Faults diagnosis of railway rolling bearing by using time-frequency feature parameters and genetic algorithm neural network

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Abstract

This paper is focused on time-frequency feature parameters and genetic algorithm neural network techniques in fault diagnosis of railway rolling bearings. The time-frequency feature parameters for classification are extracted from vibration signals. However, the weak features of faults in rolling bearing are always immersed in noises of the environment, to solve this problem, Firstly, the wavelet analysis is used to filter and de-nosing and the time domain features are calculated. Secondly, the EMD (Empirical Mode Decomposition) method is used to decompose the signal into a number of intrinsic mode functions (IMFs), and then the IMF energy-torques could be calculated through the de-nosing signal. Finally, the genetic algorithm neural network is used for the classifications of the time-frequency feature parameters. The results of the time-frequency feature parameters and genetic algorithm neural network (GNN) show the effectiveness and the high recognition rate in classifying different faults of railway rolling bearing.

Keywords: time-frequency feature parameters wavelet analysis, EMD, IMF, genetic algorithm neural network, railway rolling bearing, fault diagnosis

1 Introduction

The rolling bearing is one of the important components in the railway sector, whose operation condition directly affects the whole performance of the railway, therefore, bearing fault diagnosis is important, and plays a key role in the reliable operation of the railway. Hence, bearing fault diagnosis and condition-based monitoring are of great significance [1].

There are extensive techniques, such as fast Fourier transform (FFT), envelope analysis, time-domain averaging and other techniques [2-6], have been fully developed and established for processing vibration signals to obtain diagnostic information about rolling bearing. However these methods only provide limited effectiveness for bearing diagnostics. So this paper deals with the application of time-frequency feature parameters and genetic algorithm neural network for fault diagnosis of railway rolling bearing. The vibration signals of bearing can be affected by noise possibly associated with external perturbations and the signal-to-noise ratio (SNR) is so low that feature extraction of signal components is very difficult, so the wavelet analysis is used to filter and de-nosing and then the time domain features are calculated. To obtain additional fault characteristic information, time and frequency domain features are extracted from the rolling bearing vibration signals. Moreover the EMD are applied to decomposing the vibration signals. Then energy features are extracted from the decomposed frequency-band signals of the intrinsic mode functions (IMFs) of EMD. The time-frequency feature parameters are then put into the classifiers based on genetic algorithm neural network. The results show that this approach can performance effectiveness and high recognition rate in classifying different faults of railway rolling bearing.

The rest of the paper is organized as follows. In section 2, the wavelet analysis and time-domain feature extraction method will be introduced, while EMD algorithm and frequency-domain feature extraction method will be described in section 3. Section 4 describes the principle of GNN. In section 5, the results are provided to demonstrate the effectiveness of the proposed algorithm for faults diagnosis of railway rolling bearing. Finally, the conclusions are drawn in Section 6.

2 Wavelet analysis and time-domain feature extraction

2.1 WAVELET ANALYSIS

The wavelet transform is a linear transform which uses a series of oscillating functions with different frequencies as window functions $\psi_{a,b}(t)$ (“a” is the dilation parameter for changing the oscillating frequency and ‘‘b’’ is the translation parameter) which transforms the signal $x(t)$. At high frequencies, the wavelet reaches to a high time resolution with a low frequency resolution, whereas at low frequencies, a low time resolution with a high frequency resolution is achieved, which make them more suitable for non-stationary signal analysis. The basis function for the

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wavelet transform is given in terms of translation parameter b and dilation parameter a with the following mother wavelet [7]:

$$\psi_{a,b} = \frac{1}{\sqrt{a}} \psi(\frac{t-b}{a}),\ a,\ b \in R,\ \ a \neq 0 . \quad (1)$$

The wavelet transform, $W(a,b)$ of a time signal $x(t)$ is given by:

$$W(a,b) = \int_{-\infty}^{+\infty} x(t) \frac{1}{\sqrt{a}} \psi^*(\frac{t-b}{a}) dt , \quad (2)$$

where $\psi^*(t)$ is the complex conjugate of $\psi(t)$.

2.2 TIME-DOMAIN FEATURE EXTRACTION

Three time-domain features, namely, kurtosis factor, margin factor and pulse factor, are calculated. They are defined as follows [8].

Kurtosis factor:

$$K_v = \frac{\sum_{i=1}^{n} x_i^4}{n x_{rms}^4} . \quad (3)$$

Margin factor:

$$CL_f = \frac{x_{peak}}{x_r} . \quad (4)$$

Pulse factor:

$$I_f = \frac{x_{peak}}{|\bar{x}|} , \quad (5)$$

where x_i is i-th sampling point of the signal x; n is the number of points in the signal, x_{rms} is the root mean square of the signal, x_r is the square root of amplitude of the signal, and $|\bar{x}|$ is the absolute average of the signal.

3 EMD algorithm and time-frequency domain feature extraction

3.1 EMD ALGORITHM

EMD is a method of decomposing a non-linear and non-stationary signal into a series of zero-mean amplitude-modulation frequency-modulation (AM-FM) components that represent the characteristic time scale of the observation [9]. This is done by iteratively conducting a sifting process. The zero-mean AM-FM components are called Intrinsic Mode Functions (IMFs); they must satisfy the following requirements:

1) The number of extremes and the number of zero crossings must be equal or only a difference of one is allowed.

2) The mean between the local maxima envelope and the local minima envelope at any point must be equal to zero.

If the two previous conditions are not satisfied, i.e. the resulting signal $x_1(t)$ is not an IMF, then the previous steps are repeated. The procedure becomes iterative and it is called sifting process. Obviously, functions $s_{\max}(t)$ and $s_{\min}(t)$ are recomputed at each iteration and the newly evaluated $m(t)$ is subtracted from the obtained signal $x_1(t)$.

The sifting process runs until the extracted signal respects the two IMF conditions; then the function obtained represents the first intrinsic mode function $C_1(t)$ and it is subtracted from the initial signal [10]:

$$r_1(t) = x(t) - C_1(t) , \quad (6)$$

where $r_1(t)$ is the residual signal. This signal represents the input for the second IMF calculation by means of the sifting process. The EMD algorithm, applied to the original signal $x(t)$, stops when the residual signal $r_N(t)$ is a constant or monotonic function, after the extraction of the N-th intrinsic mode function. The stop criteria can be expressed in terms of a standard deviation and number of extremes:

$$\sigma(r_N(t)) < \sigma_{stop} ,\ n_{\max}, n_{\min} = 0 . \quad (7)$$

The decomposition stops when both conditions are satisfied.

Since the decomposition objective is the identification of all the original signal structures, the original data can be reconstructed by adding the extracted IMFs to the residual signal.

3.2 TIME-FREQUENCY DOMAIN FEATURE EXTRACTION

Five time-frequency domain feature parameters are extracted from the vibration signal of rolling bearing in this work. The steps of time-frequency domain feature extraction are as follows:

1) The wavelet analysis is adopted to decompose the vibration signal of railway rolling bearing.

2) The de-noised vibration signals are decomposed into some IMFs by using the EMD method, the first n IMFs $c_i(t)$, $i = 1,2,3,...,n$, which include the most dominant fault energy are chosen to extract the feature.

3) Calculate the energy-torque of every small time block

The Equation to calculate IMF energy-torque is:

$$E_i = \int_{-\infty}^{+\infty} t |c_i(t)|^2 dt . \quad (8)$$

For discrete signals, the formula to calculate energy-torque is:

$$E_i = \sum_{k=1}^{m} (k \cdot \Delta t) |c_i(k \cdot \Delta t)|^2 , \quad (9)$$

where m is the total number of sampling points, k is the sampling points, Δt is the sampling period. Calculating the energy-torque $E_1, E_2, \cdots$ for each chosen IMF based on the Equation (9).

4) Constructing the feature vector T in the elements of the energy-torque.

$$T = [E_1 \quad E_2 \quad \cdots \quad E_n]. \tag{10}$$

When the energy-torque is a larger numerical, normalizing T and get the normalized feature vector T'. Among them:

$$E = \left(\sum_{i=1}^{n} |E_i|^2 \right)^{\frac{1}{2}}. \tag{11}$$

The Equation to calculate IMF energy-torque is [11]:

$$E_i = \int_{-\infty}^{+\infty} |c_i(t)|^2 \, dt. \tag{12}$$

4 Combination of neural network and Genetic algorithm

Genetic algorithms are the algorithms for optimization and learning based freely on several features of biological evolution. Genetic algorithm has been proved to be capable of finding global optima in complex problems by exploring virtually all regions of the state space and exploiting promising areas through mutation, crossover and selection operations applied to individuals in the populations. It applies selection, crossover and mutation operators to construct fitter solutions. A genetic algorithm process the populations of chromosomes by replacing unsuitable candidates according to the fitness function.

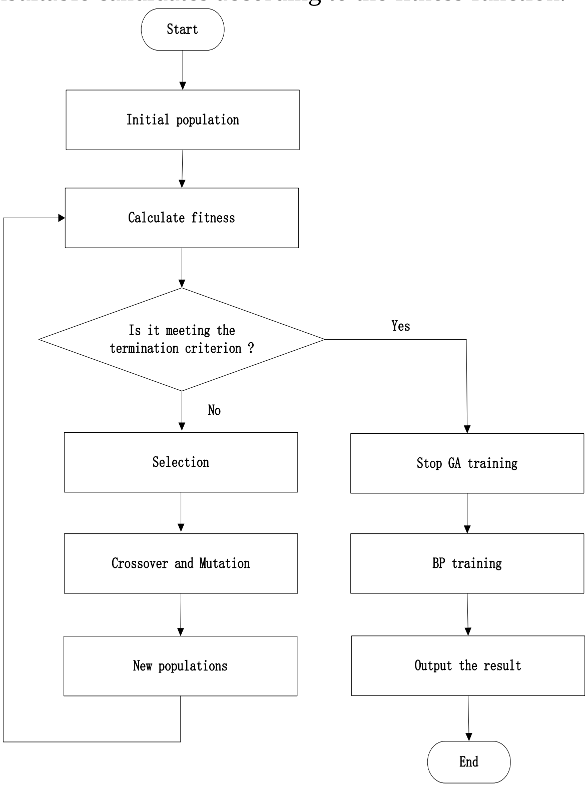

FIGURE 1 Framework of training a neural network using GA

The conventional BP algorithm is prone to falling into the local minimum point. To overcome this problem, this study attempts to combine genetic algorithms, avoiding local minimums.

The steps of combination of neural network and Genetic algorithm are shown in Figure 1 [12].

5 Experimental results

5.1 EXPERIMENTAL SETUP

The effectiveness of the proposed algorithm is further tested using experimental railway rolling bearing vibration signals. The railway rolling bearings are: normal bearing, inner ring fault bearing and rolling fault bearing.

5.2 THE PROCESS OF TIME-FREQUENCY DOMAIN FEATURE EXTRACTION

Here the wavelet analysis is employed to obtain a filtered signal with clear fault-revealing trend lines in its time-frequency representation, the time-domain feature parameters are calculated. The original vibration signals and the de-nosing vibration signals are shown in Figure 2 and Figure 3. The de-nosing vibration signals of railway rolling bearings are decomposed by EMD and the result is shown in Figure 4, and then the time-frequency feature parameters are calculated. All time-frequency feature parameters are divided into two groups, namely, the training group and the testing group. The training group is in Table 1. The testing group is in Table 2. The GNN is used to diagnose the faults; the inputs and outputs of the GNN are all memberships concretely, the inputs are the memberships of the kurtosis factor, margin factor, pulse factor and IMFs energy-torque on each characteristic domain, and the outputs are memberships of each fault.

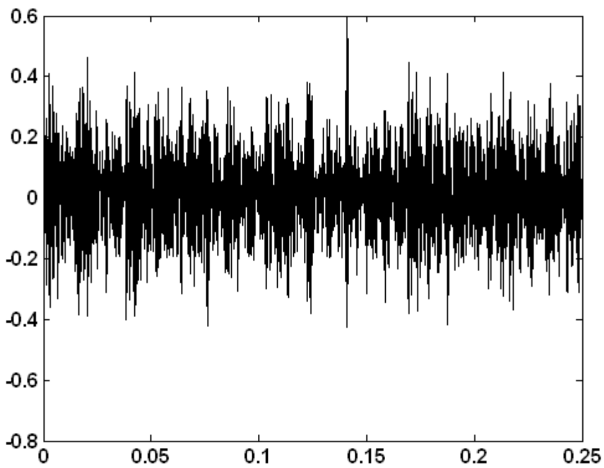

FIGURE 2 The time domain of outer ring fault signal

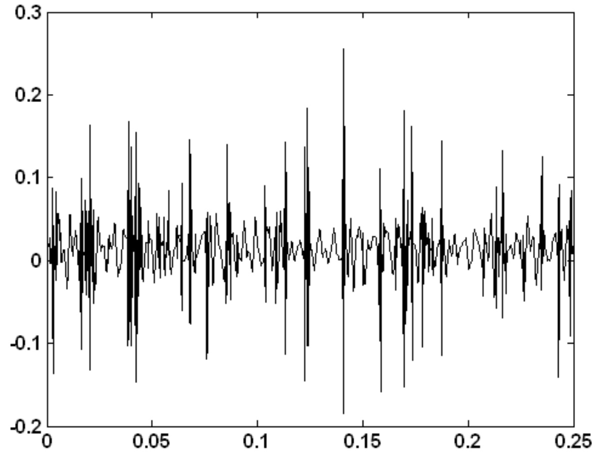

FIGURE 3 The de-nosing signal of outer ring fault

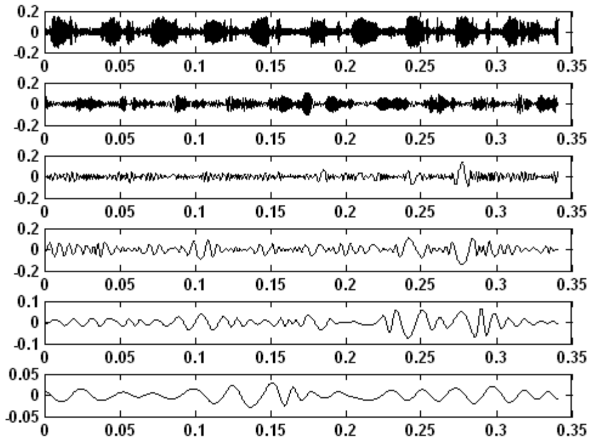

FIGURE 4 Decomposition of the outer ring fault signal into intrinsic mode functions

TABLE 1 Sample data of bearing operation

Kurtosis factor	Margin factor	Pulse factor	E_1	E_2	E_3	E_4	E_5	Fault status	Fault vector
3.612	5.979	4.979	0.924	0.147	0.193	0.283	0.075	normal signal	(1 0 0)
3.801	7.919	6.548	0.962	0.162	0.106	0.179	0.059	normal signal	(1 0 0)
3.704	6.015	5.044	0.970	0.120	0.174	0.114	0.032	normal signal	(1 0 0)
3.883	6.687	5.586	0.278	0.668	0.643	0.244	0.047	rolling fault signal	(0 1 0)
3.420	6.091	5.106	0.235	0.734	0.602	0.197	0.047	rolling fault signal	(0 1 0)
3.968	5.673	4.812	0.168	0.650	0.673	0.304	0.037	rolling fault signal	(0 1 0)
23.789	29.190	19.649	0.881	0.424	0.096	0.125	0.135	inner ring fault signal	(0 0 1)
25.857	32.435	21.979	0.871	0.444	0.168	0.096	0.069	inner ring fault signal	(0 0 1)
25.098	34.427	22.848	0.870	0.439	0.128	0.174	0.038	inner ring fault signal	(0 0 1)

TABLE 2 Testing data

Kurtosis factor	Margin factor	Pulse factor	E_1	E_2	E_3	E_4	E_5	Fault status	Fault vector
3.477	7.284	6.088	0.953	0.121	0.144	0.224	0.068	normal signal	(1 0 0)
3.754	6.517	5.504	0.33	0.67	0.587	0.28	0.036	rolling fault signal	(0 1 0)
31.027	33.756	22.602	0.888	0.407	0.107	0.087	0.157	inner ring fault signal	(0 0 1)

5.3 THE PROCESS OF GNN

The genetic algorithm neural network is used for fault diagnosis consist of three layers: an input layer, a hidden layer and an output layer. Before training, those neural networks were optimized, and we obtained the genetic algorithm neural network architecture is 8-6-3.

The testing results of the genetic algorithm neural network are in Table 3. As shown in this table, the classification of genetic algorithm neural network are all close to the corresponding ideal outputs of the examination sample, it is found to be satisfactory and we think that this system can be used in fault diagnosis studies in the future after it is developed.

TABLE 3 Testing results of GNN

Fault status	Ideal outputs	Actual outputs	Testing results
normal signal	(1 0 0)	(1.0387 -0.1913 0.0006)	normal signal
outer ring fault signal	(0 1 0)	(-0.1031 1.4504 0.0011)	outer ring fault signal
inner ring fault signal	(0 0 1)	(0.0215 -0.1257 1.0028)	inner ring fault signal

6 Conclusions

In this paper we develop faults diagnosis of railway rolling bearing by using time-frequency feature parameters and genetic algorithm neural network. The main contributions of our work are as follows:

1) The wavelet analysis is adopted to decompose the vibration signal of railway rolling bearing and the time domain features are calculated.

2) The EMD method is used to decompose the signal into a number of IMFs, and then the IMF energy-torques are calculated.

3) The genetic algorithm neural network is used for the classifications of the time-frequency feature parameters.

The experimental results show that this method can be effectively used in railway rolling bearing faults. So this proposed method gives an effective and feasible approach for the fault diagnosis of the rotary machine.

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