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A neural network constructed by deep learning technique and its application to intelligent fault diagnosis of machines

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ABSTRACT

In traditional intelligent fault diagnosis methods of machines, plenty of actual effort is taken for the manual design of fault features, which makes these methods less automatic. Among deep learning techniques, autoencoders may be a potential tool for automatic feature extraction of mechanical signals. However, traditional autoencoders have two following shortcomings. (1) They may learn similar features in mechanical feature extraction. (2) The learned features have shift variant properties, which leads to the misclassification of mechanical health conditions. To overcome the aforementioned shortcomings, a local connection network (LCN) constructed by normalized sparse autoencoder (NSAE), namely NSAE-LCN, is proposed for intelligent fault diagnosis. We construct LCN by input layer, local layer, feature layer and output layer. When raw vibration signals are fed to the input layer, LCN first uses NSAE to locally learn various meaningful features from input signals in the local layer, then obtains shift-invariant features in the feature layer and finally recognizes mechanical health conditions in the output layer. Thus, NSAE-LCN incorporates feature extraction and fault recognition into a general-purpose learning procedure. A gearbox dataset and a bearing dataset are used to validate the performance of the proposed NSAE-LCN. The results indicate that the learned features of NSAE are meaningful and dissimilar, and LCN helps to produce shift-invariant features and recognizes mechanical health conditions effectively. Through comparing with commonly used diagnosis methods, the superiority of the proposed NSAE-LCN is verified.

1. Introduction

With the development of industry, machines have been more automatic and efficient, and their components are linked to each other inseparably [1]. Once a component has a fault, this fault would quickly produce chain reaction and lead to the damage of other components. Such unexpected faults would make machines break down, resulting in economic loss and even person safety threat [2]. Therefore, the fault diagnosis of machines has received lots of attention.

Intelligent fault diagnosis is one of the powerful tools in the field of fault diagnosis [3]. Based on massive monitored signals of the machines, it is able to replace diagnosticians with artificial intelligent techniques like neural networks to rapidly process these signals and automatically recognize mechanical health conditions [4–6]. Thus, intelligent fault diagnosis plays an irreplaceable role in modern industries especially when massive vibration signals are available. As we know, traditional intelligent fault diagnosis has two main steps: feature extraction and fault recognition [7]. Based on these steps, lots of effort has been taken on intelligent fault diagnosis. Georgoulas et al. [8] designed the features of motor faults based on time-frequency methods and employed Mahalanobis Distance classifier to recognize motor health conditions. Prieto et al. [9] proposed a method using statistical features and hierarchical networks to classify bearing health conditions. Amar et al. [10] proposed a feature enhancement procedure to obtain features from vibration spectra and applied neural networks to diagnose the bearing faults. Wang [11] designed a feature extraction algorithm that extracts redundant statistical features from different wavelet decomposition levels, and applied K-nearest neighbor algorithm to identify gear health conditions. Lei et al. [12] designed two features for gearboxes specifically and used these features and relevance vector machine to recognize the health conditions.

Although the studies above achieved good results, they may suffer the weakness as follows. In these methods, plenty of the actual effort is taken for the manual design of feature extraction algorithms since traditional classifiers cannot extract the representative features from raw signals [13]. Such feature designing processes should make full use of human knowledge in signal processing and diagnostic expertise, which costs much human labor and makes the methods less automatic. Among deep learning

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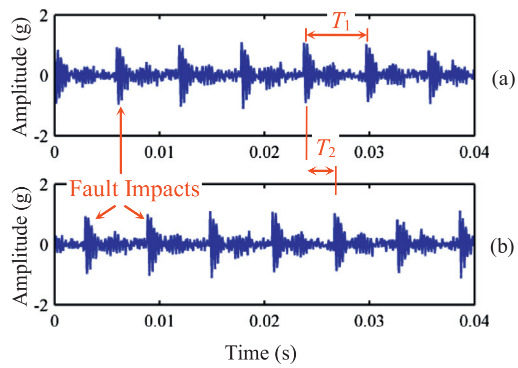

Fig. 1. Two simulated samples for mechanical fault signals: (a) the first sample and (b) the second sample.

techniques, autoencoders may help fault diagnosis to handle the weakness above since their basic motivation is to be fed with raw signals and accomplish the task of feature extraction automatically [14–16]. Currently, autoencoders have attracted attentions in the field of fault diagnosis. Thirukovalluru et al. [17] employed denoising autoencoder to extract high-level features from manual features and two classifiers to recognize mechanical faults. Jia et al. [18] used frequency spectra as the input of a deep network based on autoencoders to recognize mechanical health conditions. Chen and Li [19] applied sparse autoencoder (SAE) to get representative features from statistical values of bearing signals and recognized the health conditions using deep belief network. Mao et al. [20] proposed a fault diagnosis method using frequency spectra and autoencoder extreme learning machines. It can be seen that most of these studies, however, still used manual features as the input of the neural networks, which may deviate from the basic motivation of the autoencoders.

The following two shortcomings of the autoencoders are the main reasons why they are not easily used to learn features well from raw vibration signals of machines. (1) The autoencoders cannot be ensured to get various meaningful features from the vibration signals. The feature extraction process of an autoencoder can be regarded as the dot produce results between its weight matrix composed by a set of basis vectors and the vibration signals. So obtaining good features of raw data depends on the weight matrix of the autoencoder. In the well trained weight matrix, its basis vectors should not only have the own patterns like acting as Gabor bases to produce the meaningful features, but also be different from each other so as to produce various features. Traditional constraints applied to autoencoders, such as sparse regularization and weight decay, could force the basis vectors of the weight matrix to learn patterns but cannot force them to be different. So autoencoders learn too many similar features and prevent their applications in intelligent fault diagnosis of machines. (2) The autoencoders cannot be directly used for feature learning when the data have shift variant properties. Unfortunately, the vibration signals of a faulty machine always show such properties. In Fig. 1, we use two samples that simulate the vibration signals of a mechanical fault to illustrate the properties. It can be seen that when a fault occurs in the machines, the periodic fault impacts are excited by the contact of the fault component and other components, and the contact period is T_1. Such impulse-like vibration behavior of a vibration signal is an important characteristic for fault recognition. When machines operate, their components contact with each other in a time-varying way. So the fault impacts of the first sample and the second sample would shift by T_2. Once we use the autoencoders to extract features from these samples, the features also have shift variant properties, leading to the misclassification of mechanical fault samples.

We propose a local connection network (LCN) constructed by normalized sparse autoencoder (NSAE), namely NSAE-LCN, to overcome the shortcomings of autoencoders. LCN is constructed by four layers, i.e., input layer, local layer, feature layer and output layer, where the local layer is trained by NSAE. So when raw vibration signals are fed to the input layer, LCN first uses NSAE in the local layer to locally learn various meaningful features from the vibration signals, then obtains shift-invariant features from the learned features in the feature layer and finally recognizes mechanical health conditions in the output layer. The proposed NSAE-LCN is validated by a gearbox dataset and a bearing dataset respectively, both involving different health conditions under various operating conditions. And its superiority is verified by comparing with commonly used diagnosis methods.

The contributions of this paper can be summarized as follows.

(1) Based on sparse autoencoder, NSAE is proposed for automatic feature extraction from the vibration signals of machines. Since an orthonormality constraint is used in NSAE, the weight matrix trained by NSAE can be viewed as a set of basis showing time-frequency properties, which encourages the learned features of NSAE to not only have meaningful patterns but also be dissimilar. Thus, NSAE performs well in mechanical feature extraction.
(2) We propose NSAE-LCN for intelligent fault diagnosis. It incorporates the processes of feature extraction and fault recognition into a general-purpose learning procedure. Therefore, the proposed method can be used to directly learn features from raw vibration signals and recognize the health conditions of machines for various diagnosis tasks.

The rest of this paper is organized as follows. In Section 2, sparse autoencoder is briefly described. Section 3 details the proposed NSAE-LCN. In Section 4, the diagnosis cases of a gearbox dataset and a bearing dataset are studied separately using NSAE-LCN. Finally, conclusions are drawn in Section 5.

2. Sparse autoencoder

SAE is a widely used autoencoder that attempts to learn features from raw data. It has symmetrical neural network with an input layer, a hidden layer and an output layer [21]. The input layer and the hidden layer constitute the encoder of SAE, which transforms the input data into features. And the hidden layer and the output layer constitute the decoder of SAE, which reconstructs the input data from the corresponding features.

Given unlabeled data $\{\boldsymbol{x}_m\}_{m=1}^{M}$ where $\boldsymbol{x}_m \in \Re^{N\times 1}$, the encoder uses a mapping function f_{SAE} to calculate the feature $\boldsymbol{h}^m$ from $\boldsymbol{x}_m$ and $\boldsymbol{h}^m$ has K dimensions.

$$\boldsymbol{h}^m = f_{\mathrm{SAE}}(\boldsymbol{x}_m) = \sigma_s(\boldsymbol{W}_{\mathrm{SAE1}}\boldsymbol{x}_m + \boldsymbol{b}_1) \tag{1}$$

where $\sigma_s(z)$ is the sigmoid function, $\boldsymbol{W}_{\mathrm{SAE1}}$ is the weight matrix of the encoder and $\boldsymbol{b}_1$ is the bias vector. The decoder uses a mapping function g_{SAE} for reconstruction

$$\hat{\boldsymbol{x}}_m = g_{\mathrm{SAE}}(\boldsymbol{h}^m) = \boldsymbol{W}_{\mathrm{SAE2}}\boldsymbol{h}^m + \boldsymbol{b}_2 \tag{2}$$

where $\boldsymbol{W}_{\mathrm{SAE2}}$ is the weight matrix of the decoder and $\boldsymbol{b}_2$ is the bias vector. The reconstruction error can be calculated by

$$J_{\mathrm{SAE}} = \frac{1}{2M}\sum_{m=1}^{M}\left\|\boldsymbol{x}_m - \hat{\boldsymbol{x}}_m\right\|^2. \tag{3}$$

To get better features of the input data, sparse representation is used in SAE. So Kullback–Leibler (KL) divergence function is applied to encourage the sparsity of the feature $\boldsymbol{h}^m$ and learn the