Study on Feature Extraction and Classification of Ultrasonic Flaw Signals

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Abstract: - One of the most important techniques of ultrasonic flaw classification is feature extraction of flaw signals，which directly affects the accuracy and reliability of flaw classification．Based on the non-stationary characteristic of ultrasonic flaw signals, a new feature extraction method of ultrasonic signals based on empirical mode decomposition (EMD) is put forward in the paper. Firstly, the original ultrasonic flaw signals are decomposed into a finite number of stationary intrinsic mode functions (IMFs) by EMD, and the Fourier transformation of IMF is made. The next step is to find a set of classification values from time domain and frequency domain of IMFs relating to flaw information, and to analyze these classification values and construct vector as signal eigenvector for identification. According to specific characteristics of ultrasonic echo signal, identification defect diagnosis system for ultrasonic echo signal based on BP is built up, and the specific structure of BP neural network is designed. Finally BP neural network is made as decision-making classifier, signal eigenvector is inputted and flaw type is outputted. Experimental results show that the method has better performance in detecting ultrasonic flaw signals.

Key-Words: - ultrasonic signal; empirical mode decomposition (EMD); intrinsic mode function; feature extraction; neural network; eigenvector

1 Introduction

The key to the defect recognition is defect feature extraction and choice, a good sample of defects' characteristics can help to increase defect diagnosis efficiency, so the key to defect diagnosis is the defects' feature extraction. In time domain graph of the signal, the presence of defects can be characterized by the amplitude of the signal. However, with only the signal amplitude as the time-domain characteristic parameters, it can not get more real information of defect signals, such as defect type, size, etc. In the frequency domain graph, more characteristic parameters can be obtained than those in the time domain, such as the largest amplitude, centre frequency, bandwidth, etc. But when there are defects in the parts or when the working conditions are abnormal, the ultrasonic echo signal or vibration signal has generally non-stationary characteristics [1-4].

As the core of the traditional spectrum analysis method, Fourier transform (FT) plays an important role in feature extraction of stationary signal. But for non-stationary signals, only the statistical average can be got in time or frequency domain by FT, and full view and the local feature in time domain and frequency domain can't be given. Therefore, for non-stationary signal, an analysis method is expected by which non-stationary signal can be decomposed into stationary signals and more characteristic parameters can be got than conventional analysis methods to identify defect types finally.

Wavelet transformation method has made great contributions in the non-stationary signal analysis, and has also gained wider application in feature extraction of component defects [5][6]. Wavelet basis functions are pre-determined series of wavelet functions, its decomposition effects depend on the choice of basis functions and wavelet basis can not be changed once it is established, so it can not guarantee optimal decomposition results. Empirical mode decomposition is based on local characteristic time scales of signal, which can decompose complex signal into sum of limited intrinsic mode function. EMD decomposition is based on signal information itself, so real physical information of signal can be got and the decomposition results can be very good. Besides, the number of IMFs is limited commonly, so the method of EMD is self-adaptive and is fit for non-linear and non-stationary process [7-11]. EMD method has been widely used in nonlinear data analysis after it is proposed. It has achieved good results in various fields of scientific research of geophysics, astronomy, device diagnostics [12-16].

Neural network is composed of basic neurons interconnected, which can simulate neural information processing way of human brain, and carry out parallel processing of information and non-linear transformation. Neural network is a method of adaptive pattern recognition, through self learning mechanism decision-making region can be automatically got no need of experience knowledge about mode and discrimination function in advance. Neural network can make the best of status message, train information from different status to gain some kind of mapping relation one by one. Neural network provides a new solution for fault diagnosis problem [17-19].

EMD and artificial neural network technology are applied to identify and classify ultrasonic flaw signals in the paper. Firstly EMD is applied to decompose ultrasonic echo signals and get a number of IMFs, then time-domain and frequency domain analysis of IMFs are made to construct an eigenvector, at last BP neural network is used as a diagnostic decision-making classifier to classify defect types of signals. Experiments show that the method can effectively classify the type of defect signals.

2 The Basic Principle of EMD

Hilbert-Huang transform method was put forward by Huang E in 1998. EMD is its important part. EMD proposed by Huang is good at dealing with non-stationary and non-linear signal. Different from some traditional methods, the method is intuitive, immediate and self-adaptive. IMF is a stationary narrow-band signal, it is information of original signal at different time scales. Compared with the original signal, IMF component is much simpler. Information of the actual time-series is often more complex. Small signal is often inundated by big signal or background noise, but the small signal can be clearly manifested in IMF component, so analysis of the IMF can hold the attributive information of original data accurately and effectively.

IMF need meet two conditions:

At any point, the mean of upper envelope constituted by the maximum value function and that of lower envelope constituted by the minimum value function are all zero.

In the entire data segments, the number of extreme values (including the maximum and minimum values) and that of zero crossing point are equal or different of 1 at most.

The result of EMD is a group of IMFs. EMD algorithm includes following steps:

① Calculate all extreme values and the zero crossing points of the signal.

② Connect all extreme values with a curve to get upper envelope. By the same way lower envelope composed of minimum values can be got.

③ Calculate mean value of upper envelope and that of lower envelope to record as the average envelope m .

④ Subtract the average envelope m from the signal to get the residual signal r .

⑤ Regard the residual signal r as a signal, repeat above process until r satisfies the condition of natural mode of vibration, and then record as IMF1.

⑥ Repeat above process, the signal can decomposed into the sum of a group of IMFs and the residual signals.

3 Feature Extraction based on EMD

Plexiglass with 6mm thickness is used as standard specimen here. Probe frequency is 5MHz and probe model is creeping wave. Standard defect types of plexiglass are the crack in upper surface, the crack in lower surface and the hole in the central board, as shown in Fig.1. Ultrasonic echo signals of defects are shown in Fig.2.

3.1 Decomposition of the standard defect signal by EMD

Take a flaw signal of the crack in lower surface as an example, the same analytical methods are used in the other two flaw signals. A series of IMFs of a flaw signal in lower surface can be got by EMD method, as shown in Fig.3. IMF is a smooth narrow-band signal, which is information of original signal on different time scales. Every IMF component stands for a group data sequence of characteristic scales, and has realistic significance [4].

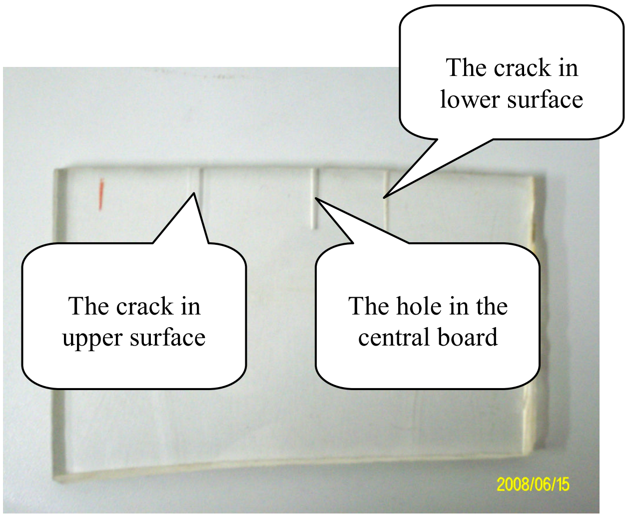

Fig.1 Standard flaws of plexiglass

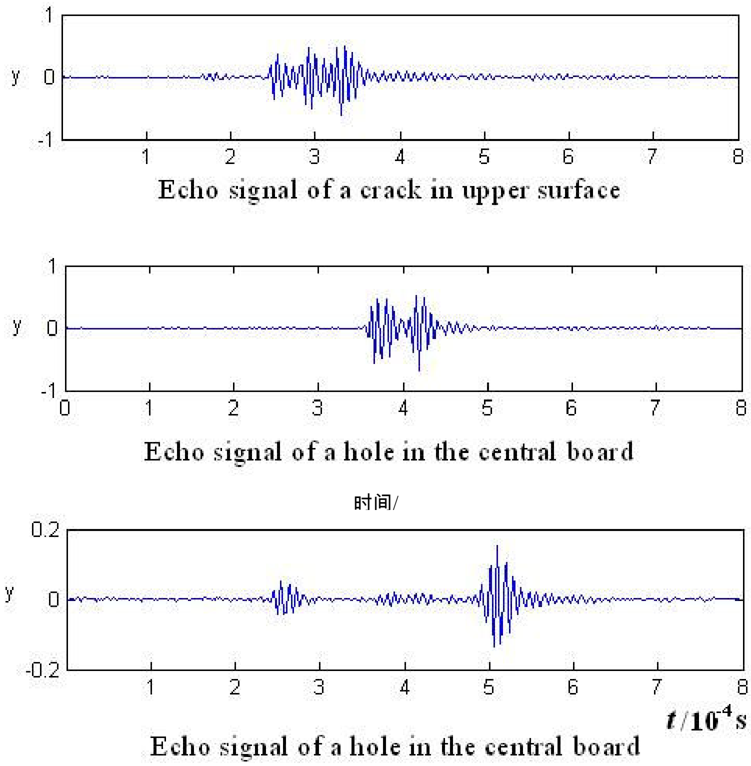

Fig.2 Three kinds of ultrasound echo signals from standard flaws

3.2 Analysis of IMFs

3.2.1 Time-domain analysis of IMFs

In the IMFs' time-domain, zero-crossing point, signal area and the largest amplitude curve are chosen as the time-domain characteristics of IMFs. Calculate Zero-crossing point, signal area and the largest amplitude of curve of each IMF. Time-domain analysis results of flaw signal of the crack in lower surface are shown in Table 1(In order to facilitate the analysis, the signal area and the largest amplitude are a number of multiples enlarged).

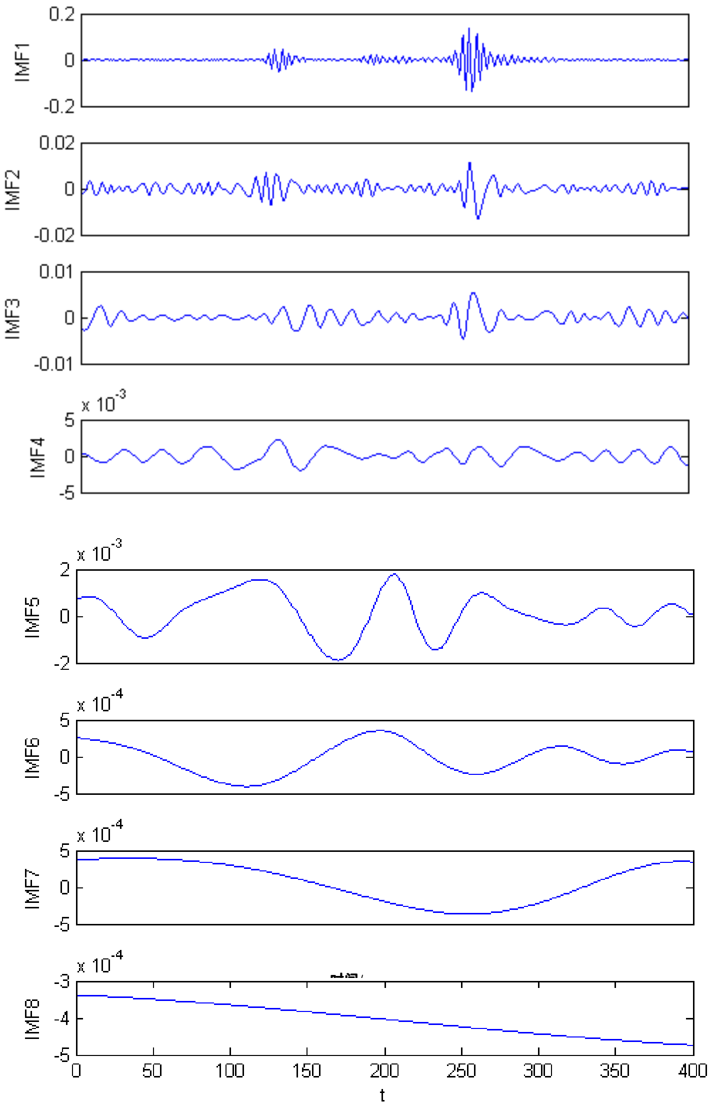

Fig.3 IMF1~ IMF8 of the crack signal in lower surface

Table 1 Characteristic parameters of IMFs in time domain

	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7
Zero-crossing point	206	102	62	29	10	6	2
Signal area	342	68.6	37.8	27.7	28.2	6.74	10.1
The largest amplitude	139	11.4	5.25	2.21	1.77	0.348	0.392

3.2.2 Time-domain analysis of IMFs

Take Fourier Transform to each IMF of the flaw signal and get amplitude-frequency diagram of each IMF as shown in Fig. 4. The largest amplitude, centre frequency, signal energy are chosen as the frequency-domain characteristics of IMFs [8]. Calculate the largest amplitude, centre frequency, signal energy of curve to each IMF, analysis results are shown in Table 2((In order to facilitate the analysis, the signal area and the largest amplitude are a number of multiples enlarged).

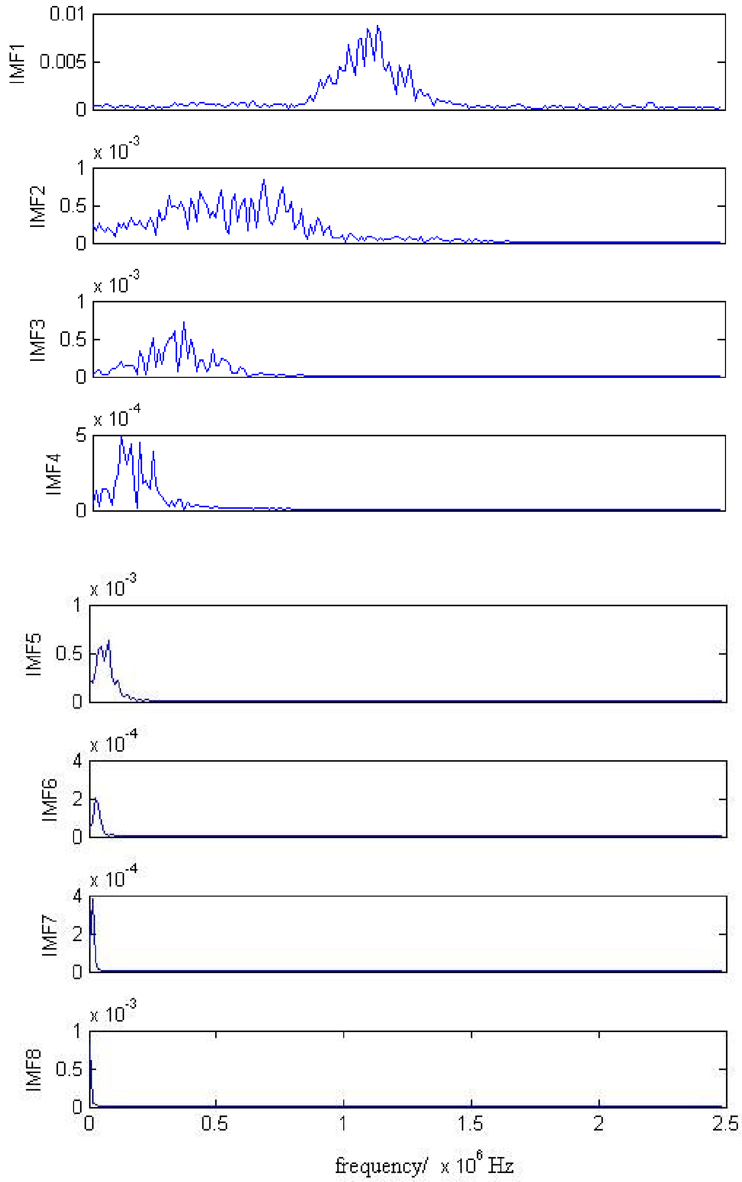

Fig.4 IMFS amplitude-frequency diagram

Table2 Characteristic parameters of IMFs in frequency domain

	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7
The largest amplitude	0.00868	0.000843	0.000719	0.000293	0.000626	0.000201	0.000378
Centre frequency	1．13e+006	6.75e+005	3.63e+005	1.13e+005	75000	25000	12500
Signal energy	0.000800	1.24e-005	3.44e-006	1.41e-006	1.53e-006	8.35e-008	1.65e-007

3.2.3 Feature Extraction

In order to distinguish characteristic of different defect signal effectively, every input feature vector should be unrelated or hardly relevant and feature parameters selected should reflect definitely the variation trend of different defects.

After above time and frequency domain analysis of IMF, a total of six feature parameters can be got by each IMF component, such as Zero-crossing, signal area, the maximum amplitude (time domain), the maximum amplitude (frequency domain), centre frequency and signal power. Euclidean distance of every two feature vectors can be calculated with the Euclidean distance formula. And then compare the size of the Euclidean distances. If Euclidean distances are significantly different and balanced between them, we think feature vectors are ideal.

4 Recognition Based on Euclidean Distance

4.1 Flaw classification

Three kinds of standard flaw (the crack in upper surface, the crack in lower surface and the hole in the central board) signals are sampled. 30 samples are collected from each kind of signal, and data length of each sample is 400. And then, the distances of the feature vector are calculated between the signal samples and the three standard signal samples. The minimum can be found out among the three European distances. The type of defect samples tested is the type that the minimum is found out.

N=5 steps EMD to sample data is adopted in experiment. The classification results can be got as shown in Table 3 by using eigenvector derived from the above analysis in the paper.

4.2 Analysis

From the Table 3, it can be found that the correct recognition rates of the upper surface crack, the hole in the central board and the crack under the bottom are 74%, 62% and 83% respectively, the average correct recognition rate is 73%. It can be found that the accuracy is much difference and the success rate to identify is not high in the results.

That the defect recognition rate is over 70% in the experiment states that Euclidean distance is successful in the application of building feature vectors, however, it is not successful in the application of defects' classification because the correct recognition rate is not high. Euclidean distance is only a primary defect classification method, it is inadequate because of a lower recognition rate in this test. Therefore, in order to solve the low recognition rate of the defect classification by the Euclidean distance, the neural network technology can be tried to determine the defect classification.

5 Recognition Based on Neural Network

5.1 Flaw classification

Learning process of BP algorithm consists of information forward propagation process and error counter propagation process. In the process of forward propagation process, input information is processed layer-by-layer from input layer to hidden layer, and transmitted to output layer. Every layer neuron's situation only affects next layer neuron's situation.

Table 3. Recognition results of collected samples

Category	Test samples number	The number divided into this category			Correct recognition rate	Average correct recognition rate
		The crack in upper surface	The hole in the central board	The crack in lower surface		
The crack in upper surface	100	74	16	10	74%	73%
The hole in the central board	100	15	62	23	62%	
The crack in lower surface	100	5	12	83	83%	

If the desired output can not be got in the output layer, it is transferred to counter propagation process and error signal returns along original connecting pathway. Error function is achieved a given value through weight value modification of each layer neuronal ultimately. The model of three layers neural network is shown in Fig. 5.

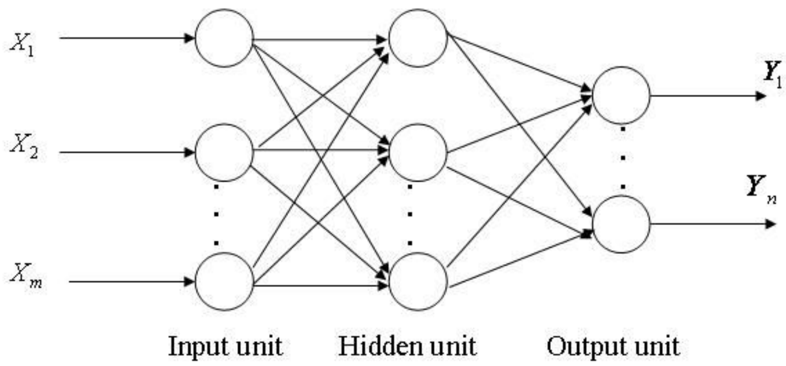

Fig.5 Three layer neural network model

5.2 BP neural network input vector selection and treatment

By above time-domain and frequency domain analysis of IMFs, Six feature parameters of Zero-crossing point, signal area, the maximum amplitude (time domain), the largest amplitude (frequency domain), center frequency, signal energy of each IMF can be got. Put these feature parameters as a group of characteristic array. A vector can be got through assembling characteristic array of five IMFs, the vector is used as neural network input vector.

5.2 Recognition of Ultrasonic echo flaw signal

Three kinds of standard flaw signals are sampled. 30 samples are collected from each kind of signal, and data length of each sample is 400. Adopt N=5 steps EMD to sample data in experiment, use above eigenvector in the paper, take six groups of eigenvector from each sample. 18 groups of data are got as training sample to be inputted into network to train. In addition, a sample is taken from there kinds of standard type signals as detecting sample to detect whether the design of flaw classifier is reasonable or not.

The specific structure of BP neural network is: the neurons number of input layer is 24 , the neurons number of hidden layer is approximately 30, the neurons number of output layer is 3. Hyperbolic secant S-transfer function “tansig” is adopted as transfer Function of hidden layer, output vector is fault code with the value of 0 or 1. S-logarithmic function “logsig” is adopted as transfer function of output layer, whose output range is limited to [0,1] by this function. “Levenberg-Marquardt BP” training function is adopted as Network training function, whose performance index is “mse” and training target is 0.01. Fault type codes are designed as in Table 4(the crack in upper surface, the hole in the central board and the crack in lower surface are abbreviated as upper, central and lower separately). Part of the training samples normalized is shown in table 5.

Network training error curve is shown in Fig.6. It is found that the gradient minimum is met after this training and its training error is very small.

In order to verify the accuracy of network, test samples with a total of 9 sets of data are used to test network model and test results are shown as Table 6. From table 6 it is found that the actual output of network is accordance with expectation output. It is proved that the neural network model is reliable to identify and classify the fault type of ultrasonic defect signal accurately.

Table 4 Flaw type code design

Parameters	Flaw types		
	upper	central	lower
Flaw codes	0 0 1	0 1 0	1 0 0

Table5 Part training sample after normalization

Flaw types	Input vectors (part)					Flaw codes of Input vectors
	T1	T2	T3	T4	T5	
lower	0.77358	-0.74125	-0.23373	-0.74142	-0.83333	1 0 0
lower	0.83019	-0.99334	-0.49712	-0.99293	0.66667	1 0 0
lower	0.92453	-1	-1	-1	1	1 0 0
lower	1	-0.94475	-0.65624	-0.94196	-0.5	1 0 0
lower	0.66038	-0.72221	-0.46914	-0.74464	-1	1 0 0
lower	0.90566	-0.92249	-0.71026	-0.92708	-0.5	1 0 0
central	0.47358	-0.68186	-0.064619	-0.7177	-0.66667	0 1 0
central	0.66792	-0.78267	-0.27465	-0.79709	-0.66667	0 1 0
central	0.32075	-0.23866	0.36901	-0.5701	-0.66667	0 1 0
central	0.18868	-0.36926	0.23517	-0.41474	-0.66667	0 1 0
central	0.33962	-0.50674	-0.0087234	-0.53633	-0.66667	0 1 0
central	0.18868	-0.64097	0.9637	0.11781	-0.66667	0 1 0
upper	-0.51321	0.48593	0.75096	0.44796	-0.66667	0 0 1
upper	-1	0.78777	0.83719	0.4385	-0.66667	0 0 1
upper	-0.24528	0.24347	0.60851	0.30255	-0.66667	0 0 1
upper	-0.84906	1	1	1	-0.66667	0 0 1
upper	-0.6792	0.94186	0.91367	0.68681	-0.66667	0 0 1
upper	-0.3773	0.56304	0.7446	0.21805	-0.83333	0 0 1

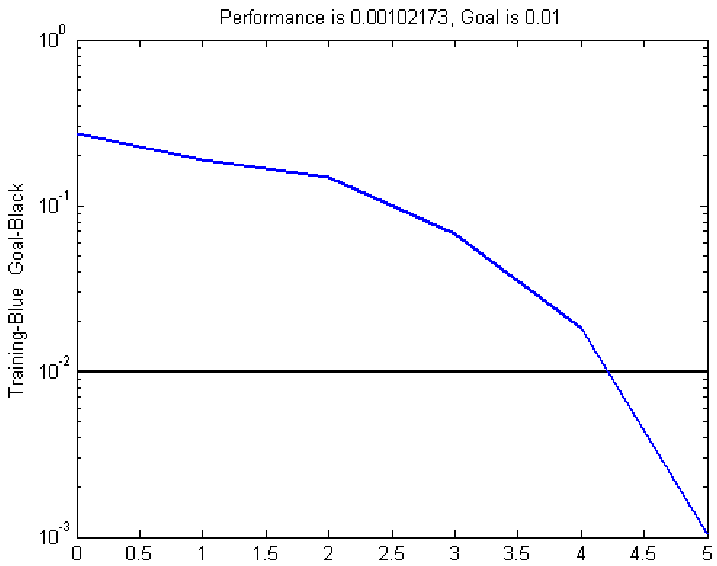

Fig.6 Train error curve

Table6 Sample test results

types	Input vectors					expectation outputs	actual outputs			results
	t1	t2	t3	t4	t5					
lower	0.92	-0.79	-0.25	-0.79	-0.33	1 0 0	0.97	0.0099	0.0015	correct
lower	0.81	-0.84	-0.42	-0.77	-0.42	1 0 0	0.98	0.032	0.0021	correct
lower	0.73	-0.53	-0.59	-0.85	-0.50	1 0 0	0.99	0.014	0.013	correct
central	0.094	-0.16	0.56	-0.35	-0.33	0 1 0	0.017	0.99	0.097	correct
central	0.14	-0.30	-0.29	-0.69	-0.67	0 1 0	0.00042	0.91	0.0053	correct
central	0.38	-0.43	-0.13	-0.82	-0.67	0 1 0	0.021	0.98	0.028	correct
upper	-0.30	0.51	1.1	0.42	-0.67	0 0 1	0.020	0.00013	1.0	correct
upper	-0.62	0.72	0.89	0.69	-0.67	0 0 1	0.0036	0.014	0.93	correct
upper	-0.76	0.82	0.89	0.71	-0.67	0 0 1	0.0043	0.0013	0.97	correct

6 Conclusion

A method is put forward in which eigenvector is constructed based on time domain and frequency domain analysis of intrinsic mode function and neural network is used to classify defect signals. The method has higher recognition rate and it is expected to have better applicability. However the number of standard flaw types is less in this paper, so the number of flaw type detected by eigenvector based on limited flaw types is less. In addition, the way of construct eigenvector is not perfect, there is no unified standard of characteristic extraction, and different flaws need different analysis. All of these questions have to be resolved in further analysis.

References:

[1] R.Vicen, R.Gil, P.Jarabo, M.Rosa, F.Lopez, D.Martinez, Non-linear Filtering of Ultrasonic Signals Using Neural Networks, *Ultrasonics*, Vol.42, No.1-9, 2004, pp.355-360.

[2] Shou-peng Song, Pei-wen Que, Wavelet Based Noise Suppression Technique and Its Application to Ultrasonic Flaw, *Ultrasonics*, Vol.44, No.2, 2006, pp.188-193.

[3] Qiang, G., Xiaojiang, M., Haiyong Z., The Partial Wave Method for the Analysis of Non-stationary Signals and Iits Use in Machine Fault Diagnosis. *Proceedings of the International Symposium on Test and Measurement*, No.2, 2001, pp. 1465-1468.

[4] Kang Huang, Dave Tateh Chang, Thomas Hou, A Bridge Monitoring Method Based on Vibration Characteristics Under a Transient Load. *Proceeding of the International Symposium of Civil Engineering in the 21st Century*, Beijing, China, 3, 2000, pp.563-565.

[5] M.A Rodriguez, J.L. San Emeterio, J.C.Lazaro, A.Ramos, Ultrasonic Flaw Detection in NDE of Highly Scattering Materials Using Wavelet and Wigner-Ville Transform Processing, *Ultrasonics*, Vol.42, No.1-9, 2004, pp.847-851.

[6] Niola Vincenzo, Buccelli Claudio, Gervasio Luca, Pilleri Michele, Policino Fabio, Quaremba Giuseppe, The Impact Of The Wavelet Transform On The Problem Of Firearm Identification: First Evidences, *WSEAS Transactions on Signal Processing*,Vol. 2, No.2, 2006, pp.67-73.

[7] Huang N E, Shen Z, Long S R, et al, The Empirical Mode Decomposition and the Hilbert Spectrum for Nonlinear and Non-stationary Time Series Analysis, *Proceedings of the Royal Society Lond*, Vol.454, 1998, pp.903-995.

[8] Timashev SA, Shlin MG, Precise Analysis of Non-stationary Vibration Processes Using the Hilbert Transform, *ACSIM 2000 Proceeding*, 4, 2000, pp.395-404.

[9] Zong Meng, Guiping Dai, Bin Lin, Characteristics Study on Time-frequency Analysis Method Based on Empirical Mode Decomposition, *Chinese Journal of Sensors and Actuators*, Vol.19, No.4, 2008, pp.1029-1032.

[10] Flandrin P, Rilling G, Goncalves P, Empirical Mode Decomposition as a Filter Bank, *IEEE Signal Processing Letters*, Vol.11, No.2, 2004, pp.112-114.

[11] Jaejoon Kim, Comparative Study of Noise Reduction in Ultrasonic Inspection System, *WSEAS Transactions on Circuits and Systems*, Vol. 9, No.2, 2010, pp.91-100.

[12] Bravier B.M., N.N.J., Pelstring J.A., An Assessment of the Application of the Hilbert Spectrum to the Fatigue Analysis of Marine Risers. *Proceedings of the International Offshore and Polar Engineering Conference*, 2, 2001, pp.268-275.

[13] Loh CH, er al, Application of the Empirical Mode Decomposition-Hilbert Spectrum Method to Identify Near-fault Ground-motion Characteristics and Structural Responses, *Bulletin of The Seismological Society of American*, Vol.91, No.5, 2001, pp. 1339-1357.

[14] Bennett M, Michael S, Empirical Mode Decomposition and Tissue Harmonic Imaging, *Ultrasound in Medicine & Biololgy*, Vol.31, No.8, 2005, pp.1051-1061.

[15] Jaejoon Kim, Comparative Study of Noise Reduction in Ultrasonic Inspection System, *WSEAS Transactions on Circuits and Systems*, Vol. 9, No.2, 2010, pp.91-100.

[16] Fang-Neng Huang, Cheng-Jun Huang, Yong Qian, Xiu-Chen Jiang, Investigation Of Empirical Mode Decomposition Based Denoising In Partial Discharge Detection. *WSEAS Transactions on Circuits and Systems*, Vol. 5, No.1, 2006, pp.92-97.

[17] Zhanguo Xia, Ke Wang, Zhixiao Wang, BP Algorithm Based on Network Complexity, *Computer Engineering and Design*, Vol.30, No.12, 2007, pp.2109-2114.

[18] Linyu Yang , Run-qiao Yu , Chao Lu , Wei Zhang, Carbon Fiber Composites Defect Recognition Based on BP Neural Network in Ultrasonic Testing, *Nondestructive Testing*, Vol.29, No.8, 2007, pp.450-452,460.

[19] Y. F. Hsiao, Y. S. Tarng, K. Y. Kung, Comparison of the Grey Theory with Neural Network in the Rigidity Prediction of Linear Motion Guide, *WSEAS Transactions on Applied and Theoretical Mechanics*, Vol. 4, No.1, 2006, pp.32-41.