A Fault Degree Classification Method for AE Signal Based on VAR-DBN

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Abstract. It is difficult to find the train axle fault earlier by traditional calculation method. In this paper, a time series analysis and pattern recognition analysis based model is presented to improve the performance on diagnosing fault of AE signal. The suggested methodology mainly involves three parts. First, empirical mode decomposition (EMD) is used to transform the AE signals into stationary signals by decomposing the original signal into several intrinsic mode functions (IMFs) and one residue. Then, vector autoregressive (VAR) model is selected to reflect the characteristic included in IMFs by establishing feature vector comprised by the coefficients of the VAR model. In the end, a Deep Belief Network (DBN) is introduced to classify the AE signals and detect the fault signals caused by faults. The result of the experiment shows that compared with other time series parameter analysis based classification study, the proposed method has better behavior in accuracy when identifies different conditions of railway vehicle axle on AE signal.

Introduction

As a fail-sensitive method of signal analysis with high signal-to-noise ratio, AE signal analysis has attracted much research interest and plays an important role in the field of fault diagnosis in recent years. the AE signal, however, is sensitive to the noise. Hence, the approach to effective feature extraction and accurate classifier on AE signal is still a challenging issue.

Time series analysis is a useful tool for feature extraction. The parameters of time series model contains important information about the signals modeled and they are sensitive to the change of state [1]. Parametric based spectral estimation is a commonly used method for signal analysis. Parametric methods obtain power spectrum by estimating the parameters of time series model recursively and adaptively rather than using basis function. Besides, with the development of machine learning, the characteristics implied in parameters can be identified easily and efficiently by machine learning model. Thus, some recent research efforts are paid on the fault diagnosis method combining time series model with machine learning method [2]. Machine learning based feature extraction shows better performance than spectral estimation method when analyzes vibration signal [3]. However, there are only a few researches and applications on it over AE signal.

Stationary processing is necessary for most linear autoregressive when processes non-stationary signal such as AE signal. Empirical mode decomposition (EMD) is a novel self-adaptive analysis method for non-linear and non-stationary signals [4]. EMD decomposes signals into several linear and stationary components called intrinsic mode functions (IMFs) based on the local character of the signals themselves. Due to the strong ability in non-linear and non-stationary signal analysis, EMD is used for fault diagnosis gradually in recent years and has been proved to be an efficient stationary transformation for time series modeling [5]. Almost all the works in this field, however, simply use AR model and pay no attention to the difference between various time series models. This negligence may cause the decrease of the accuracy. IMFs are a set of components of the original signal and the correlation between the developments of each IMF cannot be reflected by AR. Vector autoregressive (VAR) is an improved simultaneous equation model based on AR [6]. VAR model
contain multiple endogenous variable and establish equations for every variable related to every variable in the model. Hence the model is able to show the dynamic relationship between the IMFs. However this kind of model is rarely used in field of signal analysis and fault diagnosis.

In this paper, we present an effective method combining both time series model and machine learning to recognize defect on AE signal. The provided method includes three steps: signal preprocessing, feature detection and classification. In the first step, EMD is used to decompose the AE signal into a set of stationary IMFs and a residue. In the second step, VAR model is established by several selected IMFs to reserve the correlation between IMFs which may be ignored by AR model. And the feature vector is extracted from parameters of the model. In the final step, a DBN is introduced as a classifier instead of commonly used vector machine (SVM) to achieve higher accuracy. The results of experiments demonstrate that the proposed method has higher accuracy compared with other time series parameter analysis based methods.

The remainder of this paper is organized as follows. In Section 2, we introduce the detail of the proposed method which contains pretreatment, feature extraction and classification. And then, we report experimental results and give discussion in Section 3, before concluding our work in Section 4.

Proposed Method

In this section, we present our new approach for fault diagnosis on AE signal which we call EMD-VAR-DBN model. This proposed method is detailedly introduced in three parts which include pretreatment, feature extraction and classification. The flowchart of the method is shown in Figure 1.

Pretreatment

The original AE signals collected from axles are non-stationary and have some difference with each other. This kind of signal cannot be used to obtain feature directly. Therefore pretreatment is a necessary procedure before feature extraction. As an efficient and popular approach for analyzing
non-linear and non-stationary signals, EMD is used as the stationary transformation in this paper for the normalized signal. IMFs decomposed into by EMD must meet the following definition:

1. The number of extreme points and the number of zero crossings must either equal or differ at most by one in the entire component;
2. At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima must be zero.

EMD decomposes data set into IMFs by sifting process. The decomposition can be described as a set of IMFs with a residue by following equation:

\[
x(t) = \sum_{i=1}^{n} f_i(t) + r_n(t),
\]

where \( f_i(t) \) (i=1,2,…,n) represents the n IMFs sifted by EMD, and \( r_n(t) \) is the residue separated from \( x(t) \) after sifting process.

**Feature Extraction**

The signals collected from different severity of faults may be decomposed into different number of IMFs. This kind of difference causes the dimensions of feature vectors different with each other. Otherwise, AE signal has high frequency and the meaningful information generally distributes in the top several IMFs with higher frequency. Thus, it is necessary to standardize the number of IMFs and select the several meaningful IMFs for the following process.

In this paper, correlation coefficient is used to sift those IMFs which involve most of information. The definition of correlation coefficient between two series \( X \) and \( Y \) is as follow:

\[
r(X,Y) = \frac{\text{Cov}(X,Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}},
\]

where \( \text{Var}(X) \) and \( \text{Var}(Y) \) is the variance of series \( X \) and series \( Y \) respectively, \( \text{Cov}(X,Y) \) is the covariance of two series. The IMFs whose correlation coefficient is higher among the set of components are selected as the meaningful IMFs.

After the screening process of IMFs, a VAR model is established for those selected IMFs. The VAR model for \( m \) IMFs and \( p \) order lag used in this work is defined as following form:

\[
\begin{bmatrix}
y_{1,t} \\
y_{2,t} \\
\vdots \\
y_{m,t}
\end{bmatrix} = \sum_{k=1}^{p} \begin{bmatrix}
\phi_{11,k} & \phi_{12,k} & \cdots & \phi_{1m,k} \\
\phi_{21,k} & \phi_{22,k} & \cdots & \phi_{2m,k} \\
\vdots & \vdots & \ddots & \vdots \\
\phi_{m1,k} & \phi_{m2,k} & \cdots & \phi_{mm,k}
\end{bmatrix} \begin{bmatrix}
y_{1,t-k} \\
y_{2,t-k} \\
\vdots \\
y_{m,t-k}
\end{bmatrix} + \begin{bmatrix}
\epsilon_{1,t} \\
\epsilon_{2,t} \\
\vdots \\
\epsilon_{m,t}
\end{bmatrix},
\]

where \( y_{m,t} \) is the data in the \( m \)-th IMF at point \( t \), \( y_{m,t-k} \) is the \( k \)-th order lag data of the \( m \)-th IMF from point \( t \) and \( \phi_{mn,k} \) is the regression parameter of \( y_{n,t} \) for \( y_{m,t} \), \( \epsilon_{m,t} \) is the residual of \( y_{m,t} \).

The parameters in VAR model are chosen as features to identify the health condition of system. For structuring a feature vector by parameters, the parameters in each parameter matrix are arranged as rows and vector \( T_k \) is obtained:

\[
T_k = [\phi_{11,k}, \phi_{12,k}, \ldots, \phi_{1m,k}, \phi_{21,k}, \ldots, \phi_{2m,k}, \ldots, \phi_{mm,k}] \quad (k = 1, 2, \ldots, p)
\]

Then, we combine the vectors expanded by the parameter matrix of each lag as a feature vector for an AE signal:

\[
V = [T_1, T_2, \ldots, T_p]
\]

Notice that, the dimension of feature vectors is decided by the minimum order \( p \) among the set of models established by all AE signals.
Classification Process

After extracting features from VAR model, a Back Propagation Deep Belief Network (BP-DBN) [7] constituted by DBN and an output layer is used as classifier to identify the condition of system.

Restricted Boltzmann Machines (RBM) is the basic unit of DBN. RBM contains a hidden layer H and a visible layer V. The only interaction terms in RBM are between the units in hidden layer and the unit in visible layer. The state of a unit is denoted by biases bi and cj for each unit in layer V and in layer H respectively, and weights wij between the i-th unit in V and the j-th unit in H. The probability of binary state for each unit is as follows [8]:

\[ p(h_j = 1|v) = \sigma(c_j + \sum_i v_i w_{ij}) \]  
(6)

\[ p(v_i = 1|h) = \sigma(b_i + \sum_j h_j w_{ij}) \]  
(7)

where vi,hj are the binary states of the i-th visible unit and the j-th hidden unit, \(\sigma(x)=1/(1+\exp(-x))\) is the logistic sigmoid function. The energy of RBM is given by:

\[ E(v,h) = -\sum_i b_i v_i - \sum_j c_j h_j - \sum_{i,j} v_i h_j w_{ij} \]  
(8)

The probability that the network assigns to a visible vector is given by summing over all possible hidden vector:

\[ p(v) = \frac{1}{Z} \sum_h e^{-E(v,h)} = \frac{\sum_h e^{-E(v,h)}}{\sum_v e^{-E(v,h)}} \]  
(9)

The hidden units are considered as another manifestation of visible units when the refactored visible vector obtained by Eq. 7 and Eq. 8 are similar enough to the original one. Thus the purpose of training RBM is to adjusting the weights and biases to lower the energy and achieve the highest \(p(v)\) in Eq.9.

The training of BP-DBN includes unsupervised pre-training and supervised fine adjustment. The unsupervised learning process for RBM described above is used for DBN pre-training layer by layer. Then the BP-DBN is adjusted by commonly back propagation algorithm until convergence. The BP-DBN model used in this paper is shown in Figure 2.

Experimental Evaluation

To evaluate the effectiveness of the proposed method in this paper, an experiment of identifying railway vehicle axle crack is discussed in this section. The experimental results obtained during the processes of feature extraction are described in detail, and the classification result of our method is compared with it of another recent work based on time series analysis.

Signal Category

The conditions corresponding to signals collected from axles are mainly generalized into three categories:

(1) Health (H): Health is defined as the condition that there are few crack in axle and the process of crack formation is slow and smooth.

(2) Early fault (EF): Early fault is considered as the process that tiny cracks appear frequently and continuously. The signals collected from this status always contain some AE signals occurred by cracks and a lot of noise generated by environmental factors or normal operation of machine.
(3) Serious fault (SF): When the axle is bended to some extent, these tiny cracks extend and larger energy is released. In this case, cracks are produced more frequently and dramatically and the fatigue fracture process is also speed up. Signal to noise ratio of this status is much higher than Early fault.

Figure 2. BP-DBN structure used in this paper.

The wave forms of normalized signals gathered from three kinds of health conditions are shown in Figure 3. Then, we segment the signals into pieces with size of 2000 points. We randomly select 45 segments from each kind of signal as the training samples and 15 segments as test samples.

Figure 3. AE signals of different health conditions. (a) SF; (b) EF; (c) H.

Feature Extraction

The 180 samples from training sample set and test sample set are decomposed into IMFs by EMD. Figure 4 shows the average correlation coefficient between IMFs and their original sample. Obviously, the average correlation coefficients of IMF1 to IMF5 are much higher than others. Therefore, IMF1 to IMF5 are chosen to establish VAR model for samples both in training set and test set. Figure 5 shows the selected IMFs of three kinds of signals respectively.

By the feature extraction process introduced in section 2.2, a feature vector of 150 dimensions comprised by the top 6 parameter matrixes of every model is obtained for each training sample and test sample.
Identification and Contrast Experiment

The feature vectors obtained in section 3.2 are input in a BP-DBN to train the classifier model and identify fault. A feature matrix which is made up of the 135 feature vectors of the training samples is firstly used to train the BP-DBN. After training the BP-DBN, we use the test sample set to test the effectiveness of BP-DBN in identifying these three kinds of signals collected from different health conditions.

To demonstrate the advantage of the proposed method in this paper, we compare the recognition results of our study with an effective recent work, EMD-AR-SVM model [9]. First, we present a transitional method by replacing the feature extraction process in EMD-AR-SVM by ours, we call it EMD-VAR-SVM model. Then, we compare the result obtained from the three different model to explain the performance of both the feature extraction and classifier introduced in this paper. The accuracy of each model is shown in Table 1.

![Figure 4. Average correlation coefficients of each IMF calculated from three kinds of signals.](image)

![Figure 5. Selected IMFs of each kind of signals. (a) H; (b) EF; (c) SF.](image)

Table 1. Accuracy of the Identification results by three method.

| Identification method | Health condition | Overall accuracy |
|-----------------------|------------------|-----------------|
| EMD-AR-SVM            | 93.3%            | 80%             |
| EMD-VAR-SVM           | 93.3%            | 88.9%           |
| EMD-VAR-DBN           | 93.3%            | 93.3%           |

According to the result shown in Table 1, the EMD-AR-SVM model behaves badly when recognize early fault. By contrast, the accuracy always improves when ameliorate the feature
extraction and classifier respectively. It is obvious that although the EMD-VAR-DBN model behaves much better when recognize early fault.

Summary

In this paper, we introduce a time series analysis based adaptive AE signal analysis method, EMD-VAR-DBN model, to identify faults more accurately. EMD is used to decompose the AE signal into several stationary IMFs. To extract features from sifted IMFs more completely and efficiently, VAR model based method is proposed in this paper instead of the widely used AR based method. And then, DBN is used to classify the features extracted from VAR model. As a mature DL method, DBN can learn the characteristic of signals reflected in feature parameters more deeply comparing with traditional ANN or other classifier. According to the result of a carefully designed contrast experiment with another efficient method proposed recently, the feature extraction process and the classification method of the proposed model both have a better performance for identifying signals collected from different severity of faults, especially the early fault.

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