A Method for Railway Gearbox Faults Detection Based on Time-Frequency Feature Parameters and Genetic Algorithm Neural Network

Dechen Yao[*,1,2], Limin Jia[1], Yong Qin[1] and Jianwei Yang[2]

[1]*State Key Laboratory of Rail Traffic Control and Safety, Beijing Jiaotong University Beijing, 100044, China*

[2]*School of Mechanical-electronic and Automobile Engineering, Beijing University of Civil Engineering and Architecture, Beijing, 100044, China*

Abstract: Early identification of faults in railway gearboxes is a challenging task in gearbox fault detection. There are extensive studies, such as patents and papers have been fully developed for processing vibration signals to obtain diagnostic information about gearbox. We have proposed a new technique for detecting faults in the railway gearbox by applying the time frequency parameters and genetic algorithm neural network to deal with railway gearbox fault signals. In this method, wavelet analysis and empirical mode decomposition (EMD) are carried out on gearbox vibration signals for extracting the time-frequency feature parameters. Then genetic algorithm neural network (GNN) is used for the classifications of the time-frequency feature parameters. The analysis results show that the effectiveness and the high recognition rate in classifying different faults of railway gearboxes.

Keywords: EMD, fault detection, genetic algorithm neural network, railway gearbox, time-frequency feature parameters, wavelet analysis.

1. INTRODUCTION

Gearbox is the most widely used mechanical components in railway sector. A sudden fault in the gearbox during operation may result in heavy financial loss, therefore, it is critical to regularly investigate and check railway gear box for avoiding such kind of problems. Different methods have been developed for diagnosing and detecting gear box faults. One of the widely known technique for diagnosing gearbox faults is the vibration-based analysis [1].

Numerous condition monitoring and diagnostics methodologies are utilized for identifying the gearbox faults [2-7]. However, these methods only provide limited effectiveness for diagnosing complicated defects. In fact, when gear fault arise, the vibration signals demonstrate non-stationary behavior. Therefore, to understand the characteristics of the fault from the non-stationary vibration signals is the crux of the diagnosis of the fault [8]. Empirical mode decomposition (EMD) method is based on the local characteristic time scale of signal. It can split the complicated signal into a number of intrinsic mode functions (IMFs). By analysis of every resulting IMF component which carries the local characteristic of the signal, the characteristic information of the signal can be obtained accurately and effectively [9]. At the same time, artificial neural networks and genetic algorithms have been successfully applied to automated detection and diagnosis of gearbox [10-11]. So this paper proposes an approach for railway gearbox fault detection by using time-frequency feature parameters and genetic algorithm neural network.

2. TIME-DOMAIN FEATURE PARAMETERS

The kurtosis factor, margin factor and pulse factor are calculated. They are defined as follows:

Kurtosis factor:

$$K_v = \frac{\sum_{i=1}^{n} x_i^4}{n x_{rms}^4} \tag{1}$$

Margin factor:

$$CL_f = \frac{x_{peak}}{x_r} \tag{2}$$

Pulse factor:

$$I_f = \frac{x_{peak}}{|\bar{x}|} \tag{3}$$

where x_i is ith 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 METHOD AND TIME-FREQUENCY DOMAIN FEATURE EXTRACTION

3.1. EMD Method

The EMD method is based on the theory that every signal is combination of a series of simple but different intrinsic modes of oscillation. Each linear or non-linear mode will consist of equal number of extreme and zero crossings, and there is only one extreme between successive zero crossings. Every mode must be independent of others. In this manner, every signal can be divided into a number of IMFs, and each IMF should satisfy the below definitions [12]:

(1) The number of extrema and the number of zero crossings must be either identical or should differ at most by one;

(2) The running mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero [13].

An IMF represents a simple oscillatory mode compared with the simple harmonic function. By following this definition, a signal $x(t)$ can be decomposed as given below [14]:

(1) First of all, segregate all the local extrema, and connect the local maxima by a cubic spline line as the upper envelope.

(2) Repeat this process for the local minima for producing the lower envelope. The upper and lower envelopes must cover all the data between them.

(3) The mean value of upper and lower envelope is called m_1, while the difference between the signal $x(t)$ and m_1 is the first component, h_1, i.e.

$$x(t) - m_1 = h_1 \tag{4}$$

Ideally, if h_1 is an IMF, then h_1 is the first component of $x(t)$.

(4) If h_1 is not an IMF, h_1 is treated as the original signal and repeat (1), (2), then

$$h_1 - m_{11} = h_{11} \tag{5}$$

After repeated sifting, i.e. up to k times, h_{1k} becomes an IMF, that is

$$h_{1(k-1)} - m_{1k} = h_{1k} \tag{6}$$

Then it is designated as

$$c_1 = h_{1k} \tag{7}$$

The first IMF component is obtained from the original data. c_1 should contain the finest scale or the shortest period component of the signal.

(5) Separate c_1 from $x(t)$. We get

$$r_1 = x(t) - c_1 \tag{8}$$

where r_1 is treated as the original data and repeat the above processes. The second IMF component c_2 of $x(t)$ can be obtained. Let us repeat the process as described above n times. Then n-IMFs of signal $x(t)$ can be obtained. Then,

$$r_1 - c_2 = r_2 \tag{9}$$

$$\vdots$$

$$r_{n-1} - c_n = r_n$$

The decomposition process can be stopped when r_n a monotonic function from which no more IMFs can be extracted. By summing up Eqs.(5) and (6), we finally obtain

$$x(t) = \sum_{j=1}^{n} c_j + r_n \tag{10}$$

Thus, one can achieve a decomposition of the signal into n-empirical modes and a residue r_n, which is the mean trend of $x(t)$. The IMFs c_1, c_2, $\vdots$, c_n include different frequency bands ranging from high to low. The frequency components contained in each frequency band are different and they change with the variation of signal $x(t)$, while r_n represents the central tendency of signal $x(t)$.

3.2. Time-Frequency Domain Feature Extraction

The steps of time-frequency domain feature extraction are as follows:

(1) The vibration signals are divided into few IMFs by using the EMD method, the first n IMFs $c_i(t)$, $i = 1,2,3,\cdots,n$, where the most dominant fault energy is selected for extracting the feature.

(2) Calculate the energy-torque of every small time block

The IMF energy-torque is calculated as the following equation:

$$E_i = \int_{-\infty}^{+\infty} t\left|c_i(t)\right|^2 dt \tag{11}$$

For discrete signals, the energy-torque is calculated as the following equation:

$$E_i = \sum_{k=1}^{m} (k \cdot \Delta t)\left|c_i(k \cdot \Delta t)\right|^2 \tag{12}$$

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 formula (12).

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

$$T = [\ E_1 \quad E_2 \quad \cdots \quad E_n\ ] \tag{13}$$

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

Among them:

$$E = \left(\sum_{i=1}^{n} \left|E_i\right|^2\right)^{\frac{1}{2}} \tag{14}$$

The IMF energy-torque is calculated as the following equation:

$$E_i = \int_{-\infty}^{+\infty} \left| c_i(t) \right|^2 dt \tag{15}$$

4. GENETIC NEURAL NETWORK

The ability of a neural network for predicting accurate outcomes is dependent on the selection of proper weights during the neural network training. Because of the complicated nature of training neural networks, even simple functions can have very complex error surfaces. The nature of BP is to converge locally, therefore we can show that these solutions are mainly dependent on the initial random draw of weights. If these initial weights are located on a local grade, which is probable, the BP algorithm will likely become trapped in a local solution that may or may not be a global solution. This local convergence could present serious problems when using neural networks for real-world applications [15].

Genetic algorithm has been proposed for training neural network for overcoming the local convergence problem for nonlinear optimization problems. Genetic algorithm is a global search method which searches from one point of population to another, focusing on the best solution to that point, while sampling the total parameter space constantly.

The steps of combination of neural network and genetic algorithm as shown in Fig. (**1**) [16].

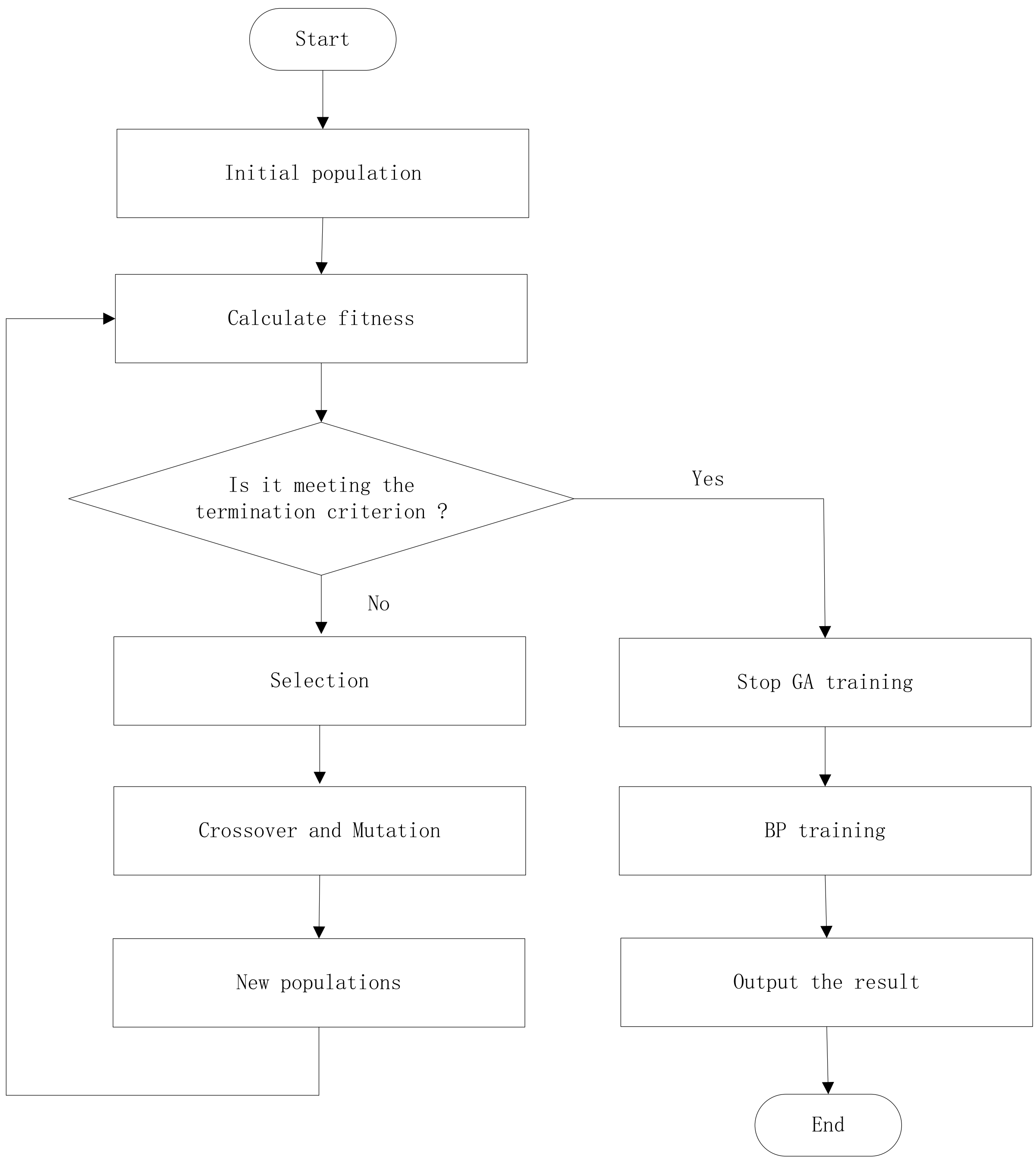

Fig. (1). Framework of training a neural network using genetic algorithm.

5. EXPERIMENTAL VALIDATION

For verifying the validity of the proposed method, the time-frequency feature parameters and genetic algorithm neural network is applied to the experimental railway gearbox vibration signal analysis. The original vibration signals of the railway gearbox are shown in Fig. (**2**). The kurtosis factor, margin factor and pulse factor are calculated. Then these signals are split by EMD method as we have discussed in the beginning of this paper. The decomposed signal by EMD is shown in Fig. (**3**). After having the IMFs, the time-frequency feature parameters are extracted, the Table **1** shows the training group, and Table **2** shows the testing group. Then GNN is used for the classifications of the time-frequency feature parameters. The GNN used for fault diagnosis is a combination of three layers which are (a) an input layer, (b) a hidden layer and (c) an output layer, and the architecture is 8-6-3.

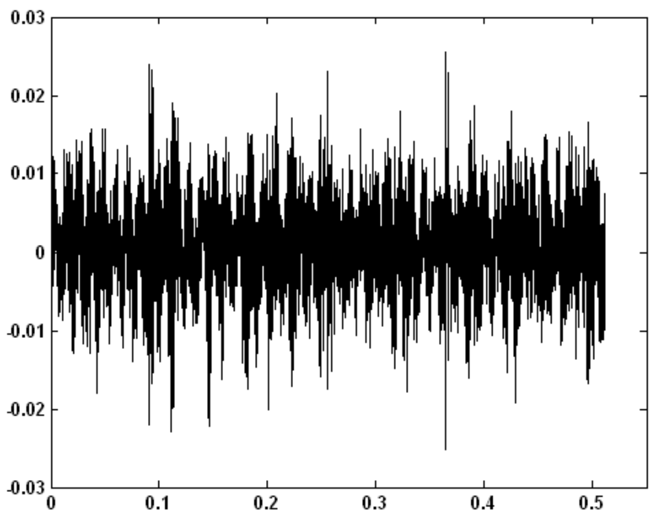

Fig. (2). The time domain of the whole tooth break signal.

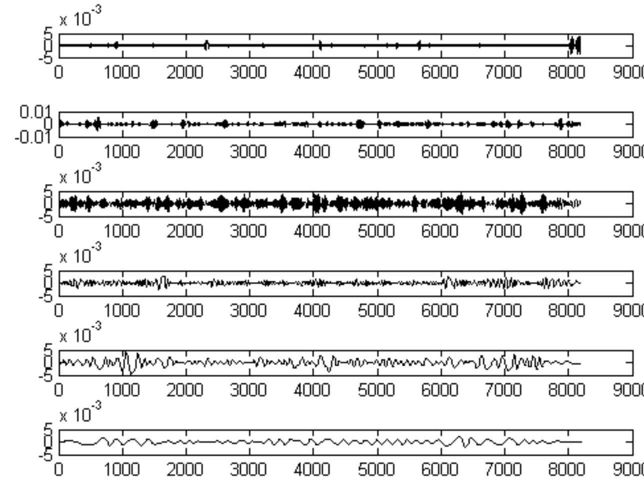

Fig. (3). Empirical mode decomposition of the whole tooth break signal.

The fault diagnosis results of the GNN are mentioned in Table **3**, which establishes that fault diagnosis of a railway gearbox is successfully achieved and the three different gearbox working conditions are accurately identified. This procedure can be applied in the fault diagnosis studies in the future when it is further developed.

CONCLUSION

For practical application, it is important that a reliable and accurate procedure for detecting the railway gearbox faults is developed. For this purpose, a method based on time-frequency feature parameters and GNN has been

Table 1. Sample data of gearbox operation.

	Kurtosis Factor	Margin Factor	Pulse Factor	E_1	E_2	E_3	E_4	E_5	Fault Status	Fault Vector
1	3.4283	5.6369	4.7971	0.3311	0.7592	0.5186	0.0918	0.1911	normal	(1 0 0)
2	3.2145	3.4006	4.4736	0.4170	0.6755	0.5323	0.1204	0.2684	normal	(1 0 0)
3	3.8868	3.8088	4.7620	0.3048	0.7205	0.5179	0.0920	0.3336	normal	(1 0 0)
4	3.5846	6.5516	5.4896	0.1028	0.1977	0.3837	0.4581	0.7703	half of tooth break	(0 1 0)
5	3.4310	4.8642	4.2135	0.1046	0.2379	0.3012	0.5691	0.7196	half of tooth break	(0 1 0)
6	3.2302	4.6089	3.9670	0.1272	0.2348	0.3080	0.7278	0.5515	half of tooth break	(0 1 0)
7	3.2422	5.9013	4.9738	0.1171	0.5098	0.5319	0.3207	0.5837	whole of tooth break	(0 0 1)
8	3.3526	5.2782	4.4863	0.1017	0.5311	0.5458	0.2543	0.5874	whole of tooth break	(0 0 1)
9	2.9803	5.3420	4.5222	0.1436	0.5150	0.5256	0.3010	0.5893	whole of tooth break	(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
1	3.4441	5.8564	5.1786	0.3445	0.7057	0.5250	0.1152	0.3072	normal	(1 0 0)
2	5.0815	6.5215	6.7372	0.0741	0.1676	0.3217	0.2330	0.8992	half of tooth break	(1 0 0)
3	3.0189	6.2494	5.3184	0.0615	0.2906	0.6746	0.2480	0.6286	whole of tooth break	(1 0 0)

Table 3. Testing results of GNN.

Fault Status	Ideal Outputs	Actual Outputs	Testing Results
normal	(1 0 0)	(1.0231 -0.1052 0.0002)	normal
half of tooth break	(0 1 0)	(-0.1611 1.1091 0.0023)	half of tooth break
whole of tooth break	(0 0 1)	(0.0106 -0.1114 1.0061)	whole of tooth break

proposed for railway gearbox faults detection in this paper. The advantage of the proposed method is that EMD is performed on the raw vibration signals, the time-frequency feature parameters are extracted, and the genetic algorithm neural network is used for the classifications of the time-frequency feature parameters. The proposed method can clearly classify all the three operating conditions of the gearboxes. The experimental results have shown that this method is effective and feasible for feature extraction and fault detection of railway gearboxes.

CURRENT & FUTURE DEVELOPMENTS

This paper proposes diagnosis of railway gearbox faults using time-frequency feature parameters and GNN, where in, a novel time-frequency analysis and GNN have been used to analyze the vibration data obtained from railway gearbox. The feasibility and effectiveness of those new approaches were validated and illustrated by a case study of fault diagnosis on railway gearbox. This paper provides the theoretical foundation for fault diagnosis in rotary machines.

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CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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