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A New Machine Learning Method for Ball Bearing Condition Monitoring Based on Vibration Analysis

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ABSTRACT: In recent years, with the advent of the Fourth Industrial Revolution concepts and the development of artificial intelligence technologies, new approaches such as the digital twin have been introduced. In a digital twin, a virtual counterpart of the physical system during its whole life is created, with abilities such as analyzing, evaluating, optimizing, and predicting. The first step in creating a digital twin model is to construct a (multi) digital health indicator that describes different aspects of the physical component state during the whole life of the component. In this research, a new method for constructing health indicators based on vibration measurement and a deep learning model has been introduced. For this purpose, the Continuous Wavelet Transform was used to convert the raw vibration signals into two-dimension images; Then, the deep learning model was used to extract features from the images and the health indicator is constructed based on the differences of the images in normal and failure stages. In this article, various Autoencoder architectures are discussed, and it is demonstrated that the Convolutional Autoencoder has better performance in terms of detecting incipient faults. The performance of the proposed model is evaluated by the vibration data of the bearing, and the constructed health indicator exhibited a monotonically increasing degradation trend and had good performance in terms of detecting incipient faults.

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1- Introduction

Performance degradation is an inevitable part of each asset that can lead to machinery damage, severe financial losses, or even personal injury. In order to prevent or eliminate the failure of the asset, condition monitoring methods have been developed. Condition monitoring methods are mainly categorized in run-to-failure maintenance, preventive maintenance, and predictive maintenance. Among these approaches, predictive maintenance provides better reliability [1]. The first step in predictive maintenance implementation is to construct a (multi) health indicator that describes different aspects of the physical component state during the whole life of the component. This health indicator should represent the deviation between the initial conditions of the component and its actual conditions during its lifetime [2]. constructing a health indicator can be performed in three steps: (1) signal acquisition; (2) signal processing; and (3) feature extraction [3]. Vibration measurement provides a very efficient way of monitoring the dynamic conditions of a machine. Traditional analysis method of the vibration data such as fast Fourier transform, Wavelet transform have two deficiencies: (1) Feature selection is heavily dependent on prior knowledge and diagnostic expertise. Moreover, it often focuses on a specific fault type, thus it may be unsuitable for other faults. (2) In real industries, acquired signals are usually exposed to environmental noises, and are transient and non-stationary [4]. As a step toward the development of a single framework for system health management, this paper proposes a method to construct a health indicator from the vibrational signal, based on unsupervised deep learning. This method establishes an online construction of a health indicator in the sense that the input data can be acquisitioned while the equipment is being exploited. The proposed method is applicable for equipment that operates under stationary and non-stationary conditions and does not require expert knowledge.

2- Methodology

In order to construct the health indicator automatically, a method based on deep learning algorithm is proposed in this study. For this purpose, the image of Continuous Wavelet Transform (CWT) of the raw vibrational signal of the ball bearing are used as the deep learning model input. The method consists of three main stages. In the first stage, the healthy vibrational signal from the ball bearing is acquired. The CWT image of the healthy vibrational signal of the ball bearing is used as the training repository for deep learning model. In this

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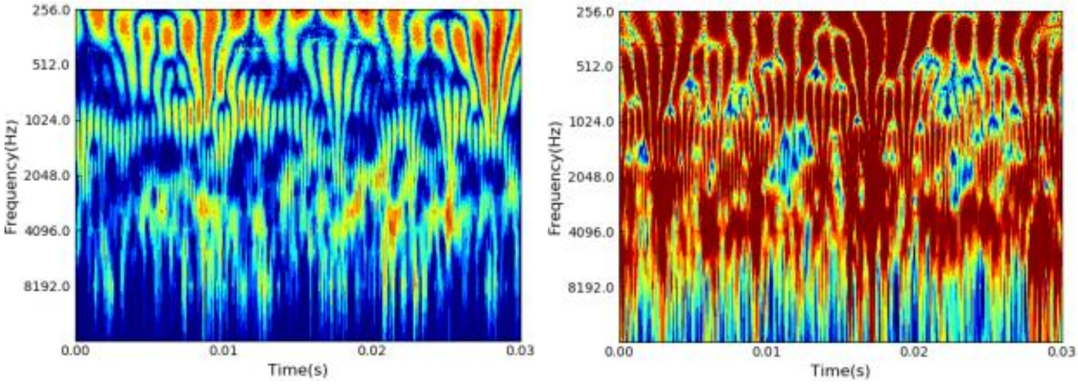

(a) (b)

Fig. 1. (a) CWT image of healthy stage, (b) CWT image of failure stage.

stage, it is assumed that the bearing is in healthy conditions and it is free from the defects at the beginning of its life cycle. In the next stage, the deep learning model is trained by the CWT image of bearing in healthy condition. Finally, in the third stage, throughout the bearing failure phase, the health indicator is constructed. For this purpose, the difference in values of the bottleneck nodes values between the failure stage and the healthy stage of the bearing is measured by using the Mahalanobis Distance formula. In order to evaluate the effectiveness of the proposed method, the bearing dataset, generated by the National Science Foundation (NSF) University of Cincinnati Center for Intelligent Maintenance Systems (IMS), is employed [5].

3- Signal Processing

The purpose of CWT of the raw vibrational signal is to preprocess the raw vibration in the time-frequency domain and convert a 1D signal to a 2D image, as the input of the deep learning model. The wavelet transform can analyze a localized area of a large signal without losing the spectral information contained therein. Therefore, the wavelet transform can reveal some hidden aspects of the signal which other techniques fail to detect [6]. The degradation process of the bearing generally includes two stages: the normal operation stage and the failure stage. During a normal operation stage of the bearing, a sliding window is used to capture the vibrational signal, and for each window, the power spectrum of the CWT is used to convert a 1-D vibrational signal into a 2-D image. The transformed image contains both time and frequency domains information and can represent the non-stationary and transient evolution of the signal.

4- Deep Learning Model

In this study, two types of Autoencoder deep learning models are completely studied and the best one is selected. An autoencoder is an unsupervised neural network used for feature extraction and dimensionality reduction and is characterized by having the same number of nodes in the inputs and outputs layers [7]. The main role of the deep learning model is to learn to extract the main features of the CWT image in healthy and faulty conditions of the ball bearing. Therefore, an autoencoder model which is able to predict the input layer more accurately in the output layer, is more suitable. Comparison between deep Autoencoder (AE) and Convolutional Autoencoder (CAE) has been performed and it is demonstrated that the CAE model is superior.

5- Construction of Health Indicator

After the CAE model is trained by the healthy CWT image of the bearing, a health indicator is constructed for the failure stage automatically. A suitable health indicator is expected to exhibit a monotonically increasing trend and should be robust to noise and stochastic fluctuations. The CAE model is to learn to extract distribution characteristics of the healthy CWT image through its deep structure and to reproduce images similar to the training dataset with a small reconstruction error in the output layer. Once the failure stage started for the bearing, damage evolution of bearing leads to a more turbulent vibration pattern in CWT images. Fig. 1 demonstrates the CWT mage in the healthy and failure stage. When the CWT image of the failure stage is input to the trained CAE model, the dissimilarity between the extracted vector of features in normal stage images and the faulty sample image is measured to demonstrate the corresponding degradation indicator. For this purpose, the extracted features in the bottleneck layer are used to estimate the distance between the normal stage and the failure stage by the Mahalanobis Distance formula. This strategy is used to construct health indicator during the failure stage. In this method, the feature extraction and health indicator construction are performed automatically by the CAE model.

6- Results and Discussion

The trained deep learning model is used to construct

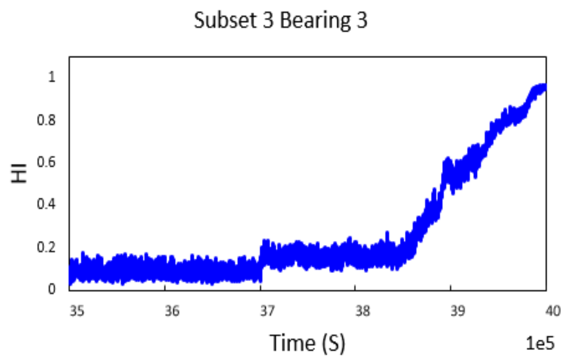

Fig. 2. Bearing health indicator during failure stage.

health indicator by estimating the distance of the values of the bottleneck nodes between the normal stage and failure stage. The results show that the constructed health indicators are smoother, and gradually increasing, while the degradation trends are effectively captured as well. Furthermore, the results prove that the proposed method is able to detect early bearing defects and abnormal bearing health conditions. Moreover, this method provides a health indicator that is well correlated with progressively increasing bearing degradations. The constructed health indicator for the one IMS bearing is shown in Fig. 2.

7- Conclusion

In this study, a new method for condition monitoring of the bearing based on artificial intelligence is proposed. The proposed method includes three main stage. In the first stage, the raw vibration signal of the bearing in a healthy state is converted to two-dimensional images using the CWT technique. In the next stage, an autoencoder model is trained by the healthy CWT images of the bearing. In this study, two different type of autoencoder model are studied and it is shown that the CAE model has a more accurate output than the AE model. Finally, the CWT image of the failure stage is fed to the trained CAE model and the distance between the values of bottleneck nodes in healthy and failure state is measured by Mahalanobis Distance formula, then the health indicator is constructed. The experimental results on the IMS bearing data set show the effectiveness of the proposed method.

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