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Practice article

Fault diagnosis of rolling bearings with recurrent neural network-based autoencoders

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A B S T R A C T

As the rolling bearings being the key part of rotary machine, its healthy condition is quite important for safety production. Fault diagnosis of rolling bearing has been research focus for the sake of improving the economic efficiency and guaranteeing the operation security. However, the collected signals are mixed with ambient noise during the operation of rotary machine, which brings great challenge to the exact diagnosis results. Using signals collected from multiple sensors can avoid the loss of local information and extract more helpful characteristics. Recurrent Neural Networks (RNN) is a type of artificial neural network which can deal with multiple time sequence data. The capacity of RNN has been proved outstanding for catching time relevance about time sequence data. This paper proposed a novel method for bearing fault diagnosis with RNN in the form of an autoencoder. In this approach, multiple vibration value of the rolling bearings of the next period are predicted from the previous period by means of Gated Recurrent Unit (GRU)-based denoising autoencoder. These GRU-based non-linear predictive denoising autoencoders (GRU-*NP*-DAEs) are trained with strong generalization ability for each different fault pattern. Then for the given input data, the reconstruction errors between the next period data and the output data generated by different GRU-*NP*-DAEs are used to detect anomalous conditions and classify fault type. Classic rotating machinery datasets have been employed to testify the effectiveness of the proposed diagnosis method and its preponderance over some state-of-the-art methods. The experiment results indicate that the proposed method achieves satisfactory performance with strong robustness and high classification accuracy.

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1. Introduction

Rolling bearing is one of the most common and easily damaged parts in mechanical system. The failure of a rolling bearing may lead to huge loss of production and casualties in engineering practice. Therefore, it is quite attractive to study in the in-time fault diagnosis for rolling bearings to prevent such unexpectedness from happening.

Localised faults in rolling element bearings produce a series of broadband impulse responses in the acceleration signal as the bearing components strike the fault repeatedly. The acceleration produced by the strike are characteristic of bearings under healthy conditions and differ across fault modes. Similarly, the acceleration signals change when the faults in the rolling bearings occur, and different faults produce different vibration signals. Thus, the health conditions can be determined by signals of vibration sensors attached on the rolling bearings. Previous studies have shown that the high accuracy of fault diagnosis always benefits by extracting effective fault features from original signals [1]. Effective feature extracting methods, as the premise of accurate fault diagnosis, can help to filter redundant information. However, ambient noise in the original signal brings about the difficulty in extracting useful message from mixed observed data. In order to enhance the diagnosis accuracy, signal processing methods, such as wavelet transform (WT) [2–4], independent component analysis (ICA) [5], and empirical mode decomposition (EMD) [6], have become the comprehensive technology for providing characteristics analysis in both time and frequency domain. For example, Serhat Seker et al. extracted information from selected frequency bands by wavelet transforms and multi-resolution analysis, and observed the changes in the vibration signals at various sub-band levels to obtain conclusions about the trending of bearing degradation [7]. Fannia Pacheco et al. proposed an unsupervised feature selection

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algorithm based on attribute clustering and rough set theory, in which the classification results showed that the new approach can select adequate features as same as other feature selection method [8]. However, conventional signal processing methods have their own weakness respectively. WT is an effective way to analyze nonlinear and non-stationary signal, but it is restricted by the base function and decomposition scales. Compared to WT, EMD is self-adaptive to decompose the signal into several intrinsic mode functions (IMFs). But the mode mixing problem and end effect often appear in application of EMD. In addition, taking complexly ambient working conditions into consideration, the noise is still a strong interference for classification methodologies that prevents good use of observed information.

Therefore, a multitude of work focuses on applying machine learning techniques to improve the fault diagnosis accuracy recently [9–11]. Compared to conventional signal processing method, machine learning is strong self-adaptive for the training process of model is totally data-driven [1]. In numerous fields, machine learning has been proved an effective alternative to imitate human brain disposing process and acquire connotative relationship in the training datasets [12]. Due to its ability in discovering useful representations and general applicability to other cases, machine learning is introduced in pattern recognition for multiple fault classification lately. For instance, support vector machines (SVM) [13], neural network [14,15], extreme learning machine (ELM) [16], random forest (RF) [17] and auto-encoder (AE) [18] are effective techniques for the multiple classification task and fault diagnosis applications. Liang Guo et al. proposed a recurrent neural network based health indicator for bearing remaining useful life prediction. Their work provided a new train of thought for extracting statistical features with a specific range. The results of experiment verification showed that the proposed method can achieve better performance than the commonly health indicator [19]. Wenjun Sun et al. utilized sparse auto-encoder to learn features of induction motor. Compared with traditional neural network, the proposed method was able to achieve superior performance for feature learning and classification in the field of induction motor fault diagnosis [20]. Minmin Chen et al. proposed a novel approach that marginalizes noise to overcome high computational cost and lack of scalability to high-dimensional features of traditional stacked denoising autoencoders [21]. However, almost all of data processing methods of the aforementioned techniques are dividing the vibration data into segment and taking them as separate vectors. In fact, the vibration data should be viewed as time sequences in which the relevance between present and previous values cannot be ignored. Recurrent neural network (RNN), which is a generative model investigated in the field of text generation [22], handwriting recognition [22], and music improvisation [23] fields, has an advantage in dealing with time sequence data benefited by its recurrent architecture. The capacity of RNN has been proved outstanding for catching time relevance about time sequence data. Furthermore, as an important part of the complex mechanical system, bearings always run with other loading devices and drive equipment. The corresponding vibrations always contain the vibrational characteristics of other units. Consequently, fault diagnosis of rolling bearings with data collected from multiple sensors can obtain more helpful information and gain accuracy of diagnosis result [24–26]. However, familiar approaches, ANN, SVM et al. cannot make full use of multi-source data. Instead, a designed RNN model is capable of discovering useful feature and characteristics among the multiple time sequence data. In spite of the great potential advantages of RNN model, the application of RNN on fault diagnosis for rolling bearing has rarely been found in literature.

In this paper, a novel method based on RNN model is proposed for rolling bearing fault classification. Multiple vibration data under different health conditions are used for training Gated Recurrent Unit (GRU)-based non-linear predictive denoising autoencoders (GRU-*N*P-DAEs) respectively. GRU-*N*P-DAE models are trained to repeat the multiple vibration value of the rolling bearings from the previous period. During the supervised learning process, data destruction method is adopted and length loss method is proposed to enhance robustness of models. Several experiments were conducted to confirm that the proposed learning method can reduce the influence of ambient noise and complex work conditions. Subsequently, the trained GRU-*N*P-DAEs are received a multiple input data and the fault diagnosis result is determined by the relevant GRU-*N*P-DAE that produces the minimum reconstruction error between the delay of the input and the model output. The concept of classification accuracy is adopted to evaluate the feasibility of the proposed method for health condition detection and fault type classification. In addition, existing fault diagnosis methods, such as SVM, AE and DE are introduced for comparison. Classic rotating machinery datasets are employed to validate the effectiveness of the proposed method.

Benefit from the great potential advantages of RNN, the prime contributions out of this work for rolling bearing fault classification are as follows:

1) This work combined non-linear predictive denoising autoencoders with RNN model to improve the robustness of time series data reconstruction. In addition, a data length variant process method was proposed to fully consider the previous information and the experiment results showed the better generalization ability of proposed model compared with model trained by fixed-length data.
2) The proposed method provided a new way to make use of multiple vibration data. Conventional machine learning architectures commonly divide vibration data into segments with same length, thus the time relevant information between previous and current state of multiple data and the relationship of different sources are ignored. The novel RNN-based autoencoders in this paper took vibration data collected from different sensors as input in each time step. The correlation relationship of different parts of rolling bearings was learned by the RNN-based autoencoders, which enhanced the fault diagnosis accuracy of rolling bearings.

The remainder of this contribution is organized as follows. In Section 2, the description about the proposed method and its training process is given. Several experiments were conducted to determine the key parameters of model. Then the method is applied to classic rotating machinery datasets compared with existing methods and the result is presented in Section 3. Section 4 finally presents our conclusions.

2. Fault diagnosis with the RNN-based classification

This section details the proposed RNN-based fault diagnosis method. Section 2.1 overviews the basic architecture of the RNN. Section 2.2 introduces the principle and training process of RNN-based non-linear predictive denoising autoencoder. Section 2.3 presents the overall stepwise procedure for the employed fault diagnosis approach.

2.1. Recurrent neural network

Recurrent Neural Network (RNN) is a type of artificial neural network in which dependencies between nodes form a directed cycle [27]. This architecture allows the network to preserve a status

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