



Integration of Multi-Gaussian fitting and LSTM neural networks for health monitoring of an automotive suspension component

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ABSTRACT

For mechanical structures under harsh operational conditions, a structural health monitoring method is a promising tool to reduce safety risk and maintenance costs. With the rapid development of advanced sensing and data analysis techniques, a massive research effort has been performed to monitor structural health from vibration signals. However, practical engineering components usually have nonlinear dynamic characteristics and high volume of measured data. Therefore, applying a health monitoring system to an actual project is far from an easy work. Based on the recent field studies, a novel method is proposed to achieve a trade-off between prediction accuracy and computation efficiency. In this method, we integrate a multi-Gaussian fitting feature extraction method and an LSTM-based damage identification method to develop a health monitoring system with available vibration signals. Through the proposed method named GaPSD/LSTM, frequency-domain features from sequential vibration signals are firstly extracted by multi-Gaussian fitting of power spectral density (PSD) curve. Then, a long short-term memory (LSTM) neural network is used to predict partial damage level. The proposed GaPSD/LSTM is validated by automotive suspension durability tests. The experimental results prove that the proposed method can significantly reduce computation time in the condition of achieving great prediction accuracy, compared with several state-of-the-art baseline methods.

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1. Introduction

A suspension component is one of the most important automotive components, which transfers all forces and moments between the automotive body and wheels. Under tough driving conditions, it exposes to harsh loads conditions and easily suffers from fatigue damage. To reduce safety risk and maintenance costs of an automotive suspension component, a crucial problem is to identify damage and predict remaining useful life in real-time when the suspension component is under real driving conditions. Therefore, it has attracted increasing attentions to develop an applicative health monitoring system for an automotive suspension component [1–3].

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The methodologies behind existing structural health monitoring systems can be divided into two categories: physics-based and data-driven models [4–6]. Physics-based models utilize domain knowledge of physical models, which is a mathematical representation of the degradation processes or knowledge-based model describing the change of observed parameters under different damage stages. These models are objective in the interpretation of their results and able to achieve effective results, if a correct model has been built. However, several obvious disadvantages of physics-based models make them be not feasible for complex structures. Firstly, an accurate and explicit physical model is often unavailable in monitoring health status of complex structures, due to the non-linear dynamics, complex operation conditions and large size of the measured data sets. Therefore, the physics-based models would cause low performance in real applications. Secondly, even when the physical model is achieved, it can be only applied to a specific case. Consequently, physics-based models tend to be used in simple structures, for well-understood damage status. Compared to physics-based models, data-driven models can achieve representation learning from historical sensory data without expert knowledge. In addition, the development of advanced computing methods facilitates the improvement of data-driven models at modelling complex nonlinearity and dynamics from large volume of data sets. Therefore, data-driven models provide an effective and efficient way to monitor structural health status and are more promising to become a general health monitoring platform. According to the statement mentioned above, the work focuses on a data-driven framework. A data-driven health monitoring system involves multi-disciplinary technologies, consisting of three steps: data acquisition, feature extraction and data analysis [7,8].

The work aims to develop an applicative health monitoring system for an automotive suspension component based on a data-driven framework. The system is designed to monitor structural health status in real-time by analyzing the measured data from available vibration signals. To be specific, 'available' means that the signals are measured by widely used sensors in series-production cars, including accelerometer, gyrometer and linear variable displacement transducer.

As real driving conditions of series-production cars are extremely complex, the health monitoring system needs to process huge information [9]. Moreover, due to complicated automotive structures, the system has to deal with high nonlinearity and dynamics [10]. These two problems widely exist in developing structural health monitoring system for complex engineering structures [11–13]. To address them, there is a stringent need for a health monitoring method that can achieve a trade-off between prediction accuracy and computation time.

In the process of developing a data-driven health monitoring system, two major tasks have to be solved for improving prediction accuracy and computation efficiency: proper feature extraction from large-scale sensory data and an accurate data analysis model.

With regard to feature extraction, currently many signal processing technologies are applied to extract features in engineering applications. They can be divided into two major categories: frequency-domain and time-domain. The core of frequency-domain technologies lies in extracting frequency-domain features of sequential signals. In Refs. [14–17], frequency-domain features are obtained in the form of local information of power spectrum density (PSD) curve. In Refs. [18–22], they are in the form of statistical features of PSD curve, such as spectrum moments, spectrum kurtosis or power spectrum entropy. For time-domain technologies, the extracted features are in a sequential form, such as time-domain statistical features (maximum and mean values) [23], the automatic extracted features from raw sensory data by convolutional neural networks (CNN) model [24–32] or the raw sensory data [9,33,34]. Other signal processing technologies with little practical application have not been discussed in the work, such as time frequency feature [35] and prelockup feature [36]. Among these feature extraction technologies, time-domain statistical features technologies reflect least information of sensory data, unable to achieve good performance. The feature extraction technology based on a CNN model is the state-of-the-art to our knowledge. However, as output information from CNN model is full of uncertainty and the original research subjects of CNN model are image and speech recognition [37], this technology may cause instability and large number of iterations in the data analysis step. Compared with CNN-based technologies, current frequency-domain technologies are less informative; however, they have great advantages in reducing computation time. For data-driven health monitoring system, which processes raw sensory data directly, usually employs a nonlinear filter method to identify structural health status for low computation time. As nonlinear filter methods heavily depend on expert knowledge of structural nonlinearity and are unable to capture long-term dependencies, they show poor prediction accuracy for complicated mechanical structure.

With regard to a data analysis model, the state-of-the-art sequential data processing model named long short-term memory (LSTM) neural network has shown high ability in addressing large-scale sequential data. It has been successfully applied in various engineering fields, including language process [38,39], traffic forecast [40,41], power data classification [42] and actual tool wear of milling machine [23]. In the above studies, LSTM outperforms traditional data analysis models including Kalman filter (KF), support vector regression (SVR), multi-layer perceptions (MLP), radial basis function neural network (RBF) and basic recurrent neural network (RNN). The great performance of LSTM neural network in these studies suggests that this advanced machine learning approach is suitable for health monitoring of an automotive suspension component.

The work is motivated by two requirements of structural health monitoring: high prediction accuracy and low computation time. To achieve these goals, a novel method is proposed to develop a health monitoring system, integrating a multi-Gaussian fitting feature extraction method with an LSTM-based damage identification method. Firstly, a multi-Gaussian fitting method is devised to obtain comprehensive frequency-domain information of each sub-sequence of the available vibration signals. This method can capture representative information from the available vibration signals and reduce the input data size of the following data analysis model. Subsequently, an LSTM neural network is applied to capture nonlinear relationship between the sequential frequency-domain features and partial damage level, and predict real-time damage level

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