Data Processing Based on Wavelet Analysis in Structure Health Monitoring System

Xiang-jun CHEN
School of Civil Engineering, Shijiazhuang Tiedao University, Shijiazhuang, 050043, China
Email: cxj9596@sohu.com

Zhan-feng GAO
School of Information Science and Technology, Shijiazhuang Tiedao University, Shijiazhuang, 050043, China
Email: gaozhf@stdu.edu.cn

Abstract—In order to obtain the useful information from the raw data which contain the state data reflecting the structure condition and the noise, de-noising and feature extraction techniques based on Wavelet analysis were studied. An improved wavelet thresholding algorithm to eliminate the noise for vibration signals was proposed. Comparison analysis with other thresholding algorithms shows that the new algorithm performs wave filtering well and improves the quality of noise reduction. Db5 wavelet was adopted to decompose the acceleration vibration signal acquired from the monitoring spot. Laboratory study shows that the feature vibration can be extracted successfully by reconstructing the wavelet coefficients. Comparison analysis about the original acceleration vibration signal, acceleration vibration signal with 10% and 20% damage degree shows that wavelet package can be used to detection the signal mutation and realize the structural damage alarming. The applicability of the proposed methods is demonstrated by using in two actual bridge health monitoring system.

Index Terms—vibration signal, bridge structure, wavelet analysis, de-noising, feature extraction

I. INTRODUCTION

Structure health monitoring (SHM) technology has become more and more important in recent years as a reliable, efficient and economical approach to monitor the structural performance, detect damage, assess/diagnose the structural health condition, and make corresponding maintenance decisions. Data processing is one of the important procedures of SHM. It is the key to identify damage sensitive properties and distinguish between the damaged and undamaged structural states[1-2].

Wavelet analysis, as a modern data processing method, has been 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. Advantages of wavelet analysis lie in its ability to examine local data with a “zoom lens having an adjustable focus” to offer multiple levels of details and approximations of the original signal. So wavelet analysis is an effective tool for non-stationary signal processing and therefore it has been effectively applied in many field[3-4].

In the data processing of the SHM, the signal is often transformed to different domains in order to better interpret the physical characteristics inherent in the original signal acquired from the monitoring spot. The original signal should be reconstructed by performing inverse operation on the transformed signal without any loss of the data. Wavelet analysis has been increasingly applied to a great variety of engineering problems that are connected to the detection of structural damage in the last decade. Ovanesova A.V. and Suárez L.E.[5] investigated the application of wavelet transform to detect cracks in frame structures and concluded that the method is simple and reliable if the wavelet selected is appropriate. Yen,G.G. and Lin,K.C. [6] studied the feasibility of using the wavelet packet transform for vibration signal processing, defined the wavelet packet node energy and gotten the conclusion that the node energy coefficients of wavelet packet can represent the performance of the original signal more directly. Reference [7] took the wavelet packet energy rate as the damage index and verified its feasibility by the numerical simulation and experimental. Chuang et al (2003, 2005) analyzed the Timoshenko beam vibration mode with the wavelet transform and identified the location Timoshenko beam cracks through observing distribution of wavelet coefficients. In addition, spatial wavelet analysis for structural damage detection was proposed[8-9].

These applications are very versatile and a large number of articles have been published. However, most algorithms are still on the stage of academic researches [10-11]. Further studies are necessary to investigate the feasibility of wavelet analysis method in real-time data processing of actual monitoring system. This is the target and the innovation of this paper. In order to remove the
noise and obtain the vibration feature, the vibration signals acquired from the monitoring field were decomposed and reconstructed using the WT timely. The basic theory of wavelet analysis and wavelet packet was introduced first. Then the de-noising and feature extracting methods based on wavelet analysis were studied and simulated in laboratory. At last the methods were applied to two actual bridge monitoring system. The results show that wavelet analysis has particular advantages in noise eliminating and signal processing in actual monitoring system.

II. INTRODUCTION OF WAVELET TRANSFORM

Wavelet theory has become one of the fast-evolving mathematical and signal processing tools for its many distinct merits since it was first put forward definitely by Morlet in 1984[12]. Being different from the traditional signal processing tools such as STFT, the wavelet transform can extract time-frequency features of a signal effectively, so it can be used for multi-scale analysis of a signal through dilation and translation. Namely, the wavelet transform is more suitable for the analysis of non-stationary signals. Continuous wavelet transform (CWT), discrete wavelet transform (DWT) and wavelet packet transform are commonly used wavelet transform algorithm.

A. Continuous Wavelet Transform

The continuous wavelet transform of a function \( f(t) \) is defined as

\[
(W_f)(b,a) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \psi^\ast \left(\frac{t-b}{a}\right) dt
\]

(1)

where \( \psi(t) \) is the basic (mother) wavelet, \( \psi^\ast(t) \) is the conjugate of \( \psi(t) \), and \( a \) and \( b \) are the dilation parameter and the translation parameter, \( \frac{1}{\sqrt{a}} \psi \left(\frac{t-b}{a}\right) \) is the wavelet basis function (baby) wavelet.

The mother wavelet \( \psi(t) \) needs to satisfy certain admissibility condition in order to ensure existence of the inverse wavelet transform. The dilation parameter \( a \), the translation parameter \( b \), are also referred as the scaling and shifting parameters respectively and play an important role in the wavelet analysis. Both of the parameters are real and \( a \) must be positive. By changing the value of translation parameter \( b \), a signal is examined by the wavelet window piece by piece localized around the point of "\( t=b \)". Through changing the value of dilation parameter \( a \), the data portion in the neighborhood of "\( t=b \)" can be examined in different resolutions.

If the wavelet function is well chosen, computing the original signal function from its inverse wavelet transform is possible:

\[
f(x) = \frac{1}{C_\psi} \int \sum_{j,k} D_j(t) + A_j(t) \frac{dadb}{a^2}
\]

(2)

\[
C_\psi = \int_{-\infty}^{\infty} \frac{\psi(\omega)}{\omega} d\omega
\]

The original signal can be reconstructed without any loss of data according to the (2).

Performing the inverse wavelet transform on the wavelet transform of a signal, the original signal can be reconstructed without any loss of data. Parameter \( b \) only influences window's position along the time axis on the phase plane. However, parameter \( a \) not only influences the window's position along the frequency axis but also influences the shape of the window itself. So the sampling step of the WT in the time domain can be adjusted according to the different frequencies. Wavelet has good frequency resolution and coarse time resolution at lower frequency, and coarse frequency resolution and good time resolution at higher frequency. This is in accordance with the characteristic of vibration signal. Namely, vibration signal is of characteristics that the low-frequency changes slowly and high-frequency changes rapidly.

B. Discrete Wavelet Transform

The CWT is highly redundant as far as the reconstruction of the signal is concerned. This redundancy requires a large amount of computation time. The discrete wavelet transform can provide sufficient information for the original signal analysis, with a significant reduction in the computation time. It is similar to the discrete Fourier series, where only frequency is the discrete parameter. When the coordinates \((b, a)\) of the CWT shown in (1) are discretized to the coordinates \( (2^j k, 2^i) \) using two integers \( j \) and \( k \), the discrete wavelet transform (DWT) is given by

\[
d_i^j(t) = 2^{i/2} \int f(t) \psi^\ast (2^t-k) dt
\]

(3)

where \( j \) and \( k \) are integer scale and translation factors.

The DWT analyzes the signal by implementing a wavelet filter of particular frequency band to shift along the time axis. The frequency band of the filter depends on the level of decomposition, which make the local examination of the signal become possible. As a result, the signal can be decomposed into a tree structure, in which every level of the signal can be expressed as wavelet details and approximation as follows

\[
f(t) = \sum_{i=1}^{J} D_i(t) + A_i(t)
\]

(4)

where \( D_i(t) \) is the wavelet detail, \( A_i(t) \) stands for the wavelet approximation at the \( j^{th} \) level. DWT decomposition tree of three-level is shown in Fig. 1.

The signal decomposed by DWT at each level of decomposition results in halving the time resolution and doubling the frequency resolution. In addition, the signal can be reconstructed easily as the dyadic wavelet filter family forms an orthonormal basis. Namely the discrete wavelet functions can recognize the occurrence time of frequency changes caused by the attenuation of the structural stiffness. So the DWT is very suitable for online health monitoring of the structures [13-14].
Wavelet Packet Transform

Wavelet packet consists of a set of linear combined wavelet functions, which can be represented as a function \( \psi_{j,k} \) as follow:

\[
\psi'_{j,k}(t) = 2^{-j/2} \psi\left(\frac{2^{-j}t - k}{2}\right),
\]

where \( i \) is the modulation parameter, \( j \) is the dilation parameter and \( k \) is the translation parameter.

Here \( i = 1, 2, \ldots, n \) and \( n \) is the level of decomposition in wavelet packet tree. The wavelet \( \psi' \) is obtained by the following recursive relationships:

\[
\psi^{2i}(t) = \frac{1}{\sqrt{2}} \sum_{k} h(k) \psi\left(\frac{t}{2} - k\right),
\]

\[
\psi^{2i+1}(t) = \frac{1}{\sqrt{2}} \sum_{k} g(k) \psi\left(\frac{t}{2} - k\right)
\]

Here \( \psi' \) is defined as a mother wavelet and the discrete filters \( h(k) \) and \( g(k) \) are quadrature mirror filters associated with the scaling function and the mother wavelet function. Namely, wavelet packet analysis decomposes not only the wavelet approximate component at each level, but also a wavelet detail component to obtain its own approximation and detail components. A three-level wavelet packet transform of a signal is as shown in Fig. 2.

III. WAVELET-BASED SIGNAL DE-NOISING AND FEATURE EXTRACTION

Theoretically, any damage in structure may cause some kinds of change in dynamic properties of a system. These changes may affect the structure modal parameters in turn. So monitoring and analyzing the structure modal parameters such as the natural frequency and mode shape can help to detect the severity of damage and time occurrence in structure. With the influence of the acquisition devices and the working environment, the data acquired from the monitoring spot usually are the degraded signals with a variety of noises. Signal de-noising and feature extraction is necessary for diagnosis the health status of the structure.

A. Signal de-noising

Wavelet threshold de-noising has been widely used since it was provided by D.L.Donoho in 1994[15]. The procedure of de-noising can be described as follow. First the original signal is decomposed according to the wavelet and wavelet decomposition level selected. Then the coefficient is calculated and the threshold is selected. After that the detail parts through wavelet transform is compared with the threshold and the detail parts is set to zero if it is less than the threshold. At last the processed coefficients are rebuilt and the noises are filtered. Generally there are two kinds of threshold functions, which is hard threshold function and soft threshold function. The form of universal hard threshold function is

\[
s = \begin{cases} 
0 & \text{if } |x| \leq t \\
|x| & \text{if } |x| > t 
\end{cases}
\]

The form of universal soft threshold function is

\[
s = \begin{cases} 
0 & \text{if } |x| \leq t \\
\text{sign}(x)\left(|x| - t\right) & \text{if } |x| > t 
\end{cases}
\]

The hard threshold function itself and the derivative of the soft threshold function are not continuous in the whole wavelet domain. In order to overcome the shortcoming of the both methods, a new threshold function which combines the advantages of the two methods is proposed as follow.

\[
s = \begin{cases} 
0 & \text{if } |x| \leq t \\
\text{sign}(x)\left(|x| - t\right) & \text{if } x > t \\
\exp\left(\frac{|x|}{t}\right)^{1/\nu} - 1 & \text{if } x < -t 
\end{cases}
\]

Comparative analysis on the effect of different threshold is carried out using the acceleration signal of vibration obtained from the laboratory bridge model. The comparative results are described as Fig. 3. Fig. 3(a) is a reference signal acquired from the bridge model under the case without outside interference. Fig. 3(b) is the signal containing the reference signal and noise. The de-noising results of hard threshold, soft threshold and improved threshold are illustrated in Fig. 3(c), Fig. 3(d) and Fig. 3(e) respectively.
threshold method filters all the high frequency part of signal including some useful signal. The new threshold method makes up the lack of the two methods and recovers the original signal very well. In addition, the denoised signal is of good consistency with the reference signal. It can be seen that the new threshold function introduced is better than the traditional functions in signal de-noising.

B. Detection of signal mutation

Normally, in order to ensure the effectiveness of feature extraction, it is necessary to decompose the denoised signal on multiple levels first. When a signal is decomposed into its mono-components by the wavelet packet, these components often represent modal responses associated with the system natural frequencies [11][16]. Db5 wavelet was adopted to decompose the acceleration vibration signal acquired from bridge model. As illustrated in Fig.4, 4-scale details of the signal d1~d4 and the envelope of the signal a4 was gotten.

In order to verify the effectiveness of this method, an impact was added at t=7.5sec and analyzed by Db5 wavelet. The analysis result is shown in Fig.5. The peak, which represents the structural damage can be observed at t=7.5sec from the details of the signal d1 and d2. Thus wavelet package can be used to detection the signal mutation and realize the structural damage alarming.

C. Feature extraction

The evolution of natural frequencies is important for damage detection and system identification. Take bridge model acceleration vibration signal as an example, original acceleration vibration signal, acceleration vibration signal with 10% and 20% damage degree is shown in Fig. 6.
Wavelet package transform was selected to decompose the above signal. Take the fifth scale $\psi_{i,5}$ as wavelet basis and $i=1,2,\ldots,31$. The 32 wavelet packet node energy coefficients got through decomposition are shown in Fig.7. Obviously, the wavelet packet node energy coefficients of 0–10 frequency bands are of different value corresponding 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.

VI. APPLICATION

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. Both the two bridge long-term health monitoring systems consist of sensor system, data acquisition system, data transmission system, data processing and management system and security evaluation system. The monitoring system can monitor and process physical parameters such as the beam vibration, strain, displacement, deflection, the temperature of measuring point, the train speed, axle load and axle number in real time.

The new threshold function was used for monitoring data de-noising before feature extraction. The features of different monitoring signals, which are extracted using wavelet packet node energy coefficient method, are used to assess the health status of the bridge. For example, Fig. 8 is the time curve of de-noised transverse vibration signal which is monitored and transmitted to the control center when a train pass through the U59 # hole of Zhengzhou Yellow River Bridge with a speed of 58.1km/h. Vibration amplitude and its changing trend is consistent with the computed results according to the vehicle conditions and bridge design parameters.

V. CONCLUSION

As a new means of time-frequency analysis, wavelet has great advantages in dealing with the data of the structure health monitoring system. By choosing a suitable wavelet threshold and appropriate decomposition criteria, the wavelet transform can effectively de-noise the noise contained in the actual vibration signal and decompose the non-stationary structural vibration signal into components with simple frequency content.

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. Furthermore, the technique adopted implements analysis, processing of monitoring data in real-time and improve the intelligence degree of information processing.

ACKNOWLEDGMENT

The authors would like to express their appreciation for the project(2009AA11Z102) supported by Ministry of Science and Technology of China (National 863 Program); project(F2008000453) supported by Natural Science Foundation of Hebei Province; Project(09213565D) supported by Technological Research and Development Plan of Hebei Province.

REFERENCES


Xiang-jun CHEN is an Associate Professor of Civil Engineering School at Shijiazhuang Tiedao University. Engineering Ph.D., graduated from College of Civil and Transportation Engineering, Hohai University. His research interests are engineering geology, computer simulation and information processing. He has published over 15 journal and conference papers.

Zhan-feng GAO is a Professor of Information Science and Technology School at Shijiazhuang Tiedao University. Engineering Ph.D., graduated from Mechanical, Electronic and control Engineering School of Beijing Jiaotong University. Her research interests on structure health monitoring, data processing and computer applications. She has published over 20 journal and conference papers.