Applied Acoustics 86 (2014) 59–70

Contents lists available at ScienceDirect

Applied Acoustics

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

GUW-based structural damage detection using WPT statistical features and multiclass SVM

Hossein Zamani HosseinAbadi [a,1], Rassoul Amirfattahi [a,2], Behzad Nazari [a,3], Hamid Reza Mirdamadi [b,*], Seyed Abdolrahim Atashipour [b]

[a] Department of Electrical and Computer Engineering, Isfahan University of Technology, Isfahan 84156-83111, Iran
[b] Department of Mechanical Engineering, Isfahan University of Technology, Isfahan 84156-83111, Iran

ARTICLE INFO

Article history:
Received 6 September 2013
Received in revised form 24 April 2014
Accepted 8 May 2014
Available online 14 June 2014

Keywords:
Damage detection
Guided ultrasonic wave (GUW)
Structural health monitoring (SHM)
Discrete wavelet transform (DWT)
Wavelet packet statistical features
Support vector machine (SVM)

ABSTRACT

Recently, guided ultrasonic waves (GUW) are widely used for damage detection in structural health monitoring (SHM) of different engineering structures. In this study, an intelligent damage detection method is proposed to be used in SHM applications. At first, GUW signal is de-noised by discrete wavelet transform (DWT). After that, wavelet packet transform (WPT) is employed to decompose the de-noised signal and the statistical features of decomposed packets are extracted as damage-sensitive features. Finally, a multiclass support vector machine (SVM) classifier is used to detect the damage and estimate its severity. The proposed method is employed for GUW-based structural damage detection of a thick steel beam. The effects of different parameters on the sensitivity of the method are surveyed. Furthermore, by comparing with some other similar algorithms, the performance of the proposed method is verified. The experimental results demonstrate that the proposed method can appropriately detect a structural damage and estimate its severity.

1. Introduction

As an application of acoustic wave propagations, the guided ultrasonic wave (GUW) technique has been widely used to detect different damage types in aerospace, mechanical, and civil engineering structures, in recent years. This technique is used to detect the existence, localization, and severity of the damage in real applications [1]. GUWs are ultrasound stress waves enforced to follow a path dictated by the geometric boundaries of the structure [2]. GUWs are very sensitive to the discontinuities of structures. Hence, they could be employed for damage identification purposes, especially for online and continuous inspection of different structures, i.e., structural health monitoring (SHM). The methods are usually based on sparse arrays of sensors measuring the responses of a structure to an actively applied excitation [3]. The implementation issues in a SHM system are: hardware implementation of an active electromechanical system to acquire signals and a signal processing scheme to identify a potential damage. Since GUW signals usually are recorded with a large amount of noise, signal de-noising is a preliminary and important step in the processing of these signals. In addition to signal de-noising, signal processing algorithms mostly involve a feature extraction process, which identifies damage-sensitive properties from the measured signals [4].

Several signal processing approaches are developed for extracting damage-sensitive features from measured GUW signals. Amongst all, Fourier transform (FT) and wavelet transform (WT) are the two well-known and powerful tools. Fourier analysis gives a picture of the frequency spectrum of a signal and does not provide any information about which frequency component arrives at what instant of time contained in the signal. However, wavelet analysis is designed to do exactly that. It is well suited for analyzing non-stationary signals, such as GUWs [2]. Therefore, the wavelet analysis has become one of the most popular tools for de-noising, processing and feature extraction of GUW signals [5–12]. Taha et al. [5] performed a survey of wavelet transform applications in SHM and GUW-based damage detection methods.

The discrete wavelet transform (DWT) is a form of WT that is used for signal de-noising in SHM applications in a variety of studies [13–17]. An improved threshold method for SHM signal de-noising was proposed in [14]. Sigma sampling wavelet de-noising of SHM signals was introduced in [15]. Yu et al.

* Corresponding author. Tel.: +98 3113915248; fax: +98 3113912628.
E-mail addresses: h.zamanihosseinabadi@ec.iut.ac.ir (H. Zamani HosseinAbadi), fattahi@cc.iut.ac.ir (R. Amirfattahi), nazari@cc.iut.ac.ir (B. Nazari), hrmirdamadi@cc.iut.ac.ir (H.R. Mirdamadi), sa.atashipour@me.iut.ac.ir (S.A. Atashipour).
[1] Tel.: +98 3113915487.
[2] Tel.: +98 3113915382.
[3] Tel.: +98 3113915369.

http://dx.doi.org/10.1016/j.apacoust.2014.05.002
0003-682X/

in [16] used discrete wavelet de-noising using Daubechies wavelet to remove local high frequency disturbances. In addition to de-noising, compression of GUW signals were achieved by using a combined DWT and filtering process in [17]. Wavelet packet transform (WPT) is another form of WT, which is used in some damage detection and SHM application studies. It is used to decompose the measured signals, for the purpose of extracting damage-sensitive features from them. Some of these studies are including: damage detection in subsea pipeline bedding condition [18], structural health monitoring of a benchmark building structure [19], spindle health diagnosis [20], and fault diagnosis of rotary machinery [21]. It has attracted increasing attention because of its ability in providing more flexible time–frequency decomposition, especially in the higher frequency region.

Generally, in SHM signal processing algorithms, after extracting damage-sensitive features from the measured signal, a pattern recognition technique is required to detect the damage and estimate its severity [4]. To achieve this goal, artificial neural network (ANN) is one of the most popular techniques. Many studies use ANN for damage detection purposes. A few of these studies are discussed in [5]. Support vector machine (SVM) is another powerful and popular pattern recognition tool. It is used for structural health monitoring [19,22], damage detection and classification [23–27], and fault diagnosis [21,28–32] of different engineering structures and machineries. Recently, Shen et al. in [21] have appropriately diagnosed bearing and gear faults in rotary machineries by using both WPT and SVM capabilities for feature extraction and data classification. They have proposed an intelligent scheme for rotary machinery fault diagnosis, which contained three steps: the extraction of WPT decomposition statistical features as fault features, fault feature selection by distance evaluation technique, and classification of fault data by a support vector regressive classifier.

In this article an intelligent damage detection algorithm is proposed for using in SHM applications. At first, the measured signal is de-noised by DWT. After that, WPT is employed to decompose the de-noised signal and the statistical features are extracted from the decomposed wavelet packets as damage-sensitive features. Finally, a multiclass SVM classifier is used to detect damage and estimate its severity. The proposed algorithm is employed for structural damage detection of a beam using GUWs. As mentioned in [33], most of the GUW-based damage detection studies are subjected to thin structures. However, Sun et al. used GUWs for detecting structural damage in a thick steel beam in 2010 [13]. In the present study, a thick steel beam similar to the structure used in [13] is considered. The beam is experimentally investigated and also is simulated using finite element (FE) simulations for different conditions of damage. In addition to experimental GUW signals, FE simulation signals are measured. Forty-three simulation signals are used to train the algorithm. Eight simulation signals, in addition to eight experimental GUWs are used to test the algorithm. The results of damage existence and severity detection by using the proposed algorithm are compared with some similar methods. On the contrary to the study presented in [21], de-noising of the signals is surveyed in this study; the effects of choosing different mother wavelets, levels of decompositions and types of de-noising are studied. Furthermore, the effects of choosing different mother wavelets for WPT decomposition and different learning methods and kernel functions for SVMs on the damage detection results are surveyed.

The organization of the rest of this paper is as follows. In Section 2, the theoretical backgrounds of DWT, WPT, orthogonal and bi-orthogonal wavelets, and SVM are described. In Section 3, the proposed damage detection algorithm is presented. Signal de-noising, feature extraction, and pattern recognition are the three main steps of the proposed algorithm. Section 4 is allocated for FEM simulations and experimental setup. The case study is structural damage detection in a thick steel beam. In Section 5, the results of signal de-noising and damage detection are presented. The effect of different conditions in signal de-noising and damage detection algorithm is studied and the results of proposed algorithm are compared with other methods. Finally, in Section 6, some concluding remarks are drawn.

2. Theoretical background

2.1. DWT and WPT

DWT and WPT are two forms of wavelet transform that analyze a signal through decomposing it repeatedly into successive low and high frequency components. DWT of signal $x(t)$ is defined as:

$$DWT(j,k) = 2^{-j/2}\int_{\Re} x(t)\psi^{*}(2^{-j}t-k)dt \quad j,\ k\in\mathbb{Z} \tag{1}$$

where j and k are the scaling and shifting parameters, respectively. ψ is an analyzing wavelet, and ψ^{*} is the complex conjugate of ψ. DWT analyzes a signal by implementing a filter of particular frequency band, which depends on the level of decomposition, to shift along the time axis. The signal can be decomposed into a tree structure, in which the signal can be expressed as wavelet details and approximations, as follows:

$$x(t) = \sum_{j=1}^{n} D_j(t) + A_n(t) \tag{2}$$

where $D_j(t)$ and $A_n(t)$ are the wavelet detail at the jth level and the wavelet approximation at the nth level, respectively, and n is the number of decomposition levels [14]. A three-level DWT of a signal is shown in Fig. 1. As shown in the figure, only approximation signal is decomposed into two newer approximation and detail signals at each level of decomposition.

Unlike DWT, wavelet packet analysis decomposes not only the wavelet approximation signals at each level of decomposition, but also the wavelet detail signals. A wavelet packet is a linear combination of wavelet functions. It can be presented as a function $\psi_{j,k}^{i}(t)$ as:

$$\psi_{j,k}^{i}(t) = 2^{-j/2}\psi^{i}(2^{-j}t-k) \quad j,k\in\mathbb{Z}, \quad \text{and} \quad i=1,2,\ldots,j^{n} \tag{3}$$

where i, j, and k are the modulation, the scale, and the translation parameters, respectively, and n is the level of decomposition. The wavelet ψ^{i} is obtained from the following recursive relationships:

$$\begin{cases} \psi^{2i} = \sqrt{2}\sum_{k} h(k)\psi^{i}(2t-k) \\ \psi^{2i+1} = \sqrt{2}\sum_{k} g(k)\psi^{i}(2t-k) \end{cases} \tag{4}$$

where $\psi^{0}(t)$ is the scale function, $\psi^{1}(t)$ is the mother wavelet, and the discrete filters $h(k)$ and $g(k)$ are filters associated with the

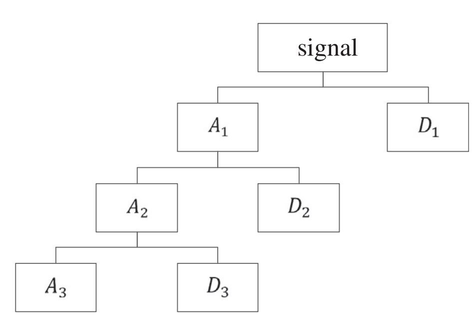

Fig. 1. DWT tree for three levels of decomposition.