Stacked Denoising Autoencoder based Fault Diagnosis for Rotating Motor

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Abstract: Fault diagnosis is vital for normal operation of the rotating motor. An effective and reliable deep learning method known as stacked denoising autoencoder (SDAE) is investigated in this paper, which can extract the features from the pending signals with disturbances. Deep adaptive networks are designed to extract features automatically from time domain data and frequency domain data of motor vibration signal, respectively. Then, the network parameters of the SDAE are trained to reconstruct the signal features, and clustering results are investigated. Finally, a classification layer is added to the top layer of the SDAE network for the fault isolation. It is shown that, the diagnosis accuracy with input of vibratory frequency signal is higher than that of time domain signal. The features extracted by SDAE can represent complex mapping relationships between signal and various running status, and the accuracy is improved comparing with traditional fault diagnosis methods.

Key Words: Rotating motor, Fault diagnosis, SDAE, Deep learning.

1 Introduction

In recent years, the high-speed railways have experienced a rapid development throughout the world, hence there's a higher requirement for the safety performance of high-speed trains[1]. With the growth of running time, actuators and sensors of the high-speed railways system are degrading with age. These fatigued components are likely to have various slowly developing faults, which will increase the risk of serious accidents in the whole system[2].Rotating motor is the traction power equipment, whose reliability relates directly to the train operation safety[3]. Any motor failure will cause unwanted downtime, expensive repair procedures, and even human casualties. As and effective component of condition-based maintenance, fault diagnosis has gained much attention to guarantee safe motor operations[4]. Locomotive rotating motor fault diagnosis is a critical technique mean to ensure the reliability of the high-speed railways. So the researched problems in the paper have important prospect of engineering application.

In the past few years, numerous physical models of electrical motors have been developed. Most of them are based either on finite-element modeling[5] or on analytical modeling[6].And numerous studies of motor fault detection and diagnosis have been reported in the literature [7,8,9,10], which could be categorized as model-based approaches and data-driven approaches. Model based approaches mainly rely on an accurate mathematical model of the rotating motor and typically include observer based techniques, Kalman filter and estimators, and parity equations. However, in practice, model-based approaches often fail to work due to the difficulty in modeling multiple coupling in system parameters and unexpected disturbances. In contrast, data-driven approaches do not require physical or accurate mathematical models but directly use the measured sensor data to infer the fault detection system. These approaches mainly involve signature analysis and artificial intelligence. The signature extraction based approach is utilized by surveying fault signatures in time or frequency domain. Signatures extracted from recorded signals are employed to diagnose faults. Significant amount of research has been done in this area[11]. Motor conditions can be reflected by vibratory[12], acoustic[13], thermal[14] and electrical[15] measurements, among others. Signals from vibration sensors are usually measured and compared with reference measurements in order to interpret motor conditions. The methods used to analyze these signals include probabilistic analysis[16], frequency analysis[17], time-domain analysis [18], and finite-element analysis[19]. Among these methods, the frequency analysis approach is the most popular one. This popularity is most probably due to the availability of Fourier transform technique. The frequency analysis technique involves frequency analysis of the vibration signal and further processing of the resulting spectrum to obtain clearly defined diagnosis information[20]. As the data is generally collected faster than diagnosticians can analyze it,

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there is an urgent need for diagnosis methods that can effectively analyze massive amounts of data and provide accurate diagnosis results automatically. These types of methods are called intelligent fault diagnosis methods. Traditional machine learning approaches like K-nearest[21], Support Vector Machine (SVM)[22], particle swarm SVM [23], logistic regression[24] and Dempster-Shafer evidence theory[25] are used for obtaining clearly defined diagnosis information such as fault detection and isolation. However, some challenges in fault detection of rotating motors still remain. One major challenge lies in their nonlinearity, unknown disturbances as well as significant measurement noise. In addition, manual feature extraction often makes raw signals lose a certain part. Thus, it is necessary to adaptively mine the characteristics hidden in measured signals to reflect the different health conditions of the machinery, instead of manually extracting and selecting features.

In recent years, Deep learning has the potential to overcome the aforementioned deficiencies in current intelligent diagnosis method. Compared to current shallow machine learning algorithms, deep learning-based methods attempt to model high-level abstractions in data using multiple processing layers with complex structures, resulting in better representations from the point of view of simplifying a learning task from input examples[26]. In consideration of the similarity between health states of complex rotating motor and heterogeneous data in image pattern classification problems with high-dimensionality, deep learning methods may show great potential in system fault diagnosis with respect to the advantage of a dominant training mechanism and deep learning architecture[27].

The existing methods of rotating motor fault diagnosis mainly include: classifying by artificially extracted features or by traditional supervised learning network.The former method depends on very few artificial extracted features, and makes raw signals lose a certain part features, so the correct rate of diagnosis is low. The latter method relies on a large number of labeled data sets for training.In this paper, the stacked denoising autoencoder (SDAE)[28],which is a kind of deep learning network, is used to diagnose the rotating motor fault of high-speed train. The network codes to learn the probability distribution of all kinds of samples, based on the unlabeled data sets.A classifier is added to the top layer of network, and is trained by supervised learning method. Only a small number of labeled data is needed in the training process.The SDAE based fault diagnosis method consists of three consecutive stages: first, the raw signal of vibration was converted into a frequency domain using DFT. Subsequently, the frequency signal was used as input to the SDAE, where it utilized these preprocessed samples for carrying out unsupervised training to realize motor fault diagnosis. Third, the proposed SDAE models are validated using testing datasets. The fault diagnosis accuracy of the proposed deep learning method can be used to form a knowledge base to determine if the approach is applicable for detecting and classifying the health states of complex systems with inevitable interference.

The method researched in this paper can overcome the shortcomings of the traditional supervised learning method, which relies on a large number of labeled data sets, and ensures the ability of the network to explain the types of the unknown faults, so the accuracy and efficiency of fault diagnosis are improved.This paper is organized as follows: SDAE methods are introduced in Section 2. In Section 3, a description of data preprocessing and model design is provided. In Section 4, the proposed model is validated using test datasets collected from the drivetrain diagnostics simulator system. In Section 5, the paper is concluded.

2 Fault diagnosis using the SDAE-BASED CLASSIFICATION

2.1 Autoencoder

A basic autoencoder (AE) is a fully-connected three-layer feed forward neural network with one hidden layer. Typically, the AE has the same number of neurons in the input layer and the output layer and reproduces its inputs at its output layer. Therefore, AE is trained in an unsupervised manner without any label information, which is suitable for learning the health reference model considered in this study. Similar to PCA, the AE aims to encode the input data to an intermediate representation which preserves most information of the input data so as to reconstruct it [29]. Fig. 1 gives the structure of AE.

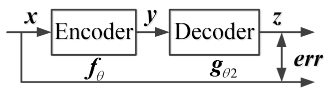


Fig. 1: Autoencoder

The dimension of the hidden layers can be either smaller than the input dimension when the goal is feature compression, or larger when the goal is mapping the feature to a higher dimensional space. An autoencoder tries to find deterministic mapping between input units x and hidden nodes by means of a nonlinear function

$$y=f_{\theta 1}(x)=s_1(W_1 x+b_1) \tag{1}$$

where W_1 is a $m\times n$ weight matrix, b_1 is a bias vector, and $s_1(.)$ is a nonlinear function such as sigmoid or tanh. This mapping is called the encoder. The latent representation is then mapped back to reconstruct the input signal with:

$$z=g_{\theta 2}(y)=s_2(W_2 y+b_2) \tag{2}$$

where W_2 is a $n\times m$ weight matrix, b_2 is a bias vector, and $s_2(.)$ is either nonlinear function like $s_1(.)$ or a linear function. This mapping is called the decoder. The goal of training is to minimize the loss function:

$$L\{W_1,b_1,W_2,b_2\}=\left[\frac{1}{n}\sum_{i=1}^{n}J(x^{(i)},z^{(i)})\right]+\lambda\sum_{i=1}^{n}(W_i)^2 \tag{3}$$

where $J(x^{(i)},z^{(i)})$ is the squared error between the input and the output, λ is the a regularization term to help prevent overfitting by decreasing the magnitude of the weights.

To further improve the autoencoder performance, a fine-tuning process using the back propagation algorithm is applied on the basis of traditional gradient descent, where the parameters of the autoencoder model are updated to minimize the $L\{W_1,b_1,W_2,b_2\}$ training error.

2.2 Denoising Autoencoder

A problem usually arises in the self-learning process when the ambient noise that cannot be ignored is mixed within the dynamic vibration signals, which is hard to deal with manually because of the large number of samples to be trained. In our study, to deal with complex noisy multivariate data and capture the hidden nonlinear correlations more robustly, we consider a newly developed algorithm in the deep learning community, the denoising autoencoder (DAE)[30], which has been extensively used for unsupervised representation learning and as pre-training building blocks in deep neural networks. The key idea of DAE is to reconstruct the original input from a corrupted one. Taking one autoencoder as an example, the data destruction method undertaken in this study is described as follows. Fig. 2 gives the structure of DAE.

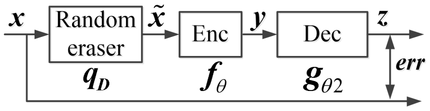


Fig. 2: Denoising Autoencoder

Let $q^0(x)$ be the joint distribution function concerned with input samples:

$$q^0(x,\tilde{x},a) = q^0(x) q^D(\tilde{x}|x)\delta_{f_\theta(\tilde{x})}(a) \tag{4}$$

where x and $\tilde{x}$ denote the initial and corrupted input data, respectively and a is the deterministic function of $\tilde{x}$. Hence $\tilde{x}$ is achieved by means of a stochastic mapping of $\tilde{x} \sim q^D(\tilde{x}|x)$. The autoencoder is thus applied for the following feature reconstruction based on the un- supervised learning process mentioned above. Note that the data destruction process is conducted in all layers of the DAE model instead of only the input layer.

2.3 Stacked Denosing Autoencoder

Stacked Denoising Autoencoder (SDAE) is the deep version of a single DAE[31]. Fig. 3 illustrates the SDAE architecture. The arrows indicate the direction of information flow. As shown in Fig. 3, the SDAE structure is a stacked multiple DAEs where the output of each DAE is removed and the hidden layer of each DAE is the input to the following one. Each DAE is trained independently and only saves the input layer and the hidden layer. The decoder of each DAE is abandoned.

To obtain the fault diagnosis, there is a classifier on the top of SDAE, i.e. output layer. In this study, the softmax regression algorithm is employed for multi-class classification[26]. We suppose the training samples are $(x^{(k)}, y^{(k)})$, and the label $y^{(k)}$ is treated as the training target for supervised optimization learning. Given an input x, the classification probability $p(y=j|x)$ achieved by the softmax regression algorithm for each category $j(j=1,...k)$ can be expressed based on the following hypothesis function:

$$h_\theta(x^{(i)}) = \begin{bmatrix} p(y^{(i)}=1|x^{(i)};\theta) \\ p(y^{(i)}=2|x^{(i)};\theta) \\ \dots \\ p(y^{(i)}=k|x^{(i)};\theta) \end{bmatrix} = \frac{1}{\sum_{j=1}^{k} e^{\theta_j^T x^{(i)}}} \begin{bmatrix} e^{\theta_1^T x^{(i)}} \\ e^{\theta_2^T x^{(i)}} \\ \dots \\ e^{\theta_k^T x^{(i)}} \end{bmatrix} \tag{5}$$

Where $\theta_1, \theta_2, ..., \theta_k$ refer to the model parameters.

To further improve the classification performance, a fine-tuning process using the back propagation algorithm is applied on the basis of traditional pattern recognition, where the parameters of the SDAE model areupdated to minimize the training error.

$$J(\theta) = -\frac{1}{n}\left[\sum_{i=1}^{n}\sum_{j=1}^{k} 1\{y^{(i)}=j\}\log\frac{e^{\theta_j^T x^{(i)}}}{\sum_{l=1}^{k} e^{\theta_l^T x^{(i)}}}\right] \tag{6}$$

Where $1\{\cdot\}$ is an indicative function, which means that, when the value of the braces is true, the result is 1; otherwise, the result is 0.

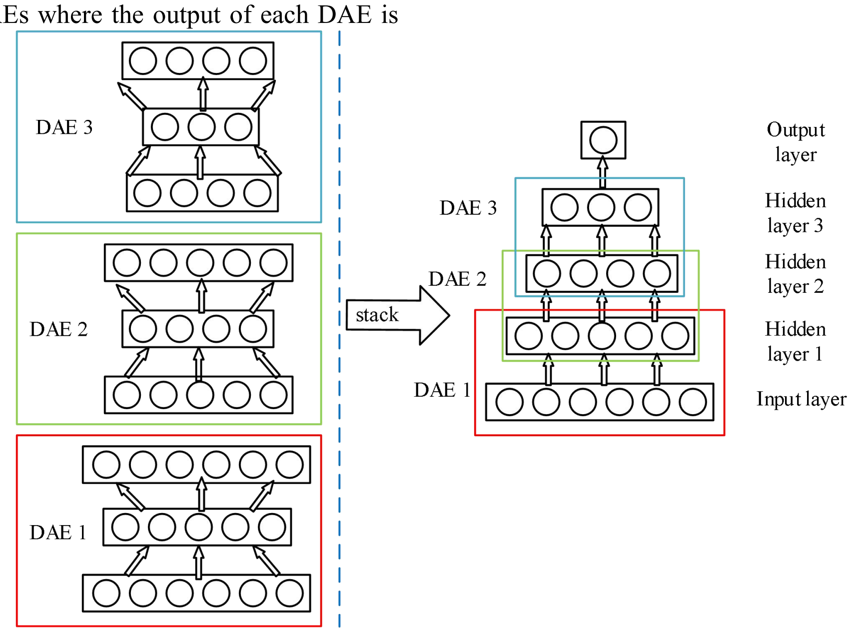


Fig. 3: The Structure of Stacked Denoising Autoencoder

3 Data preprocessing

To address the health state identification problems effectively with the SDAE, the first step is to identify the data format and diagnosis targets. Under this method, we have to preprocess the raw vibration signal and convert it to frequency domain. The general frequency analysis method is Fast Fourier Transform (FFT). FFT algorithm carries on spectrum analysis in the signal period. The expression of DFT is:

$$X(k)=\frac{1}{N}\sum_{n=0}^{N-1}x(n)e^{-j\pi nt/N} \tag{7}$$

where $x(n)$ and $X(k)$ are sample sequence of signal and the corresponding harmonic coefficients. The number of sampling points decides the computation of the transformation. FFT is a variety of DFT. The algorithm complexity of DFT is $N*N$, and the FFT is $N*\log(N)$.

When the sampling frequency is F_s , the sequence frequency F , the number of sampling points N, then the FFT results of time domain sequence are N plural. Each plural is a frequency of the signal. An important index about spectrum analysis is frequency resolution, i.e. the minimum identifiable space between two frequencies in spectrum. As we know that the resolution of FFT is F_s/N . To improve this value, reducing the sampling frequency and increasing the sampling point are required. The former reduces the analysis range of frequency and cannot raise up frequency resolution of high frequency band; the latter must increase the length of data window, now along with the application of computer, this is no longer a chief problem.

4 Experiment and Analysis

The motor data used in these experiments were collected from the locomotive rotating motor in the drivetrain diagnostics simulator system. Table 1 gives the specifications.

Table 1: Specifications of Rotating Motor

Variables	Data
Motor Speed	720r/min
Sampling Frequency	5120Hz
Sampling Point	5120
Frequency Resolution	1Hz
Maximum Frequency	2000Hz

Five experiments were carried out under different motor health conditions (given in Table 2).

Table 2: Description of experiments

Motor Condition	Description	Label
Normal	Normal Operation	0
Rotor Unbalance	Caused by Rotor Washer	1
Bearing Ball	Bearing Ball Damage	2
Bearing Outer-ring	Indentation in the Outer-ring Raceway	3
Bearing Inner-ring	Peeling Pit in the Inner-ring Raceway	4

Samples amounting to 3000 were collected for each fault in this method, with the 5120 points of vibration signal for each sample. We randomly selected 20% of them as the test samples, and the rest as a training samples. Fig. 4 gives the vertical vibration signal.

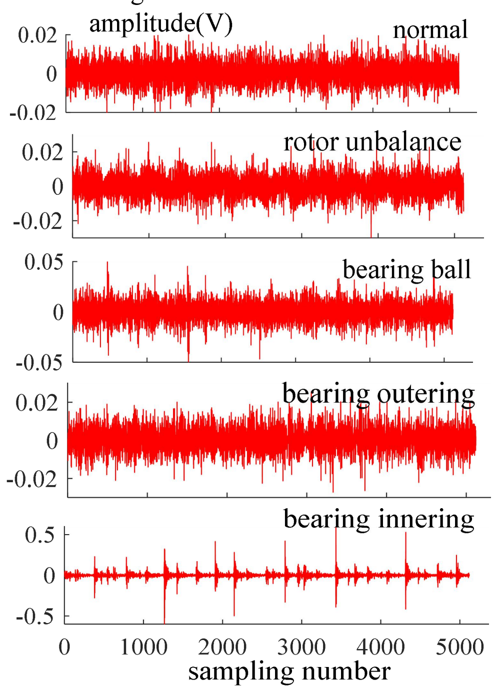


Fig. 4: Vibration Signal

As shown in Fig.4,The vibration signal embodies the energy accumulation. When the motor fails, the energy distribution of the vibration signal will change correspondingly, and these changes will be reflected in the vibration data collected.Generally, the fault frequency is one or multiple times of rotation frequency. For example, rotor unbalance fault frequency is equal to motor frequency. Passing frequency of bearing outer-ring is multiple of the motor speed as well as the number of bearing ball, and that of bearing inner-ring follows the similar rules.

Based the proposed method, we use the time domain signal and the frequency domain signal of vibration to train the SDAE neural network. At the same time, for comparison to traditional intelligent method, we use SVM based fault diagnosis. To analysis the accuracy in different layers, this study constructs several SDAE with different layers. From the experiments, it can be seen that when the hidden layers is 4, the batch-size is 34 and the learning rate is 0.01, the SDAE can give a good performance.Fig. 5 has shown the results of the comparison.

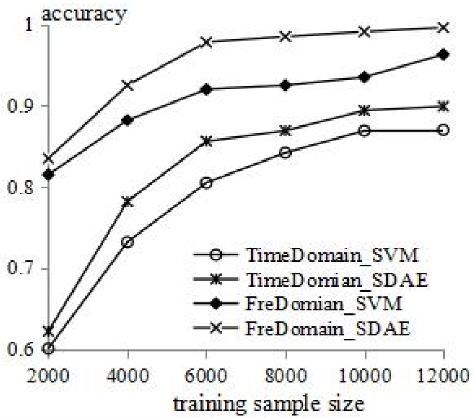


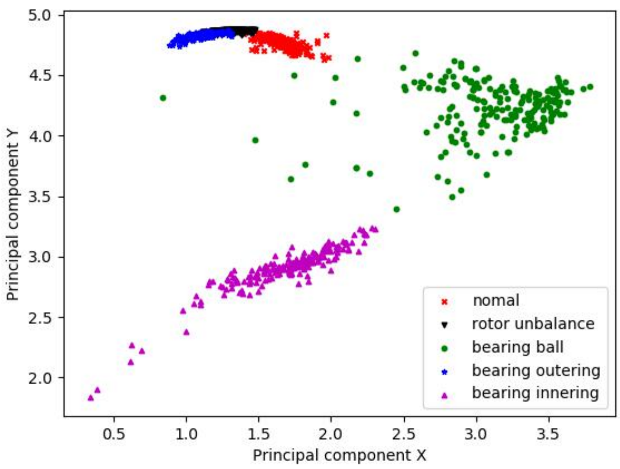
Fig. 5: Accuracy of Training

As shown in Fig.5, the accuracy rate increases with the sample size. Comparative analysis indicates the following two points.

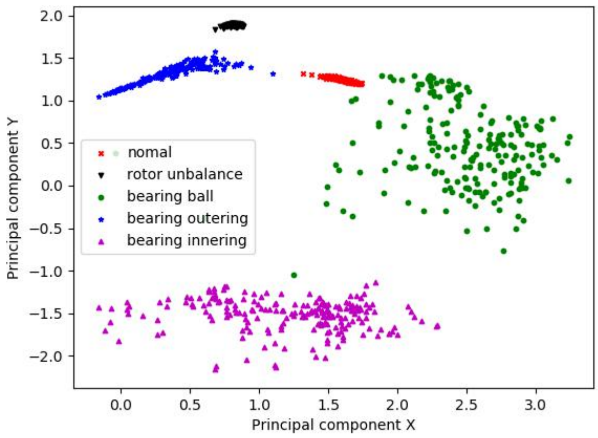
(1) Compared with time domain signal, SDAE can give a higher accuracy rate training by frequency signal.The main reason is that fault frequency is one or multiple times of rotation frequency. When bearing and rotor rotates, the vibration signal will have a larger component overlay the corresponding frequency. It is relatively difficult for neural network to extract effective features from vibration signals in time domain. Time-frequency transformation is a data preprocessing. After data transformation, the reliability of feature extraction will be higher.

(2) The SDAE network proposed can diagnose faults for rotating motors of high speed train.The diagnostic accuracy of SDAE is 99.6% when the sample size is 8000. SDAE can give a better performance than SVM. The reason is that the unsupervised feature learning method is used in AutoEncoder network. By training on the unlabeled data sets, probability distribution of various samples can be learned by SDAE network. The classifier can be trained by only a small number of labeled data sets. However, the traditional supervised learning method SVM is poor in learning data distribution, so its diagnostic accuracy is relatively low.

PCA is essential a linear method, which can give the visualized results. This study use the PCA to extract the features of the fourth layer. Fig. 6 gives the results.



(a) 50 training epochs



(b) 300 training epochs

Fig. 6: Features Extracted from SDAE

Fig. 6(a) is the features extracted by SDAE for 50 train epochs; Fig. 6(b) is the features extracted by SDAE for 300 train epochs. It shows that when the training epoch is 300, the clustering of the faults can give good performance. For 50 iterations, bearing ball faults (label: 2) and bearing inner-ring fault (label: 4) can be isolated; rotor imbalance (label: 1) and bearing outer-ring fault (label: 3) and normal cannot divided successfully. For 300 iterations, each fault can be identified.

5 Conclusion

This paper proposed an SDAE based fault diagnosis for locomotive rotating motor. The proposed method extracts the features of vibration signals by using unsupervised learning. Without the labeled data, this method can give a good performance for clustering and robustness. Given the comparison with SVM, the proposed method can present 99.6% accuracy with suitable parameters. The real experiments verify its effectiveness.

The future work should be focused on the following two aspects： 1) How to select the hidden layer number of the network, and how to select the learning rate and other parameters to improve the algorithm performance.2)Collect vibration signal of rotating motor, when the locomotive drivetrain system is actually operating. Train and test the SDAE network on the data sets, and transplant the network to the controlling system of high-speed train .

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