Al-based Signal Integrity Monitoring for Integrated Vehicle Health Management

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Abstract
As vehicle warranty claims, recalls, and maintenance costs continue to grow, new methods are needed to predict, detect, and diagnose vehicle health issues. By integrating artificial intelligence (AI) technology into the vehicle’s embedded electronics, automakers and fleet owners can benefit from highly effective and adaptable vehicle health management capabilities that are not available today. This paper will describe how embedded AI-based Signal Integrity Monitoring can be used to detect complex anomalous patterns and provide signal fault isolation. It will also describe how unsupervised deep learning technology can simplify the data collection and labeling process that is needed to train the AI-based VHM models.

Introduction
The increasing complexity of vehicle electronics and software is bringing an abundance of vehicle health related challenges including quality issues and increasing costs of warranty claims, recalls, fleet maintenance, and fleet downtime [1]. This negatively impacts both OEM and fleet profitability, user experience, and end customer costs. In order to reduce OEM costs and the total cost of ownership (TCO) for consumers and fleets, new methods are needed to detect, predict, and diagnose vehicle health issues.

Existing vehicle health management solutions rely on diagnostics trouble codes (DTCs) and limited amounts of telematics data. These solutions can detect known failure modes using hard-coded signal behavior validation rules that are frequently based on thresholds. They also provide alerts based on pre-defined error codes. However, they are unable to detect and diagnose unforeseen failure modes that do not have hard-coded rules, nor can they prognose future vehicle health issues. By using deep learning technology to analyze the thousands of parameters that are available onboard the vehicle in real-time, AI-based
Integrated Vehicle Health Management (IVHM) solutions can not only predict vehicle health issues, but also estimate the remaining useful life of components, detect performance degradation, and determine the root cause of problems.

By integrating AI-based Signal Integrity Monitoring into embedded vehicle electronics, automakers and fleet owners can provide:

- Early indicators of known faults before a Diagnostic Trouble Code (DTC) is triggered
- Detection of system-level faults that do not have DTCs
- Detection of complex fault patterns that are difficult to define explicitly
- Root cause analysis of DTCs using signal fault isolation
- Reduced No-Trouble-Found cases by correlating DTCs to anomalies
- Reduced repair time with enhanced diagnostics report

**Integrating AI into Vehicle Electronics**

AI-based applications are frequently implemented as a pipeline of AI algorithms and models that are designed in serial and/or parallel signal paths. These pipelines can include deep learning algorithms, and they can be trained to analyze very complex data and identify patterns, features, anomalies, or other types of valuable information. One of the advantages of deep learning is that it can analyze very large amounts of complex data that cannot be effectively analyzed using traditional signal processing methods.

For Vehicle Health Management (VHM) applications, deep learning pipelines are very effective at analyzing the behavior of complex vehicle systems. By monitoring multiple signals in real time, these deep learning pipelines can provide valuable prognostic and predictive insights about the vehicle’s health and avoid the need to upload mass data to the cloud. But in order to do this, the pipelines need to be integrated into the vehicle electronics, where they can readily access all of the relevant signals and parameters.

Fig. 1 illustrates a potential AI-based IVHM implementation in an automotive high-performance computer (HPC), such as a Central Gateway Module, Domain Controller, or Advanced Aftermarket Telematics device. In this example, the VHM Edge Service Application runs as an Adaptive AUTOSAR or Linux application and it includes the edge runtime functionality to process the data. The edge runtime supports one or more AI pipelines that provide Health Indictor outputs. Input data can be provided to the VHM Edge...
Service Application, and the Health Information is sent back to the customer application using the ARA interface. Alternatively, results can also be sent using other IP based APIs.

![Image of AI-based IVHM in an Automotive High-Performance Computer](https://doi.org/10.51202/9783181023846-143)

Fig. 1: AI-based IVHM in an Automotive High-Performance Computer

**Signal Integrity Monitoring**

Signal Integrity Monitoring (SIM) is a powerful anomaly detection pipeline that monitors a group of vehicle signals and detects complex anomalous patterns and isolates signal faults. The inputs to the SIM pipeline can include sensor signals and parameters delivered through CAN bus messages, Automotive Ethernet data, or other vehicle networks/APIs. The outputs from the SIM pipeline consist of a Health Indicator, a Change Event Indicator, and a Diagnostic Vector.

As shown in Fig. 2, the Health Indicator and Change Event Indicator are calculated by the SIM pipeline’s Scoring and Decision Models block. The Health Indicator provides a score for the anomaly level of the system that is being monitored. The Health Indicator is a single score that is correlated with all of the input signals and varies in real time as the monitored system’s conditions change. Because it provides a single health score, development engineers will typically design multiple monitors using different sets of input signals in order to monitor various systems or multiple aspects of the same system.
The Change Event Indicator monitors the Health Indicator and provides the time at which it changes from a normal health score to an abnormal health score. It enables the engineer or technician to know exactly when the vehicle’s health condition changed.

The third SIM pipeline output is a Diagnostic Vector that can be used for root cause analysis. By using Explainable AI techniques, the SIM pipeline calculates causality metrics that help explain the results of the deep learning algorithms, which are typically seen as an inescapable black box [2, 3]. The Explainer Models block in Fig. 2 analyzes the causalities and relationships between the different input signals. Based on that analysis, it then creates the Diagnostic Vector, which is a set of input signal weights. If an anomaly is detected, then the Diagnostic Vector will show the correlation of each signal to the anomaly. This information can then be used to determine the root cause of the vehicle’s health issue.

One of the key features of the SIM pipeline is that it uses an autoencoder type of neural network, which can be designed very efficiently and trained in an unsupervised manner [4]. By using unsupervised training, the entire pipeline can be trained using "normal" vehicle data. This means that the SIM pipeline is trained only using data from a healthy vehicle. This greatly simplifies the data collection process and automates the training process, since it
eliminates the need for development engineers to intentionally degrade the vehicle’s performance in order to collect training data with anomalies.

The SIM pipeline must be trained using very large amounts of complex data, so called big data. This can be done most effectively by using distributed computing in the cloud. To support the big data training requirements for these deep learning algorithms, an automated cloud-based training tool, such as SafeRide’s vInsight™ Developer, needs to be utilized.

**Results**

Fig. 3 shows the SIM pipeline Health Indicator outputs for a Fuel Efficiency Monitor that was developed using SafeRide’s vInsight™ Vehicle Health Management platform [5]. The Fuel Efficiency Monitor was developed and trained to detect anomalous engine conditions that can lead to sub-optimal fuel consumption using the cloud-based vInsight™ Developer tool. It was then optimized for implementation in an automotive HPC and downloaded to the vInsight™ Edge embedded runtime engine.

In this example, 14 signals were identified and collected from an Iveco Daily light commercial van with a 2.3L gasoline engine. Using unsupervised deep learning technology, the Fuel Efficiency Monitor was trained with normal vehicle data. The trained Fuel Efficiency Monitor was then tested by introducing four malfunctions that degraded the performance of the engine. The malfunctions were each introduced separately and consisted of an injector leak, an injector malfunction, an intake manifold leak, and a blocked air filter.
As shown in Fig. 3, the Health Indicator showed a clear differentiation between the test vehicle’s normal behavior and its anomalous behavior during the tests. During the injector malfunction, intake manifold leak, and blocked air filter tests, there was distinct separation between the health scores with normal components versus those with malfunctioning components. And although there was an overlap of the health scores during the injector leak test, the leaky injector resulted in anomalous health scores over 80 percent of the time.

It should be noted that during the injector leak, intake manifold leak, and blocked air filter tests, the engine controller did not trigger a DTC, and the check engine lamp was not illuminated. If left uncorrected, these issues would result in increased fuel consumption, cause more pollutants to be emitted into the environment, and potentially damage the vehicle’s engine. However, by integrating a SIM pipeline into the embedded vehicle electronics, the degradation in the engine’s performance was detected by the Fuel Efficiency Monitor before any of the malfunctions became a serious health issue.

**Conclusion**

In order to detect vehicle performance degradation and predict future health issues, AI-based vehicle health management solutions must be integrated into the vehicle’s embedded electronics, where they can access large amounts of vehicle data in real time. An advanced anomaly detection pipeline that uses an autoencoder type of neural network, such as SIM, is
an effective method for providing these advanced capabilities. By using unsupervised deep learning technology, the data collection process can be simplified, and the neural network training can be automated. In addition, the SIM pipeline can learn and adapt to vehicle aging and wear throughout the vehicle’s lifecycle. Diagnostic capabilities can be further enhanced by using a Change Event Indicator to determine the timing of the vehicle health issue and by using a Diagnostic Vector to help determine its root cause.

References


