EMD AND GNN-ADABOOST FAULT DIAGNOSIS FOR URBAN RAIL TRAIN ROLLING BEARINGS

GUOQIANG CAI*
State Key Lab of Rail Traffic Control & safety, Beijing Jiaotong University
Beijing 100044, China
School of Traffic and Transportation, Beijing Jiaotong University
Beijing 100044, China

CHEN YANG
Institute of Computing Technology, China Academy of Railway Sciences Corporation Limited
Beijing 100081, China

YUE PAN AND JIAOJIAO LV
State Key Lab of Rail Traffic Control & safety, Beijing Jiaotong University
Beijing 100044, China
School of Traffic and Transportation, Beijing Jiaotong University
Beijing 100044, China

ABSTRACT. Rolling bearings are the most prone components to failure in urban rail trains, presenting potential danger to cities and their residents. This paper puts forward a rolling bearing fault diagnosis method by integrating empirical mode decomposition (EMD) and genetic neural network adaptive boosting (GNN-AdaBoost). EMD is an excellent tool for feature extraction and during which some intrinsic mode functions (IMFs) are obtained. GNN-AdaBoost fault identification algorithm, which uses genetic neural network (GNN) as sub-classifier of the boosting algorithm, is proposed in order to address the shortcomings in classification when only using a GNN. To demonstrate the excellent performance of the approach, experiments are performed to simulate different operating conditions of the rolling bearing, including high speed, low speed, heavy load and light load. For de-nosing signal, by EMD decomposition is applied to obtain IMFs, which is used for extracting the IMF energy feature parameters. The combination of IMF energy feature parameters and some time-domain feature parameters are selected as the input vectors of the classifiers. Finally, GNN-AdaBoost and GNN are applied to experimental examples and the identification results are compared. The results show that GNN-AdaBoost offers significant improvement in rolling bearing fault diagnosis for urban rail trains when compared to GNN alone.

1. Introduction. The rotating machine is a fairly significant piece of industrial equipment with extensive applications in variety of fields. It is apparent from urban rail train fault data for the Guangzhou Metro in 2015 and 2016, that locomotive running gear fault account for nearly 36% of all faults, with faults in rotating mechanical components accounting for nearly 80% of running gear faults. As an
important part of a rotating machine, rolling bearings have significant effect on the working status of a whole machine [6]. Research on rolling bearing fault diagnosis is, therefore, of high importance for urban rail trains.

Fault diagnosis mainly consists of two parts, the first of which is fault identification. Several approaches to machine learning, such as the support vector machines (SVM) [1] and the neural network (NN) [14] are used to identify fault types and have obtained some positive results. NN has strong robustness and ability for nonlinear approximation, adaptation, generalization, and associative memory [25]. However, some problems remain, the most important of which is associated with the use of a single fault diagnosis technique. The accuracy of fault identification is low due to the imperfection of these classifiers, such as the over-fitting of SVM [15] and the requirement of NN for a very large sample size. Sample selection and pretreatment have a significant impact on the effectiveness of NN techniques. Consequently, it is important that a combination of learning methods is applied to fault detection and identification. The genetic algorithm (GA) is an evolutionary computation model originated from the natural evolution and the genetic law, which are extensively applied to function optimization, automatic control, and other practical problems [19]. GA and NN can, to a certain extent, make up for the shortcomings of each other. The genetic neural network (GNN) is the combination of GA and NN, and is commonly applied for fault identification [9]. A boosting algorithm is a kind of ensemble learning algorithm, which originates from the probably approximately correct (PAC) model. Adaptive boosting (AdaBoost) is developed from the boosting algorithm by Yoav Freund and Robert Schapire [8, 13, 22]. AdaBoost can weaken the over-learning phenomenon of GNN and improve fault identification, to a certain extent.

The other component of diagnosis is feature parameters extraction. Traditional time-domain or frequency-domain analytical techniques, e.g. the fast Fourier transform (FFT) play critical parts in the analysis and processing of stationary signals. However, the working condition of rolling bearings is complex and there are a lot of nonlinear factors that have a significant effect on vibration signals [26]. FFT is unable to obtain combined information simultaneously in the time-frequency domain and this determines FFT is not suitable for non-stationary signal. Various time–frequency techniques have been applied in extracting fault features in non-stationary signal processing, for instance, Wigner–Ville distribution (WVD) [5] Choi–Williams distribution (CWD) [7] and short-time Fourier transform (STFT) [12]. However, all of these methods have their own limitations when dealing with non-stationary signals. For example, there is cross-term interference in the WVD and CWD methods and the window size of STFT does not change with the frequency. Empirical Mode Decomposition (EMD), an established technique in digital signal processing, can divide the complex signal into a few components, intrinsic mode functions (IMFs) EMD is mainly-used in machinery fault pattern recognition, seismic signal detection, and other practical areas since it applies a stationary processing approach to non-stationary signals, giving improved adaptability over time–frequency decomposition and other methods [20, 23, 25]. Before extracting feature parameters, signal denoising is needed to remove the interference of unnecessary noise. Wavelet transform (WT), as one of the famous techniques to reduce noise, is often employed to separate original signal and ensure the availability of feature parameters [4].
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From above discussion, this paper proposes the GNN-AdaBoost fault identification algorithm using GNN as a subclassifier of the AdaBoost algorithm to identify a rolling bearing fault state more accurately. For proving the effectiveness and availability of GNN-AdaBoost algorithm, this paper simulates an urban rail train under different operating conditions and extracts rolling bearing vibration signal features based on EMD and time-domain methods. For different working conditions of load and speed, the GNN-AdaBoost algorithm and GNN algorithm are used for fault pattern identification. The effectiveness of the fault diagnosis approach of EMD and GNN-AdaBoost can be confirmed from the experimental results.

2. Background.

2.1. EMD. EMD is a procedure for screening signal data and extracting IMFs from a given signal dataset put forward by Norden Huang [2, 10], which is called the Hilbert–Huang transformation (HHT). IMFs make the instantaneous frequency significant, which could be either a linear or nonlinear function. The procedure of EMD is as follows.

For a dataset \( x(t) \), EMD identifies all the local maximum and minimum points, \( e_u \) and \( e_l \). Then the upper and lower envelope curves of \( x(t) \) are simulated by using cubic spline interpolation for the reason that the envelope curves in theory are difficult to obtain directly. A new sequence, \( h_1(t) \), can be obtained as follows:

\[
h_1(t) = x(t) - m_1(t)
\]

where \( m_1(t) \) is the mean of the two envelope values. If \( h_1(t) \) satisfies the two conditions above, then it can be an IMF. The procedure above is known as sifting process, which can eliminate riding waves and make waveform symmetrical. If \( h_1(t) \) is not an IMF, Eq. (1) should be repeated up to \( k \) times in the subsequent steps until \( h_{1k}(t) \) satisfies the conditions of IMF:

\[
h_{1k}(t) = h_{1(k-1)}(t) - m_{1k}(t)
\]

At this time, it is set that \( c_1(t) = h_{1k}(t) \).

To ensure that the IMFs adequately reflect the actual amplitude and frequency of \( x(t) \), the sifting process should stop when the stopping condition is reached. The value of standard deviation (SD) is selected as the stopping condition, which is set between 0.2 and 0.3. SD is calculated as follows:

\[
SD = \sum_{i=0}^{T} \left[ \frac{|h_{1(i-k)}(t) - h_{1k}(t)|^2}{h_{1(i-k)}^2(t)} \right]
\]

The residue of \( x(t) \), \( r_1(t) \), can be obtained as follows:

\[
r_1(t) = x(t) - c_1(t)
\]

Then \( r_1(t) \) is regarded as original data, the sifting process should be repeated for \( n \) times until \( r_n(t) \) becomes a monotonic function, shown as follows,

\[
\begin{align*}
r_2(t) &= r_1(t) - c_2(t) \\
r_3(t) &= r_2(t) - c_3(t) \\
&\vdots \\
r_n(t) &= r_{n-1}(t) - c_n(t)
\end{align*}
\]
From Eq. (4) and Eq. (5), no more IMFs can be extracted and the expression for the original data \( x(t) \) can be finally obtained as follows:

\[
x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{6}
\]

IMFs, \( c_i(t) \), are decomposed from the original signal during the sifting processes. Each IMF has actual physical meaning and contains the information of a certain frequency band, which as a reflector of rolling bearing health conditions. Comparing the calculated IMFs directly, the vibration characteristic of the rolling bearing can be more accurately reflected by IMF energy, the feature parameters of which can be obtained as follows:

For continuous signal

\[
E_i = \int t |c_i(t)|^2 dt \tag{7}
\]

For discrete signal

\[
E_i = \sum_{k=1}^{n} (k \cdot \Delta t) |c_i(k \cdot \Delta t)|^2 \tag{8}
\]

where \( \Delta t \) is the sampling period, \( n \) is the sample number, and \( k \) is the sampling point. Next, normalization processing is carried out as follows:

\[
T = \frac{[E_1, E_2, E_3, \ldots, E_n]}{\sum_i E_i} \tag{9}
\]

where \( T \) is the feature parameters vector, which acts as an input parameter for fault pattern identification. The data resulting from Eq. (9) can reflect the size and the variation of the IMFs with time [3,17].

2.2. GNN-AdaBoost algorithm.

2.2.1. GNN. NN imitates the structure of a brain and has widely used in the fields of intelligent computation. NN can optimize weights and thresholds through its self-adaptation ability. The most employed of NN is back propagation neural network (BP-NN), which was proposed by Rumelhart and McClelland in 1986. However, there are some disadvantages to BP-NN; most notably that the determination of structure relies solely on the experience of experts and this lack of global search capability can easily lead to local convergence and a slow convergence speed [11,24].

The GA follows Darwin’s theory of natural selection/survival of the fittest: a process that consists of coding, choice, heredity, and variation. The emergence of GA and the combination of GA and BP-NN has enabled BP-NN to be applied more extensively, since GA brings significant advantages through its global search ability, parallelism, robustness, adaptability, and convergence speed [9].

The basic principle of the combination of GA and NN is the use of a training network to apply weighting through the process of sample training, and through the optimization of connection weights and thresholds to achieve better results. The process steps involved in optimizing the weights and thresholds of NNs by GA are as follows.

1. Determine the network structure, learning rules and termination condition, generate a set of weights and thresholds randomly and encode. The code chain links to an NN with particular weights and thresholds.
2. Calculate the error and determine the fitness function value. The larger the error, the smaller the fitness function.
(3) Chose the individuals with higher fitness as the male parent of the next generation and eliminate the worse parts.
(4) Evolve the current population by crossing and variation to generate a new population.
(5) Repeat steps 1–4 until the goal is reached.

2.2.2. GNN-AdaBoost. AdaBoost algorithm is an iterative algorithm that aims at constructing a strong classifier by taking iterative processes. Its basic idea is to employ learning to get a number of weak classifiers on the same problem, and then to combine these weak classifiers with a strong classifier through a certain relationship. At each cyclic iterative process, the AdaBoost algorithm changes weights to produce another basic learning classifier according to the basic classifier [16,22]. After T cycles, T basic classifiers are processed by a weighted voting method to obtain a final, strong, classifier.

In this section, the GNN-AdaBoost classification algorithm is proposed. The process flow of the GNN-AdaBoost algorithm is illustrated in Figure 1 and process steps of the GNN-AdaBoost algorithm are as follows.
(1) Select data and initialization. From sample space, random selection is used to obtain m groups training samples the weights of which are initialized as follows:

\[ D_1(i) = \frac{1}{m}, \quad i = 1, 2, \ldots, m \]  

where \( D_1(i) \) is the initial weight.
(2) Use GNN to train weak classifier \( h_t(x_i) \). After training a weak classifier, the testing samples are intended to test the classification performance by training error as follows:

\[ \varepsilon_t = \sum_{i=1}^{N} D_t(i); \quad (h_t(x_i) \neq y_i) \] 

where \( \varepsilon_t \) is the training error, \( h_t(x_i) \) is the actual prediction result of the weak classifier, and \( y_i \) is the expected result.
(3) Determine the weights of weak classifiers. According to the prediction results, the weights of the weak classifiers, \( \alpha_t \), can be obtained as follows:

\[ \alpha_t = \frac{1}{2} \ln \left( \frac{1 - \varepsilon_t}{\varepsilon_t} \right) \] 

(4) Update the weights of the training samples for the next round by increasing the weight of wrongly classified samples, shown as follows:

\[ D_{t+1}(i) = D_t(i) \frac{e^{-\alpha_t}}{Z_t} \begin{cases} e^{\alpha_t} & \text{if } h_t(x_i) = y_i \\ e^{-\alpha_t} & \text{if } h_t(x_i) \neq y_i \end{cases} \] 

\[ = \frac{D_t(i) \exp \left( -\alpha_t y_i h_t(x_i) \right)}{Z_t} \] 

where \( Z_t \) is a normalization constant, and \( \sum_{i=1}^{N} D_{t+1}(i) = 1 \).
(5) Generate strong classifier. After T cycles, the strong classifier is obtained as Eq. (14).

\[ H(x) = \text{sign} \left( \sum_{t=1}^{T} \alpha_t h_t(x) \right) \] 

where \( H(x) \) is a strong classifier.
The GNN-AdaBoost algorithm is shown in Figure 1. Since GNN-AdaBoost is a new integration algorithm with adaptive capability, it provides better solution for identifying the fault types of rolling bearings.

Based on the application of EMD and GNN-AdaBoost, the general procedure for rolling bearing health state diagnosis is presented in Figure 2.

3. **Experiments.** To validate the effectiveness and applicability of the methods presented, this section applies experimental techniques for rolling bearing fault identification. After feature parameters extraction, GNN-AdaBoost and GNN are used to identify rolling bearing fault types.
3.1. **Signal acquisition and pretreatment.** Experiments were designed and performed using the simulator stand for rolling bearing faults at the "Independent Research Project of State Key Lab of Rail Traffic Control & Safety", belonging to Beijing Jiaotong University, shown in Figure 3. The simulator stand consists of a drive motor, revolution speed transducer, a rolling bearing and other components.

Speed and load parameters are set to values that are close to those used in real-world examples. The speed calculation is as follows:

\[ n = \frac{v}{3600 \times l} = \frac{v}{3600 \times \pi \times d} \]  

(15)

where \( n \) is the rotational speed of the rolling bearing, \( v \) is the velocity of the urban rail train, \( l \) is the perimeter of the wheelrail, and \( d \) is the diameter of the wheelrail. In the Guangzhou Metro, the perimeter of the wheel rail is 840 mm and the top speed is 80 km/h. According to Eq. (15), when \( v = 60 \text{ km/h} \), \( n = 6.31 \text{ r/s} \) and when \( v = 80 \text{ km/h} \), \( n = 8.42 \text{ r/s} \). The speed is therefore set to 6 r/s and 8 r/s. A pressure regulating valve is used to regulate pressure on the simulator stand. Various rolling bearing health conditions are designed, including: normal, inner-race fault, outer-race fault, and rolling ball fault, and only one crackle existing in each rolling bearing. Figure 4 (a)–(d) show four conditions of testing rolling bearings. The number of samples in each group is 32,768 (\( 2^{15} \)) and the sampling frequency is 51.2 kHz. 80 groups of vibration signals were obtained under each condition for each type of failure. Consequently, a total of 1280 groups of samples (4 health conditions \( \times \) 2 speeds \( \times \) 2 loads \( \times \) 80 samples) are needed.

The sensor device is installed in the rolling bearing shell. So the interference signal generated by vibration of carriers and devices themselves is mixed with the effective signal, and the vibration signal that is collected is mixed with noise. This can have a significant impact on the signal analysis and the effect of diagnosis and wavelet thresholding technique is employed to remove noise of the original signals.

3.2. **Feature parameters extraction.**

3.2.1. **Time-domain feature parameters extraction.** As the most basic approach available time-domain waveform describes the signal integral changing tendency by time-varying. Figure 5 shows time-domain waveform figures for each of the four rolling bearing health states, under speed of 6 r/s and light load. The time-domain

![Figure 2. Procedure for rolling bearing fault diagnosis based on EMD and GNN-AdaBoost.](image-url)
signal is quite different for each rolling bearing state. However, the fault type cannot be distinguished correctly from visual inspection alone. For the sake of getting more meaningful information from vibration signals, this paper calculates the partial time-domain characteristic parameters. There is high sensitivity and poor stability of the skewness and kurtosis when fault occurs, but the variance is relatively stable. Therefore, variance, skewness and kurtosis are selected as time-domain parameters.

The calculation methods for variance, skewness, and kurtosis are as follows:

\[
\sigma_x^2 = \frac{1}{N} \sum_{n=0}^{N-1} [x(n) - \mu_x]^2
\]  
(16)

\[
\beta = \frac{1}{N} \sum_{n=0}^{N-1} x^4(n)
\]  
(17)

\[
\alpha = \frac{1}{N} \sum_{n=0}^{N-1} x^3(n)
\]  
(18)

where \(\sigma_x^2\) is variance, \(\beta\) is kurtosis and \(\alpha\) is skewness [18, 21].

Using Eq. (16)-(18), the signal data under different conditions are processed, and the time-domain feature parameters are obtained, as Figure 5 shows.

3.2.2. IMF energy moments extraction. The de-noising signal is processed using a Hilbert transformation based on the EMD method and 13 IMFs are obtained, as Figure 6 shows. Each IMF contains information on the frequency band, which reflects the energy change of the rolling bearing vibration signal in different states. It can be seen clearly that the first five IMFs are particularly obvious among all the 13 IMFs. With Eq. (8), IMF energy feature parameters are calculated, which were selected as part of input vectors for final rolling bearing fault identification.
A group of eight feature parameters consisting of five IMF energy feature parameters and variance, skewness, kurtosis parameters form the input feature parameters vectors for fault identification.

3.3. Fault identification. Two methods are applied for rolling bearing fault identification: GNN; and GNN-AdaBoost based on the feature parameters vector above. A comparison is made of their performance in correct identification to see if an advantage exists to either method. A study with speed of 6 r/s and with light load is used as an example signal. For this example, 80 groups of vibration signals are needed for each of the four conditions, giving a dataset of 320 samples in total.

3.3.1. Fault identification based on GNN. The GNN has three layers with different node number: the input layer, containing eight nodes; the hidden layer, containing ten nodes; and the output layer contains four nodes. The output corresponds to the four rolling bearing health states: normal, inner-race fault, outer-race fault, and rolling ball fault. For each class, the 320 feature parameters are divided into two groups randomly. A total of 240 groups of data were taken as training samples, with the other 80 used as testing samples. The desired output codes are shown in Table 1.
Figure 5. (Cont.)
Figure 5. Time-domain waveform figures of four rolling bearing states under the working condition of 6 r/s speed and light load: (a) normal; (b) inner-race fault; (c) outer-race fault and (d) rolling ball fault.

Table 1. Expected output code.

| Fault type       | Expected output code |
|------------------|----------------------|
| Normal           | (1 0 0 0)            |
| Inner-race fault | (0 1 0 0)            |
| Outer-race fault | (0 0 1 0)            |
| Rolling ball fault | (0 0 0 1)           |

Next, the trained GNN is used to predict the rolling bearing fault type. If the error between the output from the GNN and the testing samples is less than 0.05, then the result is credible.

3.3.2. Fault identification based on GNN-AdaBoost. The initial weight of each testing sample is 1/80. The sample selection, structure of GNN, expected output code and training process in GNN-AdaBoost are the same as for the GNN in Section 4.3.1.

In this approach, GNN is now iterated 25 times to obtain 25 weak classifiers; the error and weight changes of the four rolling bearing conditions are shown in Figure 7. As the error of each condition decreases in a fluctuating way, the weight value increases with each iteration. The bigger the error, the greater the weight value. The classification accuracy of each iteration is, thereby, better than the accuracy of the preceding iteration—the classification accuracy is improved by increasing the weight of the error samples.

Figure 8 shows the relationship between error, $\varepsilon$, and iterations of GNN-AdaBoost. As the number of iterations increases, the error shows a downward trend. After 23 iterations, the error remains approximately constant, showing that 25 iterations are, in this case, sufficient to enable the effective performance of the GNN-AdaBoost algorithm.
The best feature is selected as a weak classifier in each iterative learning step and all 25 weak classifiers are used for constructing the strong classifier $H(x)$. In order to define a suitable strong classifier, a normalization process is carried out on the 25 weak classifiers with appropriate weights applied. Finally, the resulting strong classifier is used for identifying the fault type of the testing sample.

4. Results and discussion. The main contribution of this paper is proposing a fault diagnosis approach for the rolling bearings of urban rail trains based on EMD and GNN-AdaBoost. The experiments simulate the working condition of rolling bearings on urban rail trains based on the example of the Guangzhou Metro.
order to process the data and reach fault type identification, the following work is completed: a soft threshold de-noising method is employed to pre-process the original signals; in Section 4.2, the input vectors for GNN and GNN-AdaBoost consist of IMF energy feature parameters and some typical time-domain feature parameters, utilizing signal characteristics as far as possible. The experimental results are illustrated in Figure 9 and Table 2.

Figure 9 shows the test results for GNN-AdaBoost and GNN under different working conditions. GNN is effective when the rolling bearing is normal, but makes incorrect decisions in the fault states. There is a significant improvement in fault diagnosis when using GNN-AdaBoost when compared to GNN.

Table 2 shows the accuracy rates of different classifiers under different rolling bearing working conditions. Irrespective of speed, the diagnosis results for GNN-AdaBoost exceed a 95% accuracy rate for both light and heavy load, which is better
Table 2. Accuracy comparisons between GNN-AdaBoost and GNN under different working conditions.

| Experimental condition         | GNN-AdaBoost | GNN     |
|-------------------------------|--------------|---------|
|                               | Right | Wrong | Accuracy (%) | Right | Wrong | Accuracy (%) |
| Speed 6 r/s, light load       | 77    | 3     | 96.25      | 71    | 9     | 88.75      |
| Speed 6 r/s, heavy load       | 78    | 2     | 97.5       | 74    | 6     | 92.5       |
| Speed 8 r/s, light load       | 78    | 2     | 97.5       | 73    | 7     | 91.25      |
| Speed 8 r/s, heavy load       | 79    | 1     | 98.75      | 76    | 4     | 95         |

than that found from GNN alone, and meets the requirements of field application. GNN-AdaBoost has, therefore, better performance and greater accuracy.

5. **Conclusion.** In this paper, an automatic diagnosis system for urban rail train rolling bearings based on EMD and GNN-AdaBoost is presented. To reduce noise disturbances, wavelet de-noising should be carried out first to process the collected signal. EMD can adaptively decompose signal efficiently and it has good performance when analyzing signals with nonlinear and non-stationary properties. A number of IMFs are obtained by EMD and IMF energy feature parameters can better reflect vibration characteristic of signal. Some time-domain feature parameters such as variance, skewness, and kurtosis have strong association with different rolling bearing health state. Both them are employed to form input feature vectors of GNN-AdaBoost—an algorithm with strong classifying ability that combines GNN and AdaBoost. To provide further validation of the effectiveness of GNN-AdaBoost, GNN is used in parallel with GNN-AdaBoost to classify the fault type in the same experiment. The results prove that GNN-AdaBoost performs better at rolling bearing fault identification than GNN alone. Irrespective of the working condition, in terms of load and speed, the accuracy of GNN-AdaBoost is significantly improved when compared with the use of GNN alone. Future research should be carried out to investigate the potential application of GNN-AdaBoost to more complex problems.

![Figure 9](image-url)
Figure 9. The testing results of GNN-AdaBoost and GNN under different working conditions: (a) 6 r/s and light load; (b) 6 r/s and heavy load; (c) 8 r/s and light load; (d) 8 r/s and heavy load.
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E-mail address: gqcai@bjtu.edu.cn
E-mail address: 15120952@bjtu.edu.cn
E-mail address: 16120955@bjtu.edu.cn
E-mail address: 16125752@bjtu.edu.cn