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Research article

Rolling bearing fault diagnosis using adaptive deep belief network with dual-tree complex wavelet packet

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ABSTRACT

Automatic and accurate identification of rolling bearing fault categories, especially for the fault severities and compound faults, is a challenge in rotating machinery fault diagnosis. For this purpose, a novel method called adaptive deep belief network (DBN) with dual-tree complex wavelet packet (DTCWPT) is developed in this paper. DTCWPT is used to preprocess the vibration signals to refine the fault characteristics information, and an original feature set is designed from each frequency-band signal of DTCWPT. An adaptive DBN is constructed to improve the convergence rate and identification accuracy with multiple stacked adaptive restricted Boltzmann machines (RBMs). The proposed method is applied to the fault diagnosis of rolling bearings. The results confirm that the proposed method is more effective than the existing methods.

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1. Introduction

Rolling bearing is one of the most widely used components in rotating machinery. With the rapid development of science and technology, modern rotating machinery equipment becomes larger, more complex and more precise, which makes the rolling bearing always run under the operating conditions with heavy load, strong impact and high speed [1]. If no effective actions are taken, rolling bearing faults will inevitably occur and such faults may lead to serious casualties. Thus, it is of significance to accurately and automatically identify rolling bearing faults.

Vibration signals collected from rolling bearings usually carry rich information on machine operation conditions [2]. According to [3–5], three main steps are necessary for rolling bearing fault diagnosis based on vibration analysis: feature extraction, feature selection and pattern recognition. Though traditional pattern recognition methods such as artificial neural network (ANN) and support vector machine (SVM) have been widely used in mechanical fault diagnosis [6–9], they still have two inherent shortcomings: (1) The diagnosis performance of the shallow learning models depends heavily on the quality of the selected features from the original feature set. However, the sensitive features input into intelligent classifiers are selected manually, largely depending on prior knowledge of diagnosticians [10]. Besides, the features are selected according to the specific fault diagnosis issue and they are probably unreliable for the new issues [11]. Consequently, manual feature extraction is time-consuming and labor-intensive. (2) ANN and SVM belong to shallow learning models, which is, with no more than one nonlinear feature transformation [12]. Several study results have shown that shallow learning models lack a powerful representation efficacy [13–15], and they are very difficult to effectively express the complex relationships in fault diagnosis issues. Therefore, it is meaningful to construct deep architectures for automatic feature learning and accurate fault diagnosis.

In order to overcome the shortcomings of shallow models, deep learning based on feature learning methods was first proposed by Hinton [16]. Since then, deep learning has attracted considerable attention and has motivated a plenty of successful applications. The most significant difference between deep learning methods and shallow learning methods is that the former can automatically learn the sensitive and valuable feature representations from the original feature set, instead of selecting features manually [17]. Deep belief network (DBN) is the most popular deep learning model and it is composed by multiple restricted Boltzmann machines (RBMs) [18]. The success of DBN is partially attributed to two main aspects: Firstly, DBN can automatically learn effective information from the raw feature set, which removes the necessity for manual feature selection. Secondly, it should also belong to the scope of neural networks with great capabilities of nonlinear mapping, and the multiple hidden layers make it more effectively and flexibly learn the complex relationships in fault diagnosis issues compared with the shallow

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learning models such as ANN and SVM.

Despite it is not surprising that DBN has produced extremely satisfactory results for various tasks, it is still in its infancy in rotating machinery fault diagnosis [19,20]. In 2015, our group proposed optimization DBN for rolling bearing fault diagnosis [21]. However, in this work, we did not take time-frequency domain characteristics into consideration. In engineering practice, due to the different influence of nonlinear factors such as load, friction, clearance and stiffness to vibration signals, it is very difficult to accurately identify the bearing faults when the work conditions of rolling bearing are analyzed only in time domain or frequency domain [22]. Wavelet packet transform (WPT) is an advanced time-frequency analysis technique and it has gained enormous applications for rotating machinery fault diagnosis. However, the main disadvantages of WPT are its frequency aliasing and shift-variant, which may cause the loss of useful fault information [23]. Dual-tree complex wavelet transform (DTCWT) has lots of properties such as reduced aliasing and nearly shift-invariance, which are very beneficial for feature extraction in mechanical fault diagnosis [24,25]. Dual-tree complex wavelet packet transform (DTCWPT) is an extension of DTCWT and overcomes the shortcoming that DTCWT cannot realize multi-resolution analysis in the high frequency band. Consequently, in this paper, DTCWPT is introduced to preprocess the raw vibration signals to refine the fault characteristics.

In view of the above principles, based on the remarkable benefits of DBN and DTCWPT, a novel method called adaptive DBN with DTCWPT is developed in this paper. The proposed method is applied to identify the different rolling bearing faults. The results confirm that the proposed method can remove the necessity for manual feature selection, and it is more accurate and robust for multi-mode process rolling bearing fault diagnosis than the existing methods. The main contributions of this paper can be summarized as follows.

(1) In order to effectively extract underlying fault characteristic information, dual-tree complex wavelet packet is adopted to refine the measured vibration signals to design an original feature set.
(2) In order to get rid of the dependence on manual feature selection, deep belief network is proposed to automatically learn the representative features from the original feature set.
(3) In order to further improve the diagnosis accuracy and convergence performance, adaptive deep belief network is constructed by means of pre-training a series of adaptive restricted Boltzmann machines.

The rest of this paper is organized as follows. In Section 2, the basic theories of DBN and DTCWPT are briefly introduced. The proposed fault diagnosis approach is described in Section 3. In Section 4, the experimental diagnosis results for rolling bearings are analyzed and discussed. Section 5 presents the engineering application of the proposed method. Finally, conclusions are given in Section 6.

2. Brief review of DBN and DTCWPT

2.1. Deep belief network theory

The DBN structure is similar to the stacked network of a sequence of RBMs. Each RBM is a particular type of MRFs which consists of visible layer and hidden layer, as shown in Fig. 1. The visible layer accepts the input data and transfers the data to the hidden layers in order to complete the learning process.

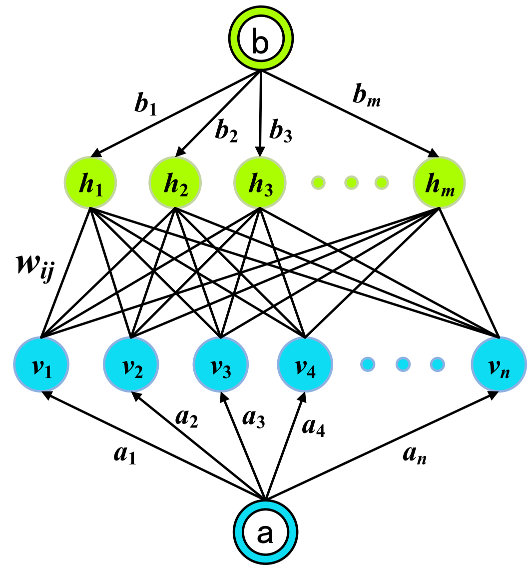

Fig. 1. RBM architecture with n visible units and m hidden units.

Table 1
The adaptive RBM learning rule.

Algorithm. The adaptive RBM learning rule

Notation:
v_2 and h_2 represent the one-step reconstructed states of v_1 and h_1, respectively. v_{2i} is the ith element in the reconstructed sample v_2.
Inputs:
A training sample v_1, maximum iteration number Q, initial learning rate η^1, increasing factor R_i, decreasing factor R_d and momentum α
Step 1: for all hidden units j **do**
- Compute $P(h_{1j} = 1|v_1)$ (for binomial units, $sigm(b_j + \sum_i w_{ij} v_{1i})$)
- Sample $h_{1j} \in \{0, 1\}$ from $P(h_{1j} = 1|v_1)$

end for
Step 2: for all visible units i **do**
- Compute $P(v_{2i} = 1|h_1)$ (for binomial units, $sigm(a_i + \sum_j w_{ij} h_{1j})$)
- Sample $v_{2i} \in \{0, 1\}$ from $P(v_{2i} = 1|h_1)$

end for
Step 3: for all hidden units j **do**
- Compute $P(h_{2j} = 1|v_2)$ (for binomial units, $sigm(b_j + \sum_i w_{ij} v_{2i})$)

end for
Outputs:
- $\Delta w_{ij}^q = \eta^q\left(h_1 v_1^T - P(h_{2j} = 1|v_2) v_2^T\right) + \alpha \Delta w_{ij}^{q-1}$
- $\Delta a_i^q = \eta^q (v_1 - v_2) + \alpha \Delta a_i^{q-1}$
- $\Delta b_j^q = \eta^q\left(h_1 - P(h_{2j} = 1|v_2)\right) + \alpha \Delta b_j^{q-1}$

Let $\mathbf{v} = (v_1, v_2, \cdots v_n)^T$ be the state of the visible units and $\mathbf{h} = (h_1, h_2, \cdots h_m)^T$ the state of the hidden units. An RBM minimizes an approximation of the negative log likelihood of the data under the model which defines a probability distribution over $P(\mathbf{v}, \mathbf{h})$ via an energy function $E(\mathbf{v}, \mathbf{h}|\theta)$, which can be written as [26]

$$-\log P(\mathbf{v}, \mathbf{h}) \propto E(\mathbf{v}, \mathbf{h}|\theta) = -\sum_{i=1}^{n} a_i v_i - \sum_{j=1}^{m} b_j h_j - \sum_{i=1}^{n}\sum_{j=1}^{m} v_i w_{ij} h_j \tag{1}$$

where w_{ij} is the weight between visible unit i and hidden unit j, a_i and b_j are their bias, n and m are the numbers of visible and hidden units, respectively.

The energy function has a joint probability of $(\mathbf{v}, \mathbf{h})$ in Eq. (1) given by

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