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Introductory invited paper

Deep neural networks-based rolling bearing fault diagnosis

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ABSTRACT

Rolling bearing is one of the most commonly used components in rotating machinery. It's so easy to be damaged that it can cause mechanical fault. Thus, it is significant to study fault diagnosis technology on rolling bearing. In this paper, three deep neural network models (Deep Boltzmann Machines, Deep Belief Networks and Stacked Auto-Encoders) are employed to identify the fault condition of rolling bearing. Four preprocessing schemes including feature of time domain, frequency domain and time-frequency domain are discussed. One data set with seven fault patterns is collected to evaluate the performance of deep learning models for rolling bearing fault diagnosis, which is based on the health condition of a rotating mechanical system. The results proved that the accuracy achieved by Deep Boltzmann Machines, Deep Belief Networks and Stacked Auto-Encoders are highly reliable and applicable in fault diagnosis of rolling bearing.

1. Introduction

Rolling bearing is the key component of rotating machinery, whose running state has an important effect on the healthy condition of rotating machinery equipment. It's very necessary to monitor the condition of rolling bearing and identify its faults to avoid fatal breakdowns of machines and prevent loss of production and human casualties [1]. Accordingly, a reliable bearing health-condition-monitoring system is very useful to a wide array of industries.

Traditional maintenance operations by observing the variations and/or trends of some condition-monitoring indices is usually time consuming and not always reliable when multiple features (techniques) are applied for fault diagnostics, particularly as the data are noise affected [2]. The availability of an important number of condition parameters that are extracted from rolling bearing signals, such as vibration signals, has motivated the use of data-driven fault diagnosis. Q. Miao and Zhou [3] special investigated the relation between vibration signal characteristics and fault diagnosis for planetary gearbox. Some automatic decision-making techniques have been proposed in the literature [4–9], which can broadly be classified into mathematical model-based methods and data-driven techniques. The latter technique is employed in this paper, because an accurate numerical model is usually difficult to derive from complex mechanical systems, particularly when the machine is operating in an uncertain noisy environment, and data-driven techniques were widely applied to the fault diagnosis of rolling bearing [2].

Classical data-driven fault diagnosis techniques include statistical classifiers, geometric methods, and polynomial classifiers [10]. These techniques cannot be used for time varying systems, because these models depend on statistic measurements (e.g., density and probability) of the vibration data. Under data-driven, inference-based intelligent tools such as neural networks [11,12], fuzzy logic [13,14], synergetic schemes [15], neuron fuzzy (NF) paradigms [16,17] and Bayesian inference [18] are widely used for rolling bear fault diagnosis. In addition to, some machine learning approaches such as support vector machine and their related models also are commonly used, because of the simplicity for developing industrial applications. Signal analysis-based techniques such as wavelet decomposition and its variants also are commonly used as classical tools for the robust health evaluation of rotating machinery [19,20].

Although some intelligent tool-based techniques have been proposed for bearing fault diagnostics [21–24],it still remains as a challenging task in research and development, because a bearing is not a mechanical component (e.g., a gear or shaft), but a complex system with inner and outer rings, as well as many rolling elements. The bearing signal is non-stationary in general, particularly when slip occurs among the bearing elements (e.g., the rolling elements and ring raceways) [2].

Nowadays, deep learning techniques are becoming a promising tool for fault characteristic mining and intelligent diagnosis of rotating

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machinery with massive data [25]. Chen et al. [26] introduced convolution neural networks (CNN) to identify and classify the faults of gearbox. Tran et al. [27] suggested a deep belief network based application to diagnose reciprocating compressor valves. C. Li et al. [28] proposed multimodal deep support vector classification for gearbox fault diagnosis, where Gaussian-Bernoulli Deep Boltzmann Machines (GDBMs) were used to extract the feature of the vibratory and acoustic signal in time, frequency and wavelet modalities, respectively; and then the extracted features are integrated for fault diagnosis by using GDBMs. Li's research [28] indicated Gaussian-Bernoulli Deep Boltzmann Machines is effective for the gearbox fault diagnosis. We have presented a multi-layer neural network (MLNN) for gearbox fault diagnosis [29], where the weights of deep belief network are used to initialize the weights of the constructed MLNN. More extensive engineering verification is necessary to cognize and popularizes deep learning techniques.

In this paper, three deep neural networks (Deep Boltzmann Machines [30], Deep Belief Networks [31] and Stacked Auto-Encoders [32]) are applied to the rolling bearing fault diagnosis. The following aspects are focused on: the performance evaluation of the feature extraction and fault identification based on the raw vibration signal and the feature representations from time, frequency and time-frequency domain for the rolling bearing fault. The rest of this paper is organized as follows: Three deep learning models are introduced briefly in Section 2. Preprocessing schemes of vibration signal are presented in Section 3. In Section 4, the experiment setups are described in detail, such as how to acquire data and extract features. Results and discussions are presented in Section 5. The Conclusions of this work are given at the end.

2. Methodology

Fig. 1 outlines the schematic of the developed rolling bearing fault diagnosis system. In this section, the used deep neural networks (DNN) will be briefly introduced: Deep Boltzmann Machines (DBM), Deep Belief Networks (DBN) and Stacked Auto-Encoders (SAE).

2.1. Deep Boltzmann Machine

Deep Boltzmann Machine is a network of symmetrically coupled stochastic units, which is an undirected graphical model with bipartite connections between adjacent layers of hidden units. DBM model can be regarded as a deep learning model which is a stack of restricted Boltzmann machines (RBM) [33]. Fig. 2 indicates a Deep Boltzmann

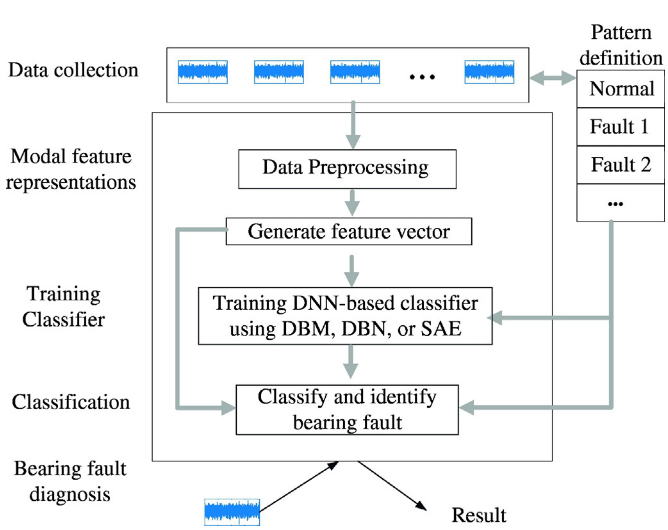

Fig. 1. Schematic of the developed rolling bearing fault diagnosis system.

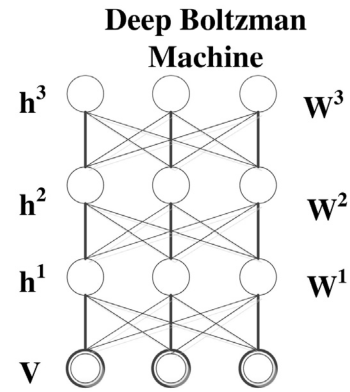

Fig. 2. Deep Boltzmann Machine with three hide layers.

Machine with three hide layers. The energy of the state $\{\mathrm{v},\mathrm{h}^1,\mathrm{h}^2,\mathrm{h}^3\}$ is defined as [34]:

$$E\left(\boldsymbol{v},\mathrm{h}^1,\mathrm{h}^2,\mathrm{h}^3,\theta\right)=-\mathrm{v}^TW^1\mathrm{h}^1-\mathrm{h}^{1T}W^2\mathrm{h}^2-\mathrm{h}^{2T}W^3\mathrm{h}^3 \tag{1}$$

where the model parameters $\theta=\{W^1,W^2,W^3\}$ represents visible-to-hidden and hidden-to-hidden symmetric interaction terms. The probability that the model assigns to a visible vector **v** is

$$P(\mathrm{v},\theta)=\frac{1}{Z(\theta)}\sum_{\mathrm{h}^1,\mathrm{h}^2,\mathrm{h}^3}\exp\left(-E\left(\mathrm{v},\mathrm{h}^1,\mathrm{h}^2,\mathrm{h}^3,\theta\right)\right) \tag{2}$$

The conditional distributions over the hidden (L expresses the number of hidden layers) and visible states are defined as in (3) and (4):

$$P\left(\mathrm{v}_i|\mathrm{h}^1,\theta\right)=N\left(\mathrm{v}_i|\sum_j \mathrm{h}_j^1W_{ij}+b_i,\sigma_i^2\right) \tag{3}$$

$$P\left(\mathrm{h}_j^l|\mathrm{h}^{l-1},\mathrm{h}^{l+1},\theta\right)=s\left(\sum_j \mathrm{h}_j^{l-1}W_{ij}^{l-1}+\sum_k \mathrm{h}_k^{l+1}W_{jk}^l+b_j^l,\sigma_i^2\right) \tag{4}$$

where l expresses l^{th} hidden layer and b is the bias value of neuron.

The training steps of the DBM model are as follows [34]:

Step 1: Train the first-layer RBM by using one-step contrastive divergence learning with mean-field reconstructions of the visible vectors. The generative probabilistic model can be written as:

$$\begin{aligned}P(\mathrm{v},\theta)&=\textstyle\sum_{\mathrm{h}^1}P\left(\mathrm{h}^1;W^1\right)P\left(\mathrm{v}|\mathrm{h}^1;W^1\right),P\left(\mathrm{h}^1;W^1\right)\\&=\textstyle\sum_{\mathrm{v}}P\left(\mathrm{h}^1,\mathrm{v},W^1\right)\end{aligned} \tag{5}$$

Table 1
Time domain features.

Description of features	Formulate
Mean value	$\overline{X}=\frac{1}{N}\sum_{n=1}^{N}X(n)$
Standard deviation	$\sigma=\sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(X(n)-\overline{X}\right)^2}$
Mean square root	$X_{\mathrm{RMS}}=\sqrt{\frac{1}{N}\sum_{t=1}^{N}x(t)^2}$
Kurtosis	$K=\frac{1}{N}\sum_{n=1}^{N}\frac{\left(X(n)-\overline{X}\right)^4}{\sigma^4}$
Shape factor	$S_f=\frac{X_{\mathrm{RMS}}}{\lvert\overline{X}\rvert}$
Crest factor	$C_f=\frac{\max(x(t))}{X_{\mathrm{RMS}}}$
Impulse factor	$I_f=\frac{\max(x(t))}{\lvert\overline{X}\rvert}$

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