www.sensorsportal.com

Sensors & Transducers

http://www.sensorsportal.com

Railway Rolling Bearing Faults Diagnosis Based on Wavelet Packet and EKF Training RBF Neural Network

[1] Xing WANG, [2] Yuan-Jing ZHAO

[1] School of Computer Science and Technology, Taiyuan University of Science and Technology, Taiyuan Shanxi 030024, China

[2] Civil Engineering Department, Shanxi Institute of Economics and Business, Taiyuan Shanxi 030024, China

[1] Tel.: 13994213969

E-mail: wangxing3969@126.com

Received: 19 August 2013 /Accepted: 25 October 2013 /Published: 30 November 2013

Abstract: Based on wavelet packet and extended Kalman filter (EKF) training RBF neural network method, a method for the fault diagnosis of railway rolling bearing is proposed in this paper. The wavelet packet and RBFNN are introduced. The wavelet packet is used to translate raw vibration signals of a railway rolling bearing into time-scale representation. Then, the wavelet packet energy eigenvector is constructed, next, those wavelet packet energy eigenvectors as fault samples for training RBF neural network. To ameliorate the algorithm, EKF is exploited to optimize the algorithm so as to determine the best values for "network connection weight", finally the fault patterns of the railway rolling bearings are identified. The results show that the proposed method is superior to the RBF neural network in extracting the fault characteristics of roller bearings. This method is effective and can be used for automotive recognition to rotary machine faults. *Copyright © 2013 IFSA.*

Keywords: Wavelet packet, Extended Kalman filter, RBF neural network, Railway rolling bearing, Fault diagnosis.

1. Introduction

The rolling bearings are among the most used elements in the railway sector, it is a critical component and required to carry heavy loads and operated at high efficiency and reliability. A fault in a rolling bearing may cause breakdown train vehicle, and serious consequences may arise due to the fault. Therefore, fault diagnosis of rolling element bearings is very important to safe operation of railway systems. Fault detection techniques such as vibration, acoustic, oil debris and thermal-based symptom analyses have been developed dealing with gears, bearings and shafts [1-4]. Among them the analysis of the fault – induced vibration signal is one of the most widely used techniques for rolling element bearing diagnosis [5].

Over the past years, various methods have been developed for identifying faults in vibration signals, such as the short-time Fourier transform (STFT) [6], wavelet transform [7], cumulant spectrum [8], neural network [9], Genetic algorithm [10], Bayesian classifier [11], etc. Wavelet packet, which is extension from wavelet theory, has several particular advantages in comparison with scalar wavelet on image fusion. At the same time neural networks have become a popular tool in the fault diagnosis due to their fault tolerance and their capacity for self-organization. So an intelligent diagnosis method for railway rolling bearings is proposed on the basis of wavelet packet and EKF training RBF neural network. The result shows that the proposed method has the superior performance in extracting characteristics of vibration signals. It can implement better in diagnosis of railway rolling bearing.

The contents of this paper are organized in the following way. Section 2 presents a brief overview of the wavelet transform and wavelet packet analysis. In section 3, wavelet packet energy eigenvector is introduced. RBFNN and EKF training RBF neural network are proposed in section 4. The performance of the proposed method is validated using bearing vibration signals in section 5. Finally, the conclusions of this paper are given in section 6.

2. Wavelet Packet Transform

As an extension of the standard wavelets, wavelet packet represent a generalization of multi-resolution analysis and use the entire family of subband decomposition to generate an over complete representation of signals [12].

The continuous wavelet packet is described as:

$$W(u,a,b)=\frac{1}{\sqrt{2\pi a}}\int_{-\infty}^{\infty}e^{-jux}\varphi(\frac{x-b}{a})f(x)dx, \quad (1)$$

where $f(x)$ represents a signal, and $\varphi(\frac{x-b}{a})$ is the scaled and shifted function of mother wavelet function.

The discrete wavelet packet is defined by [13]:

$$\begin{cases} u_{2n}(t)=2^{1/2}\sum_{k\in Z}h_k u_n(2t-k) \\ u_{2n+1}(t)=2^{1/2}\sum_{k\in Z}g_k u_n(2t-k) \end{cases}, \quad (2)$$

where $u_0(t)=\phi(t)$ and $u_1(t)=\varphi(t)$ are the scaling and mother wavelet function, respectively. And h is low pass filter, g is high pass filter. The algorithm of discrete WPT is represented by

$$b_l^{j,2n}=\sum_k h_{k-2l}b_k^{j+1,n} \quad (3)$$

$$b_l^{j,2n+1}=\sum_k g_{k-2l}b_k^{j+1,n} \quad (4)$$

The reconstruction formula is

$$b_l^{j+1,n}=\sum_k\left\lfloor h_{l-2k}b_k^{j,2n}+g_{l-2k}b_k^{j,2n+1}\right\rfloor \quad (5)$$

In the first level, the signal is decomposed into two subbands: low frequency sub-bands and high frequency sub-bands. In the next level, the low frequency sub-bands are decomposed into lower and higher frequency parts. In the meanwhile, the high frequency sub-bands are also decomposed into lower and higher frequency parts. The same decomposition goes on repeatedly. The wavelet packet tree of Fig. 1 illustrates such a decomposition.

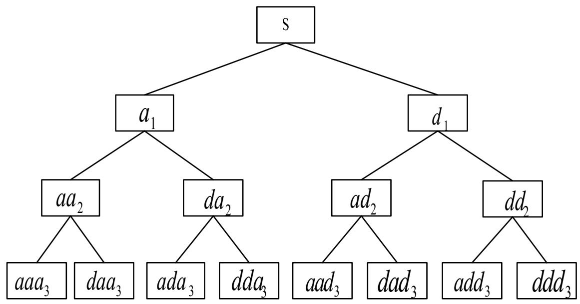

Fig. 1. Wavelet packet decomposition tree down to resolution level 3.

3. Wavelet Packet Energy Vector Algorithm

1) The wavelet packet is adopted to decompose the signal of railway rolling bearings.

2) Reconstruct the coefficients of frequency bands. For example, S_{31} represents the reconstructed signal at the 3th layer of the 1th node.

3) The total energy of each band [14]

$$E_{3j}=\int\left|S_{3j}(t)\right|^2dt=\sum_1^n\left|x_{jk}\right|^2, \quad (6)$$

where $x_{jk}(j=0,1,\ldots,7;k=1,2\ldots,n)$ represents amplitude of the reconstructed signal.

4) Construct the wavelet packet energy eigenvector.

The definition of all the energy of signal:

$$E=\sum_{j=0}^{7}E_{3j} \quad (7)$$

A band of relative wavelet packet energy:

$$p_{3j}=\frac{E_{3j}}{E} \quad (8)$$

The definition of relative wavelet packet energy feature vector:

$$K_i = (p_{30}, p_{31}, \ldots, p_{37}) \tag{9}$$

4. RBF Neural Network and EKF Training RBF Neural Network

4.1. RBF Neural Network

The radial basis function (RBF) neural network is a type of feed forward neural network that learns using a supervised training technique. RBF neural network is embedded in a three layers neural network, where each hidden unit implements a radial activated function. The input units implement the data input to the network. The output units implement a weighted sum of hidden unit outputs. The input into a RBF network is non-linear while the output is linear. Due to their non-linear approximation properties, RBF networks are able to model the complex mappings, which perception neural network can only be modeled by means of multiple intermediary layers [15].

The RBF neural networks typically have three layers: an input layer, a hidden layer and an output layer. The network structure of an RBF neural network is shown in Fig. 2.

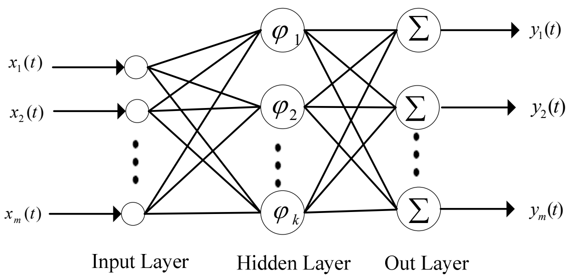

Fig. 2. The structure of RBF neural network.

4.2. RBF Neural Network

For nonlinear discrete-time system, the state space expression is as follows [16].

$$\begin{cases} \theta_{k+1} = f(\theta_k) + w_k \\ y_k = h(\theta_k) + v_k \end{cases} \tag{10}$$

If nonlinear state space in equation (10) is sufficiently smooth, $f(\theta_k)$ and $h(\theta_k)$ can be expanded to Taylor series around the estimate $\hat{\theta}_k$.

$$f(\theta_k) = f(\hat{\theta}_k) + F_k(\theta_k - \hat{\theta}_k) + A \tag{11}$$

$$h(\theta_k) = h(\hat{\theta}_k) + H_k^T(\theta_k - \hat{\theta}_k) + A,$$

where $F_k = \frac{\partial f(\theta)}{\partial \theta}\Big|_{\theta=\hat{\theta}_k}$, $H_k^T = \frac{\partial h(\theta)}{\partial \theta}\Big|_{\theta=\hat{\theta}_k}$, A is the higher order term.

Neglect the higher-order term in equation (11), the following equation is obtained:

$$\theta_{k+1} = F_k\theta_k + w_k + f(\hat{\theta}_k) - F_k\hat{\theta}_k$$

$$y_{k+1} = H_k^T\theta_k + v_k + h(\hat{\theta}_k) - H_k^T\hat{\theta}_k \tag{12}$$

4.3. RBF Neural Network

For RBF neural network, the processed state space in which Kalman filter can be used is shown as follows [17].

$$\begin{cases} \theta_{k+1} = \theta_k + w_k \\ y_k = h(\theta_k) + v_k \end{cases} \tag{13}$$

Based on the recursive equations of Kalman filter, the state estimate $\overline{\theta}$ can be calculated.

$$\begin{cases} \overline{\theta}_k = \overline{\theta}_{k-1} + G_k[y_k - h(\overline{\theta}_{k-1})] \\ G_k = P_k H_k (R + H_k^T P_k H_k)^{-1} \\ P_{k+1} = F_k(P_k - G_k H_k^T P_k)F_k^T + Q \end{cases}, \tag{14}$$

where $\overline{\theta}_k$ is the state estimate at the time, $h(\overline{\theta}_{k-1})$ is the network output at the time $k-1$, G_k is the Kalman gain, P_k is the state estimate error variance.

5. Experimental and Analysis

5.1. The Process of Wavelet Packet

The three-layer wavelet packet is used to translate raw vibration signals of a railway rolling bearing into time-scale representation. Fig. 3(a)–Fig. 5 (a) are time domain of the signal, Fig. 3 (b)–Fig. 5(b) are the fault signal decomposed with three-layer wavelet packet. Then, the wavelet packet energy eigenvector is constructed, those feature vectors are divided into two groups: the training group and the testing group. The training data is listed in Table 1. It is used to train the EKF-RBF neural network. The testing data is listed in Table 2. It is used to examine the trained EKF-RBF neural network.

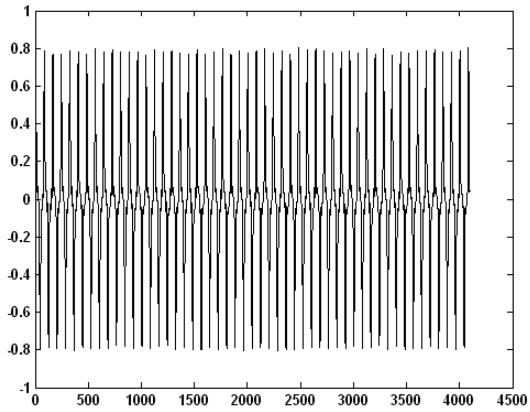

Fig. 3(a). The time domain of normal signal.

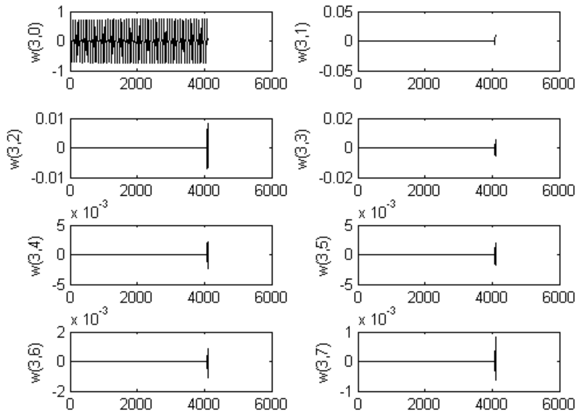

Fig. 3(b). The rolling fault signal decomposed with wavelet packet.

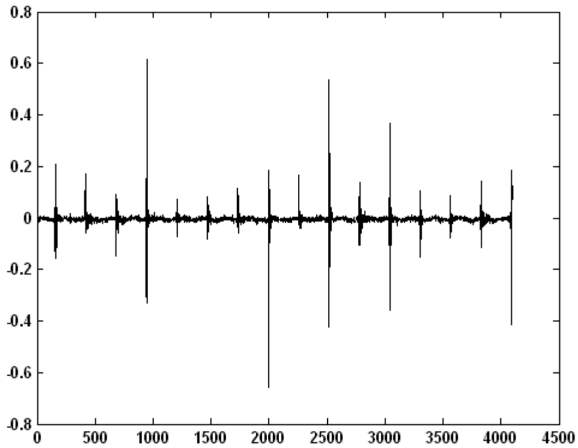

Fig. 4(a). The time domain of rolling fault signal.

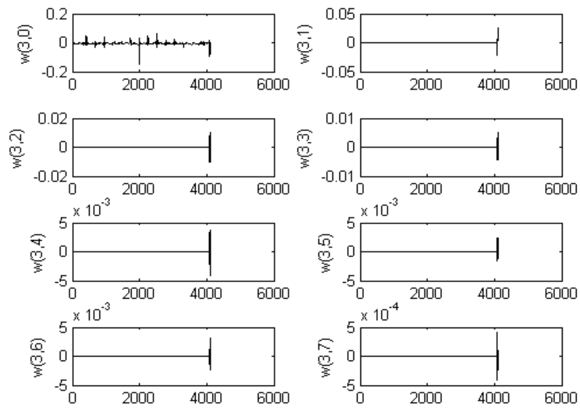

Fig. 4(b). The outer ring fault signal decomposed with wavelet packet.

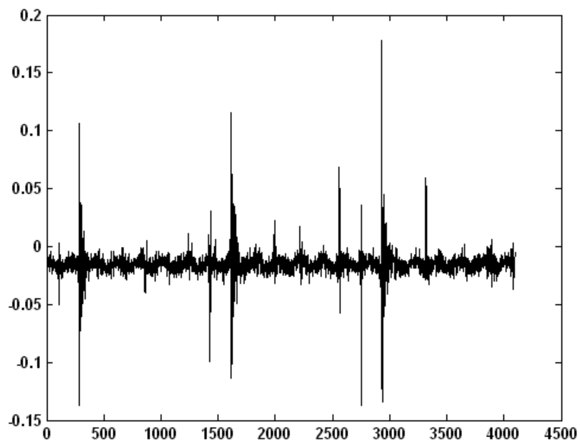

Fig. 5(a). The time domain of inner ring fault signal.

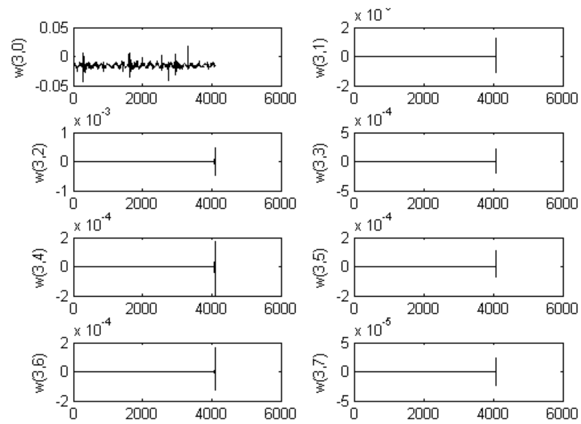

Fig. 5(b). The inner ring fault signal decomposed with wavelet packet.

5.2. The Process of Neural Network

1) Constructed EKF-RBF neural network using MATLAB.

The network architecture used for fault diagnosis consists of 8 inputs corresponding to the 8 different ranges of the frequency spectrum of a fault signal, 3 outputs corresponding to 3 respective signals, such as normal signal, rolling fault signal and inner ring fault signal.

2) Testing the trained EKF-RBF neural network.

After trained the network, the testing group is used to examine the trained EKF-RBF neural network.

The outputs of the examination sample are listed in Table 3. From the outputs of the examination sample, we can see that it is so close to the corresponding ideal outputs of the examination sample. So this method can diagnose the kind of railway rolling bearing faults.

Table 1. Sample data of bearing operation.

No.	Feature samples								Fault status	Fault vector
1.	0.9576	0.0069	0.0020	0.0078	0.0012	0.0008	0.0002	0.0004	normal signal	(1 0 0)
2.	0.9689	0.0089	0.0021	0.0068	0.0007	0.0003	0.0015	0.0003	normal signal	(1 0 0)
3.	0.9779	0.0068	0.0007	0.0095	0.0025	0.0002	0.0006	0.0009	normal signal	(1 0 0)
4.	0.0543	0.0653	0.6864	0.0310	0.0159	0.0423	0.0397	0.0596	rolling fault signal	(0 1 0)
5.	0.1485	0.0591	0.4957	0.0876	0.0253	0.0675	0.0769	0.0513	rolling fault signal	(0 1 0)
6.	0.1867	0.0087	0.5783	0.0896	0.0358	0.0457	0.0477	0.0324	rolling fault signal	(0 1 0)
7.	0.0591	0.0589	0.1655	0.0201	0.0496	0.0718	0.4985	0.0499	inner ring fault signal	(0 0 1)
8.	0.0287	0.0653	0.2754	0.0385	0.0186	0.0213	0.5561	0.0476	inner ring fault signal	(0 0 1)
9.	0.0387	0.0297	0.1978	0.0387	0.0491	0.0816	0.4757	0.0529	inner ring fault signal	(0 0 1)

Table 2. Testing data.

No.	Feature samples								Fault status	Fault vector
1.	0.9626	0.0087	0.0046	0.0207	0.0008	0.0002	0.0041	0.0006	normal signal	(1 0 0)
2.	0.0768	0.0021	0.5384	0.0701	0.0673	0.0762	0.1105	0.0643	rolling fault signal	(0 1 0)
3.	0.0285	0.0312	0.2864	0.0497	0.0482	0.0215	0.5573	0.0311	inner ring fault signal	(0 0 1)

Table 3. Testing results.

Fault status	Ideal outputs	Actual outputs	Testing results
normal signal	(1 0 0)	(0.9697 0.0165 0.0358)	normal signal
rolling fault signal	(0 1 0)	(0.0126 0.9136 0.0542)	rolling fault signal
inner ring fault signal	(0 0 1)	(0.0381 0.0183 0.9276)	inner ring fault signal

6. Conclusions

A railway rolling bearing fault diagnosis approach has been developed based on wavelet packet and EKF training RBF neural network. The vibration signal of the railway rolling bearing is first decomposed by the wavelet packet, then, the feature vectors are extracted and fed into EKF-RBF neural network to identify the bearing health conditions. The experimental results show that this approach can diagnose the kind of rolling bearing faults, it gives an effective method for the multi-concurrent fault diagnosis of the rotating machines.

Acknowledgements

International S&T cooperation program of China (SQS2014RR129).

References

[1]. X. Wang, V. Makis, Auto regressive model-based gear shaft fault diagnosis using the Kolmogorov–Smirnov test, *Journal of Sound and Vibration*, Vol. 327, Issue 5, 1995, pp. 413-423.

[2]. F. Aymerich, W. J. Staszewski, Experimental study of impact-damage detection in composite laminates using a cross-modulation vibro-acoustic technique, *Structural Health Monitoring*, Vol. 9, 2010, pp. 541–553.

[3]. C. Li, M. Liang, Separation of vibration-induced signal of oil debris sensor for vibration monitoring, *Smart Materials and Structure*, Vol. 20, Issue 4, 2011, pp. 5-19.

[4]. W. K. Wong, C. K. Loo, W. S. Lim, P. N. Tan, Thermal condition monitoring system using log-polar mapping, quaternion correlation and max-product fuzzy neural network classification, *Neuro Computing*, Vol. 74, 2010, pp. 164-177.

[5]. Chuan Li, Ming Liang, Multi-scale autocorrelation via morphological wavelet slices for rolling element bearing fault diagnosis, *Mechanical Systems and Signal Processing*, Vol. 31, 2012, pp. 428-446.

[6]. B. Yazici, G. B. Kliman, An adaptive statistical time-frequency method for detection of broken bars and bearing faults in motors using stator current, *IEEE Transactions on Industry Applications*, Vol. 35, Issue 2, 1999, pp. 442-452.

[7]. Jian-Wei Yang, De-Chen Yao, Guo-Qiang Cai, Hai-Bo Liu, Jiao Zhang, A method of bearing fault feature extraction based on improved wavelet packet

and Hilbert analysis, *International Journal of Digital Content Technology and its Applications*, Vol. 4, Issue 4, 2010, pp. 127-139.
[8]. K. W. Baugh, On parametrically phase-coupled random harmonic processes, in *Proceedings of the IEEE Signal Processing Workshop on Higher-Order Statics*, 1999, pp. 346-350.
[9]. Dechen Yao, Jianwei Yang, Fault diagnosis of railway bearing based on muti-method fusion techniques, *Machine Design and Research*, Vol. 26, Issue 3, 2010, pp. 70-73.
[10]. Guoqiang Cai, Limin Jia, Improved wavelet neural network based on hybrid genetic algorithm application in on fault diagnosis of railway rolling bearing, *International Journal of Digital Content Technology and its Applications*, Vol. 4, Issue 2, 2010, pp. 135-141.
[11]. E. Meyer, T. Tuthill, Bayesian classification of ultrasound signals using wavelet coefficients, in *Proceedings of the IEEE National Aerospace and Electronics Conference (NAECON)*, Vol. 1, 1995, pp. 240-243.
[12]. Davut Hanbay, Ibrahim Turkoglu, Yakup Demir, Prediction of wastewater treatment plant performance based on wavelet packet decomposition and neural networks, *Expert Systems with Applications*, Vol. 34, 2008, pp. 1038-1043.
[13]. L. H. Yang, D. Q. Dai, W. L. Huang, Wavelet tour to signal processing, *China Machine Press*, Beijing, 2002.
[14]. Gui-Ji Tang, De-gong Fan, Fault diagnosis of rotation machine based on wavelet packet energy eigenvector neural network, *Turbine Technology*, Vol. 48, Issue 3, 2006, pp. 215-217.
[15]. Felipe Miguel Aparicio Acosta, Radial basis function and related models: an overview, *Signal Processing*, Vol. 45, Issue 1, 1995, pp. 37-58.
[16]. Wang Lu, Pan Ziwei, Application of EKF training RBF neural network in fault diagnosis, *Journal of Vibration, Measurement& Diagnosis*, Vol. 28, Issue 4, 2008, pp. 358-361.
[17]. D. Simon, Training radial basis neural networks with the extended Kalman filter, *Neurocomputing*, Vol. 48, 2002, pp. 255-275.