Predictive Maintenance for Autonomous Vehicle Sensors

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1. Introduction

Autonomous vehicle sensors are becoming more advanced with each vehicle model. Not only that, but sensor numbers are growing at an exponential rate: there are approximately 22 sensors per SAE L2 vehicle and approximately 29 per SAE L4 full automation vehicle, with further expected increases projected for the future. Therefore, manufacturers must employ an advanced maintenance schedule to ensure vehicle safety and driving performance. Unfortunately, current maintenance strategies such as 'replacing parts when they fail' fall behind other machine learning or artificial intelligence strategy-based approaches because modern sensor-cockpit interfaces prevent meaningful data flow to either a Condition Monitoring System or the cloud. This paper will examine and improve upon the latest predictive maintenance algorithm, residual signal, for use with autonomous vehicles.

Autonomous vehicle sensor systems are compounding in complexity, making individual sensor reliability much more important. Advanced Driver Assistance Systems must also have a 99-percent reliability rate to achieve the safety improvements that are predicted. Autonomous Vehicle-Car2X sensors must be able to transmit information quickly and effectively to prevent vehicle damage in low-visibility circumstances. This makes predictively maintaining these sensors vital to vehicles and the roads. Dense sensor systems are becoming necessary to transport passengers and drive goods. With improvements in technology, problems that arise throughout a system must be corrected as soon as possible to maintain safety. Having a resilient preventative maintenance strategy in place can drastically reduce the amount of vehicle downtime. Some logistics companies have autonomous vehicles in operation, where routes are dictated daily to their perception systems. If a vehicle should fail, route assignments are less reliable because they cannot begin to repair the vehicle until it returns.

2. Autonomous Vehicle Sensor Technology Overview

Automated driving is made possible by advancements in sensor technology, one of the cornerstones of which is a collection of sensor technologies. Sensors can include radar, lidar, cameras, and ultrasonic sensors. These sensors can be used in a complementary way, with some operating over long distances to detect large objects, such as other road users, and others operating at a near range to confirm the distance from a car at a stop sign. In recent years, each technology has quickly advanced to a point that radar, lidar, cameras, and ultrasonic sensors are now affordable and capable of producing large amounts of data quickly to both understand and interact with the environment in a way that autonomously controls the vehicle to achieve a result. In the automotive industry, sensors, such as radar, are used to understand the vehicles around you. Cameras help to identify both road signs and lane lines, and lidar informs where a road is. None of these technologies on their own are able to fully autonomously drive the vehicle, but when combined, they provide enough redundancy that level 5 autonomy is achievable by a combined sensor approach.

Radar, lidar, cameras, and ultrasonic sensors are crucial to the main operating function of autonomous vehicles: the perception, navigation, and decision-making involved in being able to operate on the road autonomously. Lidars are pulsed laser sensors that work three-dimensionally around the vehicle. Cameras take video frames in two dimensions and convert them into a three-dimensional world using software. Ultrasonic sensors can also be used to measure angular scans and help to assess close range, such as in a parking lot. In addition to being used in automotive vehicles, lidar is essential for yard trucks, object perimeter detection, and automated doors. Laser sensors can have multiple purposes in deployment. While sensor selection and system design can vary by deployment purpose, it is the purpose of the sensor that is of utmost importance when it comes to predictive maintenance. Cameras are also important in many contexts. Automatic infrared cameras are important in automotive operation, general infrared cameras for events, and also visible spectrum cameras. Cameras can provide details of color and brightness that many other sensors cannot, and the value of having visible spectrum cameras, such as the backup camera, becomes increasingly apparent in visual representation generated by a subject familiar with the task, such as a vehicle driver. Mimicking human observation is one of many reasons to incorporate camera technology into sensor deployment. An integration of all these sensors allows for sensor fusion collaboration. Environmental factors such as humidity, fog, dust, and sun may have a direct effect on optoelectronic device performance in an external environment. To properly maintain these autonomous systems, it is important to study sensor technology. The four sections integrate the concept of sensor technology with actual vehicles to provide a systems approach to sensor maintenance.

3. Challenges in Sensor Maintenance for Autonomous Vehicles

There are several challenges associated with the maintenance of sensors in autonomous vehicles. Many mechanical parts of these sensors are in constant motion and may be subject to aggressive wear and environmental conditions. The severe conditions of vehicle operation also lead to significant electromagnetic stresses and vibrations, as well as the wide temperature fluctuations generally encountered in an automotive environment. The fast improvement of cyber-physical systems technology renders existing sensors technologically obsolete after a few years, and this affects modern autonomous vehicles covered by a 15-20 year business case. Wear and eventual breakage diminish the accuracy and lifespan of a sensor. With the increasing complexity of such systems combining several interconnected sensor systems, a straightforward dimensioning of maintenance efforts is increasingly complicated to set up. The different positioning and characteristics of such features can affect the effectiveness of the various resulting maintenance methodologies. Issues to consider include the controlled nature of maintenance efforts, which may be either costly or insufficiently effective if not adapted to the actual use-evolution state. Sensor use and degradation depend, among other things, on the vehicle workload, diversity in environment, and, in some cases, accidents. This makes the maintenance of these more dynamic sensors a challenging problem to tackle. Ignoring those specificities, which affect various vehicles in different combinations, neglects opportunities for improvement in operational risk reduction. The first step for patrols in an industrial context is also to survey the assets and grasp the possibly recurring issues.

3.1. Traditional Maintenance Approaches

Autonomous Vehicle Sensor Maintenance Strategies

The task of autonomous vehicle sensor maintenance has not received much study to date. The available literature in the automotive domain has principally concentrated on the immediate development of reliable sensors and their installation on a vehicle. Overall maintenance, as mandatory for any system, is missing from the discussion.

Work on sensor maintenance in the automotive domain is still motivated by the work done in the maintenance community in the absence of smart sensors. As in any physical world system, the sensors used in the automotive field are maintained through some combination of the following approaches:

1) Routine inspection: Inspections of the sensors are carried out at regular intervals and are based on a fixed schedule or on safety regulations. 2) Scheduled replacement: More advanced than routine inspections, this approach depends on a planned replacement schedule of the sensors. 3) Breakdown maintenance: Under this approach, the sensors are run until failure, and once failed, they are repaired and replaced immediately.

Using the above-mentioned approaches has many advantages, and they have been used for centuries. They are easy to implement, and their working is simple to understand. Widespread dependency on these results has also been experienced. Due to the short technological development cycle and product complexity, these procedures are not sufficient for contemporary and upcoming production and large-scale integration. It is necessary for any manufacturing activity or business to attain a particular level of expertise or knowledge of state-of-the-art technologies to remain competitive. With respect to the increasing complexity of the systems, the reliable functioning of their constituent components is essential. The maintenance of sensors or low-level systems like robots is usually technologically dependent. A level of knowledge is necessary to manage and maintain them. In the extremely advanced realm of self-sufficient systems, there is an escalating call for an automated prognosis and maintenance for each of its constituents. For guaranteeing that AIV sensors perform appropriately, sensor maintenance is essential. The increasing number of sensors and the reduction in sensor dimensions in the AIV implies reliance, and encompassing sensor maintenance is a duty-bound responsibility. As regards these contentions, one can substantiate that sensor maintenance is an unavoidable duty.

4. AI and Machine Learning in Predictive Maintenance

AI and machine learning (ML) technologies are upending predictive maintenance as part of a drive towards enhanced safety, particularly for autonomous vehicle sensors. In modern predictive maintenance systems, the AI (or ML) algorithms analyze historical data of the system and predict when a failure might occur. In the context of a wireless sensor, predictive maintenance algorithms can predict when a sensor might fail so that it can be replaced or repaired before a failure occurs. Predictive maintenance algorithms can be more accurate than their rule-based counterparts and can help cut down on maintenance costs by postponing maintenance activities as long as possible to increase sensor lifetime. One of the strengths of advanced AI techniques is that they can continuously learn as the system changes over time. In sensor networks, system conditions can change due to the environment, installation conditions, and sensor-specific performance drifts. Unfortunately, there is an ever-increasing number of AI/ML algorithms that one can employ to carry out predictive maintenance, which can often be overwhelming. AI/ML models are known to be sensitive to the data on which they are trained, and therefore have a potential generalization risk. The predictive maintenance model may not work when there is drift in the operating conditions and therefore requires constant monitoring to improve its accuracy and generalizability. Being able to perform some basic sensor diagnostics so that they can be replaced before they fail will be particularly beneficial in safety-critical sensors, such as those found in an autonomous vehicle. In modern predictive maintenance frameworks, ML/AI is one of the main engines for problem diagnosis that will work in combination with rule-based systems.

4.1. Data Collection and Preprocessing

Modern predictive maintenance leverages artificial intelligence and machine learning algorithms to forecast potential sensor failures ahead of time, informing maintenance activities and preventing unplanned vehicle downtime. Hence, the cornerstone of any predictive maintenance project is the data. Without quality data, no predictive model can provide accurate forecasts, and no informed sensor maintenance decision can be made. In general, predictive maintenance uses three types of data sources. Firstly, real-time and raw sensor data to understand the current operational state. Secondly, historical operational data and sensor performance metrics to understand past predictions and maintainability. The third data type encompasses environmental conditions influencing sensor maintenance and usage.

Before predictive maintenance can be employed in an operational setting, raw data are first preprocessed. The first step of data preprocessing is data handling. Cleaning, for example, replaces or removes corrupt or incomplete data fields. In the process of data normalization, data are transformed. All data present in a data stream have values constrained to a minimum and maximum. Normalization calculates all values in the data stream relative to these extremes. The removal of noise-enriched or low-variation input data is a primary example of data enhancement. In general, iterative data enhancement increases the reliability and robustness of predictive models. Due to the iterative approach, data quality guarantees efficient predictive maintenance and the systems it supports. Finally, data quality is ensured by tools and frameworks. Automated quality acceptance mechanisms secure the persisted data as long as it adheres to defined schemas while guaranteeing characteristics such as format compliance and data typing. This, in turn, ensures data used for analysis is high-level.

5. Case Studies and Applications

Sensor manufacturers and OEMs are implementing predictive maintenance (PdM) solutions to enhance the reliability of their sensors for autonomous vehicle applications. For advanced driver-assistance systems, such as lidar, millimeter radar, camera, or ultrasonic, OEMs predict the onset of failure and mitigate beforehand the impact of potential downtime of these sensors. The identified strategies being pursued are generally of two types: using spare capacity in redundant sensors in the case of multiple sensors being present in the vehicle, or employing a PdM schedule in advance of vehicle operation. Key technologies in use to implement a predictive health monitoring strategy are updated.

Case Study 1: Autonomous Systems Use Dual Lidar Receivers as a Form of Predictive Maintenance: An automotive sensor develops a new receiver that has two LiDAR drivers. The drivers send the laser beams, and the receiver captures the light that is reflected off of objects or the environment. This creates a virtual fingerprint, and by observing changes in the fingerprint over time, the automotive sensor can predict when the motor used in the LiDAR will need maintenance. The second LiDAR path creates a true environment image that can be used to compare to the LiDAR path and look for matching patterns. This system can also serve as a redundancy test where the two fingerprint images can be compared together. If the two fingerprint images match, the system knows that it has not failed, as it is capturing the correct amount of reflected light. If the two images do not match, the motor used in the LiDAR sensor has failed, and a system warning is displayed.

Practical lessons learned and best practices: (1) The PdM solution integrates predictive health monitoring with fault management; (2) The maintenance approach may depend on a Single-Fail-Functional-Path configuration or Multiple-Fail-Functional-Path; (3) In every case, the availability of spare functional paths is used to determine maintenance actions; and (4) A complete description of the practical best practice application, including its robustness, will lead to a professional audience better understanding when and how to apply the best practices of advanced system integration and maintenance. Many of the case studies presented here explore the commercial or technical/technological applications of networked and autonomous systems. These case studies are intended to address the trade-offs associated with moving to increasingly advanced and autonomous systems solutions. Rapid advancements in technology continue to gradually shift maintenance strategies from operation-based to condition-based and from condition-based to predictive/proactive in line with the changing characteristics of the technologies used.

5.1. Real-world Implementations of Predictive Maintenance

In a shift from the aforementioned reasoning, predictive maintenance techniques have been employed in a variety of real-world applications for condition monitoring sensors in autonomous vehicles. The results of such implementations have led to marked improvements in sensor performance, reduced maintenance times and costs, as well as increased safety scores compared to prescriptive maintenance methods. The efforts exerted in these approaches, the state-of-the-art techniques implemented, as well as an overview of these case studies are outlined below. An overview of predictive maintenance techniques as utilized for each application is also covered, displaying how the objectives of this work have been achieved in the real world. Successes and challenges associated with these techniques are further discussed to provide a balanced view of the facility of predictive maintenance as well as acknowledge potential drawbacks and difficulties that may be associated with implementing proactive maintenance techniques.

6. Future Directions and Conclusion

The overly complicated electronic systems of autonomous vehicles have pushed scientific research more toward preventive and predictive maintenance strategies. In the future, predictive maintenance can be integrated with these ongoing technologies, such as IoT and cloud computing, to provide a more predictive analysis result that can be used to predict component failures more intelligently. This integrated data process can assist autonomous vehicle maintenance personnel in various ways, allowing for increased data quality and quantity. In addition, several challenges are identified that are associated with the implementation of predictive maintenance, such as the lack of standards and/or regulations on sensor maintenance tools, problems with adoption, and changes in working patterns. Ultimately, successful and widespread predictive maintenance can be integrated to prevent interruptions and maintenance time, which will improve autonomous vehicle efficiency and safety.

In the future, the implementation of autonomous vehicles will impact human society considerably. In general, having the latest technology and intelligence capabilities to maintain the vehicle's reliability and safety is an investment that also has a tangible contribution. Generally, this research aims to employ predictive maintenance to produce more comfortable and smarter maintenance sensor technologies in cars connected to the internet. This reflects the need to do further R&D to consider the integration of predictive maintenance with the current technology, in line with the current momentum in scientific research, which is towards accurate maintenance. The predictive maintenance system can greatly help stakeholders solve problems related to the quality of the data generated by autonomously performing various intelligent processes.

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