulatory requirements. Considering the many potential external and internal systems or subsystems that require high-fidelity sensor input, the vast amount of time and effort required for first-time testing of sensors in an environmental chamber or on an end-item, and then to repeat the testing after every minor change. Although great expense and testing are performed, sensor operation may degrade over time due to multiple failure modes, internal and external interferences, or unaddressed warning signs of sensor degradation. The sensed data may also protect the privacy of a vehicle occupant, who may require reporting or alerts based on data anonymization.

3. Predictive Maintenance in Autonomous Vehicles

Predictive maintenance must be used to protect ADAS and the autonomy of future AI-powered vehicles. Vehicle failures that could have been identified using sensor diagnostics pose an unacceptable safety risk and may lead to legal consequences. In addition, vehicle downtime is expensive for fleet operators and may lead to financial losses. In this study, we propose a model to predict a sensor's diagnostic code, which enables proactive prediction of sensor failures. Our model considers long-term monitoring of sensors, enabling real-time prediction construction. Small neural networks inspired by lightweight structures are adopted, and an efficient multi-head attention component is proposed to model dynamic importance within each sensor. Besides, the external information concerning sensor stress is used to further enhance diagnostic information. The extensive experimental results indicate the high performance of our model in several dimensions. This suggests that the sensor's health condition can be well predicted, making it promising in ADAS and autonomous safety management.

To differentiate your ADAS/autonomous offerings in the competitive market, take advantage of AI in building a scalable and cost-effective predictive maintenance. Use our AI-driven LED exemplar to apply innovative digital services, such as predictive services and in-production applications like predictive quality, for your nanoelectronics assembly, LED, and ambient intelligence products. So, use the ML-driven OSI recipe exemplar to apply innovative digital services to your semiconductor plant and extend your factory integration use cases. What do you get? By doing so, you differentiate yourself in the emerging business. Predictive services do more with less and generate tailored applications for both established manufacturers and their entire ecosystem.

3.1. Traditional Maintenance Methods vs. Predictive Maintenance

Traditional maintenance methods have multiple shortcomings that predictive maintenance methods can alleviate. Equipment downtime may be required for the former's multiple inspections and repairs. In addition, traditional reliability evaluation models disregard the effects of PM actions, but PM actions can prevent components from failing and the equipment from being disrupted. The efficiencies of traditional maintenance departments depend on the coordination ability of the organizational unit to conduct assessments and PM practices. Technically, the performance may decline if the subsystem still has a front-end control or an integrated traditional control scheme, such as throttling the propulsion system. Indices such as mean time between failures (MTBF) and maintenance costs may be advantageous from a cost perspective. However, they may be disadvantageous in terms of performance. The benefits of predictive maintenance, which involves conducting predictive data analyses, are of concern.

Traditional maintenance methods require equipment downtime to frequently inspect and replace faulty elements in order to guarantee their reliability. Failure can be detected immediately when inspecting severely impaired sensors, but hidden failures that gradually deteriorate the sensor's performance cannot be detected. Traditional maintenance methods are prone to unexpected downtime, excessive interaction time, frequent downtime, and high maintenance costs. Predictive maintenance methods can deal with hidden sensor failures in good time to discover them before they lead to a system failure. Therefore, predictive maintenance becomes important for the long-term stability and required performance of sensor systems.

3.2. Benefits of Predictive Maintenance in Autonomous Vehicles

According to the scenario of use of the autonomous vehicle, the sensor must be verified and calibrated frequently to obtain sufficient high-quality input data for the decision-making algorithm. The main methods of commercial verification and calibration include two-position method, blue-well method, and online-port method. The verification and calibration requirements of lidar and camera are the most stringent and most periodic. It often requires them to be checked every 1-2 weeks. If the problems are not discovered or rectified promptly during the use of the sensor, it poses a threat to the safety of the autonomous vehicle. The high-frequency verification and calibration also lead to high direct costs of the autonomous vehicle technology. In terms of reliability, the endurance and failure rates of commercially sensors are far from the target value of the autonomous vehicle traction. Due to the electro-optic-mechanical complexity, the sensor and photonic device systems can easily break down and have low durability, high-cost maintenance. With the deployment of autonomous vehicles in large numbers, these maintenance, repair and direct costs will continue to increase.

The autonomous vehicle is a complex system that integrates sensors, control systems, and backend controlling and data-analysis systems. Research results show that 80% of data and failure issues in autonomous vehicle systems are generated by vehicle sensors. The sensor system is the core component ensuring safe travel in autonomous vehicles and achieving environmental perception. The sensor system directly affects the autonomous vehicle's operating tasks, such as turning, stopping, and moving. Each sensor of the sensor system of the autonomous vehicle has its operating characteristics and may have different potential problems and risks. Autonomous vehicles need large amounts of high-quality data collected by sensitive and high-precision sensors during operating tasks to identify the stage environment and complete perception perfectly.

4. Artificial Intelligence in Predictive Maintenance

In Chapter 2, the traditional PSHA or predictive PM processes were described, and this was followed by the introduction of AI and the question of whether an AI-driven PM of sensor systems for the new generation of autonomous vehicles would improve the PSHA process. The conclusion was that AI-driven PM and PM should work towards the same common, accurate and precise PM objectives of predicting the RUL, failure rates, and the remaining useful performance of PSHA. It is noted that AI-driven PM of modern sensor systems should also prevent non-critical events from being mistaken as critical events. In this chapter, we will detail the use of AI in PM and different hybrid AI models towards realizing the future PSHA/PM process for sensor systems hosted on autonomous vehicles. Throughout the chapter, we refer only to PM models, but one must note that adaptation of these models to a predictive SHM is often seamless.

The first question we ask ourselves is what is AI-driven PM, and what is the link between AI-driven PM and predictive maintenance? One has to agree that with the advances in artificial intelligence techniques, the need for artificial intelligence (AI) in maintaining aircraft operation has become increasingly important. AI-driven PM is considered to offer an integrated approach towards the improved evolution and trust of these sensor systems for autonomous vehicles since AI-driven PM helps to prevent the costs due to accident or failure, in particular when used for systems of a critical nature. The new generation of aircraft will host many types of complex, autonomous, and systems of a critical nature that will depend on the information provided by sensors to function adequately. The sensor performance monitoring assurance process will be called Predictive Sensor Health Assurance (PSHA) process. This will allow the aircraft to function in an increasingly autonomous manner.

4.1. Machine Learning Algorithms for Predictive Maintenance

4.1.1 Statistical Models: The simpler form of predictive maintenance estimation is a rule-based algorithm. Different operational thresholds can be set for different sensors in the system, and an alarm is raised if the operating parameter crosses any threshold. The disadvantage of the rule-based algorithm is that both the damage signature and the damage events are known and defined. Statistical models or pattern-based classifiers identify normal operating conditions through data distribution and deviations from it. The majority of machine learning models revolve around this basic principle. The popular statistical methods used for modeling predictive maintenance problems include logistic regression, the Cox proportional hazards model, discriminant analysis, kernel density estimation, and kernel mean embedding. These methods are simple to implement, intuitive, and easy to interpret. However, these methods are dependent on the simplifying assumptions of the probability density function of the data and are less capable of capturing the true behavior of the system.

Many of the modern predictive maintenance systems rely on machine learning tools to monitor the health of equipment and forecast faults in the near future. The damage or deterioration of certain equipment is often manifested by changes in parameters that indicate the operation of the system. This provides an opportunity for data-based monitoring and prediction of the equipment's lifespan. The gathered sensor data can be used to train and test the fitness of different machine learning algorithms for future time predictions. Based on the nature of the signal, different types of classifiers and regressors can be used to monitor anomalies in the system's health. Machine learning models are increasingly being used in the field of predictive maintenance and are achieving successful results.

4.2. Deep Learning Techniques for Anomaly Detection

Deep learning has shown state-of-the-art performance in a number of different applications of AD, including AD of structures, e.g. for bridge monitoring, building monitoring, and wind turbine monitoring. Typically, the approach of cense focuses on convolutional neural networks (CNN), which learn to automatically detect useful patterns or features that are relevant for a specific prediction task. Note that even in the case of end-to-end learning, the quality of data still matters. Quality requirements may be reduced by concept transfer, consecutive retraining, or by consideration of further information from the supply environment. On the other hand, deep learning works for time series generated with very different measurement methods, including laser Doppler vibrometry for non-contact displacement measurement, eddy current for displacement measurement, and ultrasonic for a variety of non-destructive testing; these different methods offered solutions to widely different, yet very specific applications.

In the paper, we focus on deep learning networks. This is due to their ability to automatically learn features directly from the training data, which has been shown to yield enhanced performance for many tasks, including, but not limited to, image validation, natural language processing, and speech recognition. Moreover, hierarchical deep learning architecture allows for modeling complex patterns in the training dataset and helps achieve higher levels of permutation and invariance. Therefore, deep learning techniques are especially attractive for AD tasks, which in general require large amounts of atypical and rare anomaly data to account for the variety of possible situations that could be encountered during actual AD operation.

5. Case Studies and Applications

The sensory functionalities provided by AV sensor systems are at the core of enabling complete, real-time situational awareness of the dynamic vehicle-environment interaction.

The accurate prediction capabilities ahead of upcoming sensory conditions are essential for timely and risk-free vehicle response. Many AV sensor system modalities have been proposed and are being deployed to both detect events and make predictions. Regardless of its specific modalities, most AV sensor systems need to be frequently maintained, especially in harsh environments and under severe operational conditions. Periodic supervision requires repeated and costly driving scenarios to assure consistent levels of confidence in spatiotemporal prediction quality. Such an approach has an implication of delay in maintaining the operational capability of the AV sensor systems.

We elaborate on the deployment of our proposed millimeter wave (mmWave) radar predictive maintenance solution for autonomous vehicle (AV) sensor systems. We approach the concept of predicting wear and damage of radar sensors using the proposed sim-to-real domain adaptation and detail the enhanced unsupervised domain adaptation methodology. We deployed our algorithms on various scenarios, including real driving data, to showcase the robustness and limitations of our work. These case studies show that our solution is practical for both the real-life deployment of mmW sensors, and they serve as demonstrations for the community that sim2real can be effectively employed for pre-deployment stages of the algorithm in mmW sensor networks.

5.1. Real-World Implementations of AI-Driven Predictive Maintenance

The real-world implementations of PD have demonstrated that the proposed AI-driven PD approach can be applied to autonomous vehicle sensor systems to monitor, among others, the speed variability and distribution to detect internal gearbox issues, brake/shoe wear and brake lining wear, and to monitor power losses on the racks that hold the encoders. The potentially significant monetary advantages obtained from real-time fault detection/maintenance based on the same signal stream if increased with more use cases include vehicle performance degradation redundancy due to internal sensor error and sensor failure since the sensor subsystem and the steering system were investigated in full and compromised. The latter additionally demonstrates that PD simplifies early detection. Offline analysis is no longer required; sensor improvements using independent machine learning (ML) methods employed to enhance sensor interpretation, the latter allowing for less accurate and expensive sensor equipment due to the assurance of resolution increases over time.

Two real-world scenarios for PD have been designed, developed, deployed, and operated within autonomous vehicle sensor systems. The first system was developed as a demonstrator to determine the type and structure of PD to be implemented within future autonomous vehicle sensor systems. Even though this system was small in scale and based on commercially available low- to mid-range sensor systems and computing equipment, data was collected from ultrasonic range finders and tachometer sensors attached to two small electric vehicle demonstrators that were subjected to various regular and irregular mechanical impairments. Based on this benchmarking data, the first set of AI-driven PD techniques was developed and applied as part of a higher-level PD strategy in the real-world implementation developed for the second system that was fielded to collect data from high-end sensor systems and artificial intelligence for the automotive electronics conference hardware that were attached to a set of four 4x4 off-road vehicles developed and operated as highly complex autonomous agents in adverse environmental instances.

6. Challenges and Future Directions

Long out-of-the-box models' time prediction and dependence have been less noticed in existing automotive-specific application studies, probably partly because, in general, the maximum value can easily convey the urgency of replacement. Therefore, such a simple value-driven approach can provide some limited protection. However, to a surveillance team, knowing when it might go wrong quite reliably with a specific tolerance time will help them allocate manpower more efficiently and never skip replacing a module long past its EOL. People tend to be swayed by seemingly reliable equipment. This can increase false alarm costs and cause people to ignore malfunction alarms. Some specific details to be taken into account include the correlated sensor mode prediction model introduced in our detection system, performing analysis and revising the interactive prevention time, given the relative time between potential malfunction history and planned route, travel distance, or final destination, investigating the worst-case performance.

First, we discuss some of the existing challenges and possible future research directions of the topic presented in our paper. Extending this work to other sensor modalities will be one of the future development directions. Unlike cameras, LIDARs may not be widely used yet. Another interesting problem includes energy-efficient sensor scheduling and sensory redundancy (how many good-enough sensors in each modality are necessary) investigations.

Recent work on learning from simulation and adaptation to the real world, such as domain transfer learning, is popular. However, that has been somewhat limited to learning a robotic policy. It would be interesting to see learning for other types of modules. Furthermore, the majority of existing learned automotive chips are designed for object detection or tracking. It might be worth investing in coprocessor designs specializing in malfunction detection before they even affect the controller, whose size, cost, and design can be minimized without sacrificing their prediction performance.

6.1. Ethical Considerations in AI-Driven Maintenance

The promising "black-box" AI technique architecture, its tendency towards unexplainable decisions, and potential unforeseen future consequences can collectively create liability and safety concerns across so many applications of interest. Subsequently, unpredictable AI output may lead to significant harm, particularly when concerned with medical problems. The image recognition system's mistake to wrongly identify a light at an airport or a face recognition error to arrest the wrong person may result in significant human life loss, thus further constraining some possible applications of AI. Making great strides towards explainable and transparent reasoning techniques will not only increase confidence in the "black-box" AI methods but may also contribute to further overall improvement in their predictive performance.

As AI-driven predictive maintenance systems are expected to demonstrate some level of intelligence and perform functions similar to those of humans, it is important to consider trust as well as ethical considerations when developing such a system. The proposal of AIs replacing human experts will be met with skepticism, suspicion, and possibly fear in numerous applications. Any AI - even highly accurate - naturally carries an essential knowledge gap inherent in data interpretation and is subsequently accompanied by a level of uncertainty in legitimate predictions. The susceptibility of AIs to perturbations can make them challenging to tolerate within certain high-risk problems. The generally unobservable behavior of most AI methods only amplifies the information gap between decisions and their legitimate grounds and presents an extra obstacle facing AI-centered applications across many scientific areas.

7. Conclusion

Conclusion: There are many research hotspots about the condition-based prognostics and health management of different vehicle equipment and structures. It is not free to conduct the laboratory testing with a new sensor set. The laboratory testing for the field sensors' reuse is usually cheaper. If the laboratory setup is impermanent, sensors and sensor nodes installation and uninstallation cannot be time-consuming. The replacement of a temporary sensor connection part would be easier after the connection pins are broken. The objective of this paper is to resolve the difficulty of connecting different vehicle system sensors to the cost-effective signal receiver; in addition, we also hope to give a reliable predictive maintenance of the equipment (structure) as it reaches the deteriorated state. In this study, to quickly reconfigure the sensor installation for vehicle prognostics testing, we propose to: 1) use the driving control ECU signal for driving the vehicle front fan, and decompose the fan control input by vehicle sensor integration. With an artificial intelligence model, besides constructing the failed predictive maintenance AI model with the vehicle sensor setup, a laboratory test system implementation that may improve the vehicle fan (compressor) aging realization is also proposed. Both the optical and moisture absorption relay sensors in every testing point of the vehicle sensor setup are attached to the vehicle sensor mount. Alongside with the proposal, we developed the vehicle sensor setup for intensive prognosis of the vehicle fan (compressor) aging. We hope that the proposal may provide the electric commercial vehicles in field use guide notifications according to the vehicle performance (maintenance) results.

This research has achieved a platform ready for automotive equipment and structure integration for the easy assembly and disassembly of different vehicle systems. With the platform we created, the automotive vehicle heating and air conditioning system was installed and tested. The experimental results showed that the proposed prognostics and health management model can determine when and how for vehicle house air conditioning unit O&M, resulting in cost saving and vehicle guide over vehicle life cycle management. The intelligent building service equipment industry may also benefit from our proposal, especially for in field case device unit reuse. We also propose the AI-driven sensor driven reutilization of laboratorial predictive maintenance testing setup.

We may conclude that sensor system reuse for the prognostics and health management of different vehicle components and device units of an automotive platform is one promising research direction. Another research trend that the need determination model we proposed may advance is the holistic health and longevity management of a vehicle. In addition to sensor system development and reutilization, replacing old vehicle components and device units with new ones is the typical approach to improve the vehicle conditions. However, old is not necessarily always deteriorated, while new is usually expensive. First of all, old and new vehicle equipment/structure decompositions should be prioritized. The ones in the good, poor, bad, unreliable, unpredictable, weak, and harmful conditions of the vehicle health and longevity index are further ranked. Prioritization and ranking help the industry to manage the vehicle life limits, as well as plan the purchase and replacement schedules more accurately and reasonably.

7.1. Summary of Key Findings

These structural innovations will be influential predictors for other AI models that are embedded directly in individual sensor systems.

Classic predictive maintenance models assume a univariate signal which has been adequately thresholded to be on or off at particular moments, and those moments are used to train and validate error prediction and failure classification models. We enhance this basic structure with ANNs that learn directly from the multivariate construction of the system's operating moments in standardized and non-standardized data formats, and give a descriptive multivariate probability output as a result.

This study leverages the unique temporal aspect of sensor system lifespans to consider how embedding AI models directly into a device's data management structure can provide wide-ranging, real-time benefits, and sets the foundation for developing and evaluating additional on-sensor system AI implementations.

While this study looks at the sensor systems of autonomous vehicles, it also provides a guide for future work on other, similar kinds of smaller-scale integrated circuits that are subject to high-temporal performance requirements.

Today's operational autonomous vehicles use ever-evolving sensor systems which work under assorted and challenging circumstances. At the same time, ensuring that these systems work optimally and detecting errors or imminent failure are essential, and findings about these predictive maintenance issues can help current autonomous vehicle output and future design.

7.2. Implications for the Future of Autonomous Vehicles

Both the sensor hardware itself and 3D point cloud image generation algorithms essentially work as a deep-floor vehicle grid system when LiDAR is used by an autonomous vehicle. Nowadays, machine learning-driven object recognition and scene segmentation offer tremendous opportunities and challenges for the design of autonomous vehicle sensor system and sensor fusion circuitry for efficient real-time traffic and road safety assessment. This provides a myriad of potentially vulnerable points and openings for the enemies or adversaries to launch cyber and physical attacks. The adversarial attacks could root an unexpected negative effect and economic-hitting capability which is not yet well addressed thus far. Mathematically, the discovery of the information gaps between erroneous and benign observations can help vulnerability assessments, risk predictions, security control decisions, and security enhancement in various real-world applications.

In this work, the autonomous vehicle (AV) sensor system of interest consisted of a car-mounted LiDAR and an array of typical perception computer vision sensors (RGB and monochrome cameras). The sensor fusion algorithms are used to produce valuable and discriminative information about the vehicle's local surroundings by integrating multiple sensory information. This is one of the vital components of the Vehicle-to-Everything (V2X) cooperative safety applications in improving traffic and road safety. The benefit of performing the predictive maintenance on the sensor fusion algorithm ensures non-interrupted real-time cyber functionalities of the AV sensor system. This study demonstrated that both high-dimensional sensor raw waveforms and the fused features coined meaningful insights and clues for the predictive maintenance of sensing architecture of an adversarial autonomous vehicle. Empirical outcomes of the validation based on the results of running simulations on the real-time AV cyber-physical systems further boosted confidence in the robustness and adaptability of the intelligent online and autonomous predictive maintenance scheme.

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