Engineering Applications of Artificial Intelligence 24 (2011) 87–92

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

# Structure damage diagnosis using neural network and feature fusion[☆]

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ARTICLE INFO

*Article history:*
Received 10 September 2008
Received in revised form
19 July 2010
Accepted 27 August 2010
Available online 28 September 2010

*Keywords:*
Wavelet packet decomposition
Frequency band energy
Neural network
Feature fusion
Damage diagnosis

ABSTRACT

A structure damage diagnosis method combining the wavelet packet decomposition, multi-sensor feature fusion theory and neural network pattern classification was presented. Firstly, vibration signals gathered from sensors were decomposed using orthogonal wavelet. Secondly, the relative energy of decomposed frequency band was calculated. Thirdly, the input feature vectors of neural network classifier were built by fusing wavelet packet relative energy distribution of these sensors. Finally, with the trained classifier, damage diagnosis and assessment was realized. The result indicates that, a much more precise and reliable diagnosis information is obtained and the diagnosis accuracy is improved as well.

## 1. Introduction

Various damages like crack or delamination in structures are unavoidable during service due to the impact or continual load, chemical corrosion and aging, change of ambient conditions, etc. It has been theoretically and practically proved that damage in a structure will cause the change of structural stiffness, natural frequency and damping, leading to the variation of dynamic response of the whole structure. Detection of related acceleration and vibration frequency response signal of non-stationary components could reflect the wealth of information injury. However the traditional signal processing methods cannot properly reflect the characteristics of non-stationary signals, making it difficult to get satisfying results (Tseng and Naidu, 2002).

Most of vibration-based damage assessment methods require the model properties, which can be obtained from the measured signals through the system identification techniques such as the Fourier transform (FT). The Fourier analysis transforms the signal from a time-based or space-based domain to a frequency-based one. Unfortunately, the time or space information may be lost during performing the transform and it is sometimes impossible to determine when or where a particular event took place (Han et al., 2005). The wavelet transform (WT) overcomes the problems that other signal processing techniques exhibit. The main advantage of using wavelets is the capacity to perform local analysis of a signal, i.e., to zoom on any interval of time or space. Wavelet analysis is thus capable of revealing some hidden aspects of the data that other signal analysis techniques fail to detect. One possible drawback of WT is that the frequency resolution is quite poor in the higher frequency region. The wavelet packet transform (WPT) is an extension of the WT, which provides a complete level-by-level decomposition of signal (Mallat, 1989). The wavelet packets are alternative bases formed by the linear combinations of the usual wavelet functions (Coifman and Wickerhauser, 1992). Therefore, the WPT enables the extraction of features from the signals that contain both the stationary and non-stationary components with an arbitrary time-frequency resolution. Moreover, each wavelet packet decomposition frequency band has component energies which are more sensitive to damage and thus can better describe structure damage feature.

The artificial neural network (ANN) model is robust, adaptive and fault tolerant (Kao and Hung, 2003). ANN can also effectively deal with quality and uncertainty, making it highly promising for detecting structural damage. The feasibility of applying ANN and WPT to detect structural damage has received considerable attention (Sun and Chang, 2002; Yam et al., 2003; Yuen and Lam, 2006; Castro et al., 2007). However, these researches are based on information from a single sensor. Since a single sensor is generally subject to its efficiency, performance and environment noise, only limited partial signals about the structures can be collected and those signals might be incomplete, inconsistent or even imprecise. Signals from different sensors may provide complementary data in addition to the redundant information content. Merging of redundant data can help improve the imprecision; and data fusion of complementary data can create a more consistent recognition of land cover patterns, in which the associated uncertainty is reduced

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[☆] Foundation item: Project (2005E205) supported by the Natural Science Foundation of Shaanxi Province

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doi:10.1016/j.engappai.2010.08.011

and the classification accuracy is improved by combining and analyzing the multi-sensor data to take advantage of their characteristics and improve the information extraction process (Smyth and Wu, 2007; Gros, 1999; Guo, 2006).

In this study, dynamic signals measured from different sensors are firstly decomposed into wavelet packet components; component energies are then calculated and fused as feature vector which are used as inputs into ANN models for damage assessment. Various levels of damage detection for this structure including the occurrence, location and severity of the damage are studied.

## 2. Wavelet packet transform (WPT) and artificial neural networks (ANN)

### 2.1. WPT

The WPT of a time domain signal $f(t)$ can be calculated using a recursive filter-decimation operation (Coifman and Wickerhauser, 1992). After $j$-levels of decomposition, the original signal $f(t)$ can be expressed as

$$f(t)=\sum_{i=1}^{2^j} f_j^i(t) \tag{1}$$

$$f_j^i(t)=\sum_{i=1}^{2^j} c_j^i(t)\psi_{j,k}^i(t) \tag{2}$$

Here, the component signal $f_j^i(t)$ can be expressed by a linear combination of wavelet functions $\psi_{j,k}^i(t)$, integers $i$, $j$ and $k$ are the modulation, scale and translation parameters, respectively; $c_j^i(t)$ and $\psi_{j,k}^i(t)$ are defined as the wavelet packet coefficient and the wavelet packet function. The wavelet packet coefficients can be obtained from

$$c_{j,k}^i=\int_{-\infty}^{\infty} f(t)\psi_{j,k}^i(t)dt \tag{3}$$

For the purpose of structural health monitoring, frequency domain information tends to be more important and thus a high level of the WPT is often required to detect the minute changes in the signals. After the WPT, the energies of these decomposed component signals can be used for structural condition assessment. These component energies are defined as

$$E_j^i=\int_{-\infty}^{\infty} f_j^i(t)^2 dt \tag{4}$$

It can be shown that, when the mother wavelet is semi-orthogonal or orthogonal (Han et al., 2005), the signal energy $E_f$ is the summation of the $j$-level component energies as follows:

$$E_f=\int_{-\infty}^{\infty} f^2(t)dt=\sum_{i=1}^{2^j} E_j^i \tag{5}$$

Generally, we use relative energy to indicate damage feature, so the relative energy $E_i$ in $i$-frequency band can be expressed as

$$E_i=\frac{E_j^i}{E_f} \tag{6}$$

### 2.2. ANN

ANN has particular advantage in establishing mapping relationships between feature proxy and physical parameters of structural damage (Fang et al., 2005). When classification and identification of structural damage should be carried out, the only required task is to train the ANN in advance using a set of known damage feature proxy and damage physical parameters of the structures to be detected.

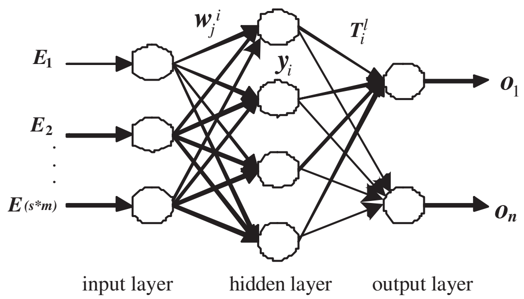

**Fig. 1.** Typical three-layer BP network.

Recent studies show that a three-layer neural network can be applied to implement damage assessment (Luo and Hanagud, 1997; Zeng, 1998). In this research the topology of the neural network is a feedforward three-layer neural network which means the weighted interconnections feed activation only in the forward direction from the input layer to the output (Zeng, 1998).

A typical three-layer feedforward neural network is schematically illustrated in Fig. 1. The network consists $s\times m$ input nodes, $i$ hidden nodes, and $l$ output nodes. The input, output and target output vectors are marked as $E_j$, $O_l$ and $t_l$, respectively. $T_{li}$ is the weight between the hidden node $i$ and the output node $l$, while $w_{ij}$ is the weight between the input node $j$ and the hidden layer $j$. Each unit is connected in the forward direction to all the units in the next layer.

$$T_{li}(k+1)=T_{li}(k)+\eta\delta_l y_i \tag{7}$$

$$w_{ij}(k+1)=w_{ij}(k)+\eta'\delta'_i E_j \tag{8}$$

$$\theta_l(k+1)=\theta_l(k)+\eta\delta_l \tag{9}$$

$$\theta_i(k+1)=\theta_i(k)+\eta'\delta'_i \tag{10}$$

Here, $\eta$ and $\eta'$ is called the learning rate for the training iteration

$$\delta_l=(t_l-O_l)f'\left(\sum_i T_{li}y_i-\theta_l\right)\quad \delta'_i=f'\left(\sum_j w_{ij}x_j-\theta_i\right)\sum_l \delta_l T_{li}$$

Back-propagation (BP) algorithm based on gradient decent method is suitable for multiplayer neural network to train under supervision. The training process of BP algorithm can be divided into two phases. In the first phase (front-propagation), output of each neuron is obtained by calculating the input information in each hidden layer. In the second phase (back-propagation), the difference between actual output and target output can be computed layer by layer in recursion and the weights are adjusted according to this difference until the expected output is acquired in the out layer. BP algorithm is adopted by most ANN in actual applications in structural damage identification.

## 3. Damage diagnosis procedure

A data fusion technique can combine data from several information sources as well as information from relative databases, to achieve a higher accuracy and more specific inferences than that could be achieved by a single source alone (Telmoudi and Chakhar, 2004). Feature fusion is one kind of data fusion; it