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Structure Data Processing and Damage Identification Based on Wavelet and Artificial Neural Network

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Abstract: Structural health monitoring is a multi-disciplinary integrated technology, mainly including signal processing and structural damage detection. The aim of the data processing is to obtain the useful information from large volumes of raw data containing noises. In order to obtain the useful information concerned, de-noising method and feature extraction technique based on Wavelet analysis is studied. An improved wavelet thresholding algorithm to eliminate the noise for vibration signals is proposed. The results of analysis show that the method based on Wavelet is not only feasible to signal de-noising, but also valuable and effective to detect the health status of bridge structure. In order to detect the damage status of the structure, a multi-layer neural network models based on the BP algorithm is designed. The model is trained with the data from an engineering beam to filter different transfer function, train function and the unit number of hidden layer by contrast to determine the best network model for damage detection. At last, the model is used to detect the damage of cable-stayed bridge with an improved method of data pre-processing using the square rate of change in frequency as input date of network. The structural damage identification results show that the BP neural network model is easy to identify the damage by the changing of vibration modal frequency and effective to reflect the injury status of the existing structure.

Key words: Artificial neural network, BP algorithm, damage identification, de-nosing, structure health monitoring, vibration signal, wavelet analysis

INTRODUCTION

Damage can be defined as any abrupt or gradual deficiency developed in a structure during its service period. The damage may be caused due to various factors such as excessive response, cumulative crack growth, wearing of working parts or other impact by an external factor. To ensure structural safety and integrity, low maintenance cost and enough service Life, Structure Health Monitoring (SHM) technology has become more and more important as a reliable, efficient and economical approach to monitor the structural performance, detect damage, assess the structural health condition, and make corresponding maintenance decisions.

Feature extraction is the process of identifying damage sensitive properties and distinguishing between the damaged and undamaged structural states. The signal is often transformed to different domains in order to better interpret the physical characteristics inherent in the original signal. The traditional Fourier analysis analyzes the response data of general transient nature over the whole time span. When the damage occurred can not be fixed, inaccurate results may be produced. Wavelet analysis, as a modern data processing method, was viewed as an extension of the traditional Fourier transform with adjustable window location and size. The Wavelet Transform (WT) decomposes a signal into a representation comprised of local basis functions called wavelets. Each wavelet is situated at a different position on the time axis, which means local in the sense that it decays to zero when fully far away from its centre. Any particular local feature of a signal can be identified from the scale and position of the wavelets decomposed. That makes the wavelet analysis suitable for time-frequency analysis. So wavelet analysis is an effective tool for non-stationary signal processing and therefore can be effectively applied for structural health monitoring (Kim and Melhem, 2003). In order to monitor the health state of the bridge structure, the vibrations of the structure was monitored using a data acquisition system installed in the field. In order to remove the noise and get the vibration feature, the vibration signals acquired were decomposed and reconstructed using the WT. The analysis results show that wavelet analysis has particular advantage in noise eliminating and signal feature extraction.

Damage identification is the ultimate objective of SHM which include the process of identifying damage sensitive properties and distinguishing between the

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damaged and undamaged structural states (Li, 2002). To detect structural damage, a complicated system that is affected by many factors should be concerned. These factors are always uncertain and interact in a non-linearity way. With the ability of solving the problem of uncertainty and non-linearity, artificial neural networks are widely used to solve these problems now. BP model is used most widely because it is easy to operate (Shang, 2004). Wu, Ghaboussi and Garrett use BP network to recognize damage of a three-tier framework with the response spectrum data (Wu *et al.*, 1992). Li Gong-yu and others build an artificial neural network model to express the relationship between the natural frequency and the crack depth and location diagnosis of the cantilever plat (Li, 1992). Wang Bai-Sheng and Ni Yi-qing use neural network analysis method in the Kap Shui Mun Bridge in Hong Kong damage identification which can also be given the size of structural damage (Wang *et al.*, 2001). The use of neural network in damage detection has variety of ways. The main difference is the selection of sensitive parameters which express the health status of structure. The purpose of this paper is to give a clear overview of applications of BP model in structural damage detection. And then further study of the neural network-based structural damage identification method for practical engineering application is carried on.

FEATURE EXTRACTION BASED ON WAVELET

Wavelet transform introduction: Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT) and wavelet packet transform are commonly used wavelet transform algorithm in engineering practice. The CWT, which is achieved in a way similar to the Short Time Fourier Transform (STFT) analysis, provides highly redundant information for reconstructing the signal and costs a large amount of computation time. The DWT can provide sufficient information for analysis of the original signal, with a significant reduction in the computation time. The signal decomposed by DWT at each level of decomposition results in half time resolution and double frequency resolution. In addition, the signal can be reconstructed easily as the dyadic wavelet filter family forms an orthonormal basis. So the DWT is suitable for on-line health monitoring of the structure (Ding *et al.*, 2006). Wavelet packet consists of a set of linear combined wavelet functions. The wavelet packets inherit properties of such as orthonormality and time-frequency localization from their corresponding wavelet functions. It decomposes not only the wavelet approximate component at each level, but also a wavelet detail component to obtain its own approximation and detail components.

Wavelet has good frequency resolution and coarse time resolution at lower frequency, and coarse frequency resolution and good time resolution at higher frequency.

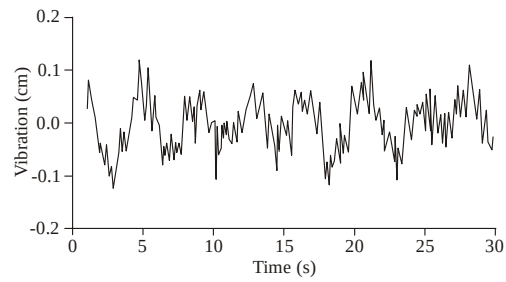


Fig. 1: An original vibration signal contained noise

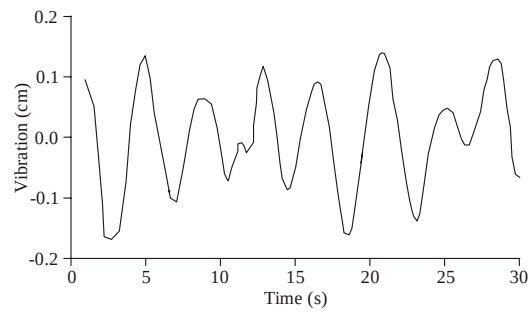


Fig. 2: The signal after de-noising

This is in accordance with the characteristic of vibration signal. That is, low-frequency changes in slow and rapidly changing high-frequency characteristics.

De-noising of vibration signal: Damage in a structural system causes a change in dynamic properties of a system which in turn affects the system modal parameters. So system modal parameters i.e. the natural frequency and mode shape can be monitored in order to detect the time and severity of damage. When a vibration signal is decomposed into its mono-components by the wavelet proposed, these components often represent modal responses associated with the system natural frequencies (Ding *et al.*, 2006).

With the influence of the acquisition devices and the work environment, the data acquired from the monitoring spot usually are the degraded signal with noises. Usually the noise is often of high frequency components, so the denoising procedure can be described as follow: first the original signal is decomposed according to the wavelet and wavelet decomposition level selected; then the coefficient is computed and the threshold is selected, and the detail parts through wavelet transform is compared with the threshold, and if the detail parts less than the threshold, it is set to zero; last the processed coefficients are rebuilt and the noises are filtered. Take horizontal vibration signal of the bridge as an example, wavelet threshold denosing method was adopted to restore the real signal. The original signal contained noise is shown in Fig. 1 and the signal denoised is shown in Fig. 2. It is obvious that the denoising based on wavelet is effective.

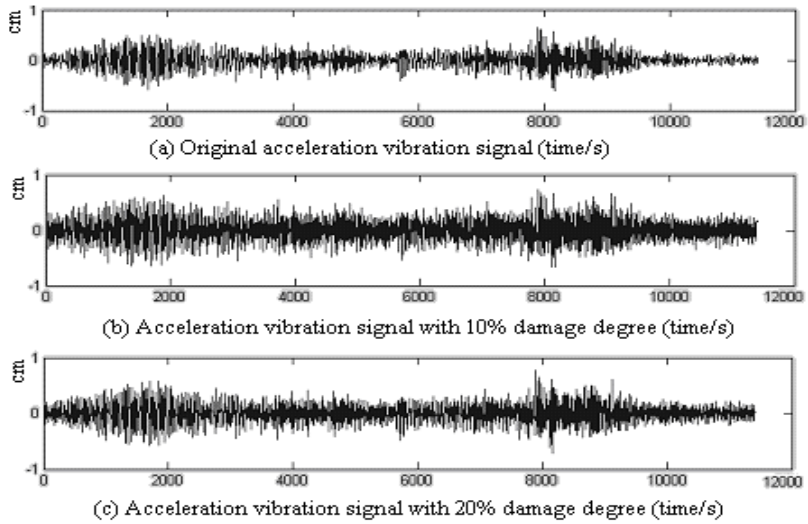


Fig. 3: Acceleration signal with different damage degree

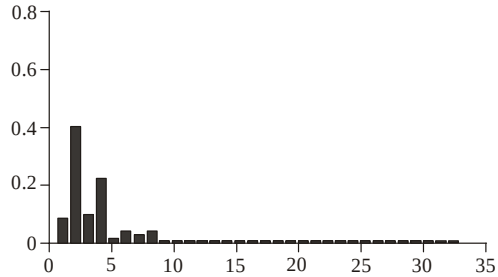
Feature extraction of vibration signal: The evolution of natural frequencies becomes important for damage detection and system identification. Take acceleration vibration signal of the bridge acquired from the monitoring spot as an example, original acceleration vibration signal, acceleration vibration signal with 10% and 20% damage degree is shown in Fig. 3. Wavelet package transform was selected to decompose the above signal. Take the fifth scale ψ_{5k}^{i} as wavelet basis, where i = 1, 2, …, 31. The 32 wavelet packet node energy coefficients gotten through decomposition are shown in Fig. 4, in which the wavelet packet node energy coefficients of 0~10 frequency bands are of different value represented along with the different damage degree. Namely, wavelet packet node energy coefficients are sensitive to different damage degree. The result shows that the wavelet packet node energy coefficients are feasible to structure damage identification as an index representing the structure feature.

DAMAGE IDENTIFICATION BASED ON NEURAL NETWORK

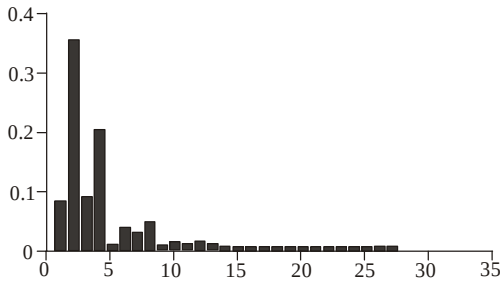
Learning rule of BP neural network: Supervised learning method is used in BP network. The learning rule of BP network mainly consists of two parts, namely, pattern forward transfer and error inverted transfer. Pattern forward transfer refers the process that the input pattern transfers from input layer to output layer through middle layers. Error inverted transfer refers to the process that the error signal between expected output and real output transfers from output layer to input layer through middle layers. Then the connection weight is adjusted from the output layer to the input layer through the middle layers gradually according to expected minimum error direction. With the error inverse propagation adjusting, the order of accuracy arises too. With repeating process of pattern forward transfer and error inverted transfer, global error of network tends to minimum and the real outputs of network approach their responding expected outputs gradually.

There are two ways to seek the minimal value of the objective function, namely, one by one process and batch treatment. In the one by one treatment, the connect weight is adjusted after each input, which often rise the phenomenon of 'learned the new, forget the old'. In order to overcome this shortcoming, the continuous loop learning is used in BP algorithm to obtain the correct solution, which makes the convergence speed is very slow. In addition, the learning effectsare impacted by the sort of learning samples in the one by one treatment. In batch treatment, the connect weight is adjusted after all samples input. When the sample number is large, the convergence of learning is easy to acquire with the 'batch' learning method than the one by one process. In addition, the learning effects are not impacted by the sort of learning samples in the 'batch' treatment.

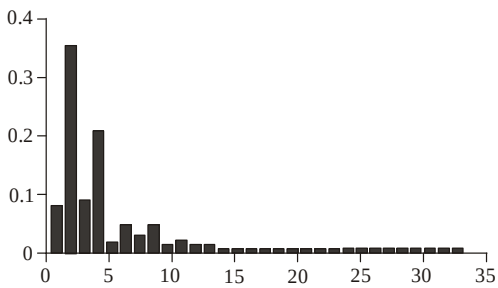
Sample data and test data processing: The reduction of elastic modulus E of a 10 m-long steel model is used to simulate the degree of damage. Respectively, the self-vibration frequency at 1.5, 4.5 and 7.5, 9.5 m with damage degree of 10, 20, 30, 40 and 50% is tested. The normalized self-vibration frequency is used as sample data to train the neural network. All the data is de-noised with the method described in part 2. The output is expressed by three binary codes to distinguish the damage degree. 10 and 20% of damage is classified as mild damage and 30, 40 and 50% of damage is classified as serious damage. The following method is used to normalize the input and the output of the actual samples to (0, 1).



(a) Wavelet package node energy coefficient without damage



(b) Wavelet package node energy coefficient with 10% damage degree



(c) Wavelet package node energy coefficient with 20% damage degree

Fig. 4: Wavelet packet node energy coefficients of acceleration signal under different damage

Suppose the upper and lower limits of input sample (x_k) is $x_{i\,max}$, $x_{i\,mix}$ then x_{ik} can be gotten as below:

$$x_{ik} = \frac{x_{ik} - x_{i\min}}{x_{i\max} - x_{i\min}} i = 1,2,\ldots\ldots n \; x_{ik} \in [0,1] \quad (1)$$

Suppose the upper and lower limits of output sample (Y_k) is y_{max}, y_{min} then y_k can be gotten as below:

$$y_k = \frac{y_k - y_{\min}}{y_{\max} - y_{\min}} \; y_k \in [0,1] \quad (2)$$

The test data are input after the neural network training is completed. The output is compared with the desired output to judge if the neural network is eligible. The neural network is eligible if the difference meets the error demand. On the contrary, the neural network is not eligible if the difference does not meet the error demands. In this case, it is obligatory to change the neural network model structure or change the initial parameters of neural networks to train the neural network again until it reaches the error requirement.

Test data come from the same 10m-long steel mode at 1.5, 4.5, 7.5, 9.5 m with injury degree of 19 and 41%, 29 and 41%, 21 and 41%, 38 and 12%. The normalization method of test data is the same as the sample data.

Neural network training: In the network training process, the choice of transfer function is very important. An inappropriate transfer function will make network convergence process very slow. We choose tan*sig* as hidden layer transfer function and log *sig* and *purelin* as output layer transfer function respectively. The neural network is trained with the sample data and two error curves are gotten. We found that the error curve is different in the initial training which indicates the transfer function has some influence on the calculation process. With the number of iterations increasing, we can see the error curve show roughly the same laws despite the transfer function of the two curves are different. One uses 147 steps to achieve the training objectives and the other uses 140 steps. It can be concluded that the transfer function shows little effect on this network performance.

Different training functions have great impact on neural networks training. Generally, *trainbfg* or *traingd* or *trainlm* can be used as training function. *Trainlm* is always the default function of BP network because its computation speed is fas. However, the function consumes a large amount of memory resources in its running process. The computation speed of the other two functions is slower but less memory is consumed. Using the sample data, the network is trained with *trainfg*, traingd and *trainlm* respectively. Simulation results show that the *trainlm* function is more appropriate to this network performance than others.

There isn't general theoretical formula to determine the number of hidden layer nodes yet. The hidden layer with a few nodes can not 'remember' learning sample well and is not easy convergent. On the other hand, the hidden layer with many nodes can 'remember' study sample well and has poor generalization ability. With the synthesis of several commonly used empirical formulas, we choose 21,24,27,30 as the number of hidden layer units and train the network using the sample data respectively. Training results proved that 21 is an appropriate hidden layer unit number in this network.

Based on the above, batch treatment method is adopted in this network. *Tansig* is used as transfer function of hidden layer and *logsig* is used as transfer

Table 1: The test result

	Actual output			Expected output			
Sequence	y_1	y_2	y_3	Y_1	Y_2	Y_3	The degree of damage
1	0	0.003	0.0195	0	0	0	Middle damage on location 1
2	0	0.0038	1.0000	0	0	1	Serious damage on location 1
3	0	0.9993	0.9260	0	1	1	Serious damage on location 2
4	0	0.9993	1.0000	0	1	1	Serious damage on location 2
5	1	0.0044	0.2645	1	0	0	Middle damage on location 3
6	1	0.0024	0.9999	1	0	1	Serious damage on location 3
7	1	0.9949	1.0000	1	1	1	Serious damage on location 4
8	1	0.9968	0.0000	1	1	0	Middle damage on location 4

Table 2: Damage identification results

Expected output						Actual output					
0.1	0.0	0.0	0.0	0.0	0.0	0.1545	0.0416	0.0244	0.0060	0.0134	0.0119
0.3	0.0	0.0	0.0	0.0	0.0	0.3323	0.0516	0.0393	0.0046	0.0142	0.0133
0.5	0.0	0.0	0.0	0.0	0.0	0.5015	0.01134	0.0590	0.0032	0.0144	0.0152
0.7	0.0	0.0	0.0	0.0	0.0	0.6903	0.0613	0.0879	0.0021	0.0134	0.0172
0.8	0.0	0.0	0.0	0.0	0.0	0.7906	0.0227	0.0154	0.0025	0.0111	0.0249
0.0	0.1	0.0	0.0	0.0	0.0	0.0119	0.1168	0.0387	0.0174	0.0097	0.0157
0.0	0.3	0.0	0.0	0.0	0.0	0.0122	0.3626	0.0462	0.0350	0.0111	0.0167
0.0	0.5	0.0	0.0	0.0	0.0	0.0142	0.4756	0.0812	0.0046	0.0127	0.0197
0.0	0.7	0.0	0.0	0.0	0.0	0.0201	0.6838	0.0647	0.0163	0.0171	0.0228
0.0	0.8	0.0	0.0	0.0	0.0	0.0217	0.8457	0.0469	0.0019	0.0200	0.0251
0.0	0.0	0.1	0.0	0.0	0.0	0.0061	0.0456	0.1467	0.0515	0.0082	0.0171
0.0	0.0	0.3	0.0	0.0	0.0	0.0075	0.0270	0.3380	0.0984	0.0099	0.0212
0.0	0.0	0.5	0.0	0.0	0.0	0.0131	0.0042	0.4955	0.0996	0.0128	0.0266
0.0	0.0	0.7	0.0	0.0	0.0	0.0520	0.0619	0.7148	0.0560	0.0116	0.0319
0.0	0.0	0.8	0.0	0.0	0.0	0.0057	0.0938	0.8285	0.0520	0.0140	0.0388
0.0	0.0	0.0	0.1	0.0	0.0	0.0026	0.0279	0.0145	0.1151	0.0135	0.0176
0.0	0.0	0.0	0.3	0.0	0.0	0.0028	0.0052	0.0621	0.2975	0.0143	0.0201
0.0	0.0	0.0	0.5	0.0	0.0	0.0029	0.0781	0.0819	0.4911	0.0192	0.0215
0.0	0.0	0.0	0.7	0.0	0.0	0.0070	0.0838	0.0798	0.7316	0.0156	0.0277
0.0	0.0	0.0	0.8	0.0	0.0	0.0091	0.0859	0.0610	0.8271	0.0170	0.0347
0.0	0.0	0.0	0.0	0.1	0.0	0.0013	0.0084	0.0294	0.0612	0.1162	0.0130
0.0	0.0	0.0	0.0	0.3	0.0	0.0009	0.0068	0.0275	0.0431	0.2967	0.0128
0.0	0.0	0.0	0.0	0.5	0.0	0.0006	0.0114	0.0305	0.0380	0.4909	0.0166
0.0	0.0	0.0	0.0	0.7	0.0	0.0005	0.0159	0.0294	0.0352	0.6814	0.0223
0.0	0.0	0.0	0.0	0.8	0.0	0.0004	0.0364	0.0333	0.0369	0.7930	0.0355
0.0	0.0	0.0	0.0	0.0	0.1	0.0070	0.0337	0.0244	0.0183	0.0453	0.1210
0.0	0.0	0.0	0.0	0.0	0.3	0.0123	0.0381	0.0151	0.0544	0.0481	0.3238
0.0	0.0	0.0	0.0	0.0	0.5	0.0146	0.0464	0.0210	0.0390	0.0506	0.5216
0.0	0.0	0.0	0.0	0.0	0.7	0.0436	0.0362	0.0511	0.0160	0.0265	0.7046
0.0	0.0	0.0	0.0	0.0	0.8	0.0430	0.0408	0.0312	0.0084	0.0332	0.8550

function of output layer and *trainlm* is used as training function. The hidden layer unit number is 21. The structure of network model is 10-21-3. Error limit is 0.01.

The test data are input to test the network. The test results are shown in Table 1. The output is treated as 1 if it is greater than 0.5, otherwise, the output is treated as 0 if it is less than 0.5. Test data come from 4 locations of the 10m-long steel model. There are 2 kinds of damage on each location. So there are 8 lines of date in Table 1. It is showed in Table 1 that the error is within the range allowed and the actual output matches expected output well.

Application in cable-stayed bridge damage: There is a 74.82 m long single tower prestressed concrete cable-stayed bridge model whose main beam is divided into 20 units in calculation model. Damage is simulated through the decrease of elastic modulus in each main beam elements. Decrease of elastic modulus in different elements marks different position of damage. Different percentages of elastic modulus decrease in same elements marks different degree of damage in that position.

The previous five frequencies of the main beam elements of number 3, 7, 9, 13, 16, 19 in the damage degree of 0, 10, 30, 50, 70 and 80% is calculated respectively. The damage identification indicator based on the change of frequency is constructed as follow:

$$\left\{ \frac{\Delta\omega_1^2}{\omega_{01}^2}, \frac{\Delta\omega_2^2}{\omega_{02}^2}, \frac{\Delta\omega_1^2}{\omega_{03}^2}, \frac{\Delta\omega_4^2}{\omega_{04}^2}, \frac{\Delta\omega_5^2}{\omega_{05}^2} \right\}$$

where, $\Delta\omega_i = \omega_{0i} - \omega_i, i = 1,2,3,4,5$

The damage identification indicator based on the previous five frequencies of the elements of number 3, 7, 9,13,16,19 in the damage degree of 10, 50, 80% is chosen as training sample data. The degree of damage is expressed as 0.1, 0.5, and 0.8 correspondingly. The structure of network model is 5-11-6. Other parameters are the same as the previous network model in part 3.3. The neural network training meets the error requirements after 18 steps.

Then the network is tested with the test data comes from the elements of number 3, 7, 9, 13, 16 and 19 in the damage degree of 10, 30 50, 70 and 80%. The damage identification results are listed in Table 2. From the Table 2 we can know that the error is within the range allowed and the damage identification of the location and degree are correct. So it can be concluded that the identification of damage based on the change of frequency is feasible with the help of neural network.

CONCLUSION

Examples study show that the wavelet transform can effectively denoise the noise contained in the actual vibration signal and identify the imbalanced structural vibration signal by choosing a suitable analyzing wavelet and appropriate decomposition criteria. As a new means of time-frequency analysis, wavelet has great advantages in data processing of the structure health monitoring system.

The study results indicate that it is a feasible way to identify the damage based on the change of frequency with the help of neural network. However, there is an inherent defect of neural network. Because all the knowledge gained through training is embedded in a large number of connection weights in the form of values, it is difficult to have a clear understanding about the ability of neural network and it is unable to obtain a clear explanation of reasoning process also. Expert system is reasoning system based on symbolic which has explanatory function. But Expert system has a visible shortcoming because it is difficulty to acquire knowledge. Neural network and expert system can complement each other. Therefore, the combination of neural network and expert system has good prospects certainly. This aspect will be explored in our future studies.

The above study results have been successfully applied to the monitoring system of the Wuhu Yangtze River Bridge and the Zhengzhou Yellow River Bridge, which are two important bridges of symbolic significance. The operation of the two bridge monitoring system shows that wavelet analysis technique selected can complete noise reduction and feature extraction of monitoring data successfully and the BP network model constructed can identify the damage of the structure effectively. The two technologies achieve analysis, processing of monitoring data in real-time and improve the intelligence degree of information processing.

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