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Application of soft-thresholding on the decomposed Lamb wave signals for damage detection of plate-like structures

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A B S T R A C T

Effective application of the Lamb waves for structural health monitoring and damage identification intensively relies on the accurate damage-related feature extraction in the received signals. Most of existing signal processing methods extract the damage-related features from the time–frequency joint spectrum which requires a quite amount of effort. In this paper, the soft-thresholding process, based on different signal decomposition methods, is introduced to damage identification so that the damage-related signal features can be manifested more distinctively. By applying two popular signal decomposition methods (i.e., the discrete wavelet transform (DWT) and the empirical mode decomposition (EMD)), the signal of interest can be represented by a series of components with different frequencies. Since most noises exist in the high frequency range, it is feasible to alleviate noise by restricting the energy of high-frequency components. Finally, a denoised signal is synthesized using the corresponding reconstruction method. As an application, the soft-thresholding process is performed to detect a small crack on an isotropic aluminum plate under the white Gaussian noise contamination. The results, from both the numerical finite element simulation and experimental test, indicate that the soft-thresholding process is capable of effectively reducing the effect of noise, convincingly improving the sensitivity of damage identification, and discriminating relatively small damage.

1. Introduction

The development of structural health monitoring system aims to evaluate structural integrity and warn about catastrophe failure in real time. Lamb waves have been proven promisingly suitable to perform long-range damage identification on the plate-like structures with good accuracy and sensitivity [1–4]. Small damage within the structures can change local acoustic properties and accordingly influence the transmitted and reflected Lamb wave signals. The changed Lamb wave signals can be captured by a set of sensors mounted in a particular configuration, and the abnormalities can be extracted based on different damage-related wave features [5–8]. With the image reconstruction method, the damage can be located in a three-dimensional damage image [9–11]. Since Lamb waves have the dispersive propagation velocities and multi-mode vibration patterns, the damage identification methods normally require a tone burst as the excitation signal [12–14]. However, the windowing process in the modulation of tone burst signal limits the excitation of

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energy input and thus reduces the signal-to-noise ratio of the monitoring signals [15]. The comparable amplitude of noise interferes the damage feature extraction and further compromises the monitoring accuracy, particularly for a paucity of sensors. Therefore, a denoising process is desired for the extraction of Lamb wave signals before they are implemented in the damage identification algorithm.

The widely adopted way to extract the damage-related signal features is to transform the Lamb wave signal from the time domain to time–frequency domains. During this process, the sought signal features can be discriminated from other interferences based on their different energy distribution in the time–frequency spectrum. The short time Fourier transform [16–19], wavelet transform [20–26], and Wigner–Ville Distribution transform [27–30] have been applied in the damage identification, and they demonstrated as reliable signal processing methods to represent the Lamb wave signals and extract the damage-related signal features. But the calculation of the time–frequency spectrum over a large frequency range is generally time and computational consuming, and only a small portion of information can be effectively utilized.

On the other hand, the signal decomposition methods provided concise ways to denoise and extract the signal features of interest. The most popular methods are the discrete wavelet transform (DWT) [31–34] and the empirical mode decomposition (EMD) [35–38], which are capable of decomposing signals into a series of intrinsic components with different frequencies. Since most of noise exists in the high frequency range, the noise interferences can be alleviated by restricting or eliminating the high-frequency components. A soft-thresholding method [39,40] was developed based on the discrete wavelet decomposition to "softly" suppress the signal amplitude exceeding the given threshold. By synthesizing these thresholded DWT components, a denoised signal can be obtained. Adaptive thresholds were derived based on this concept [41–44]. In the meanwhile, the EMD-based denoising is generally performed by the partial signal reconstruction [45], neglecting the first several intrinsic mode functions (IMF) in which the noises tend to lie. A significant IMF test was developed based on the statistical analysis of each IMF to determine which mode contains the valuable information [46,47]. Moreover, various thresholds combined with the EMD were proposed to filter the high frequency signal components instead of discarding them completely [48,49].

In this paper, the soft-thresholding method is introduced to the Lamb wave-based damage identification of plate-like structures. Based on both the DWT and EMD, two soft-thresholding filter banks are designed and successfully applied to the Lamb wave signals. The threshold values are calculated according to the decomposed signals to "softly" reduce the white Gaussian noise. As an implementation, the filter banks are applied on small crack detection in an aluminum plate so that the monitoring signals are denoised and the damage-related wave features are presented more distinctively. Both the numerical finite element simulation and the experimental vibration measurement using the scanning laser vibrometer (SLV) are conducted to produce the original Lamb wave signals. The artificial white Gaussian noises are blended to blur the damage-related wave peaks, and they are then filtered by the proposed soft-thresholding filter banks. Based on the denoised signals, the damage images are reconstructed by the delay and sum algorithm. The results, from both the numerical simulation and experiment, demonstrate the effectiveness of the proposed soft-thresholding method.

2. Formulation of the soft-thresholding method

In this section, two representative signal decomposition methods, i.e., the discrete wavelet transform (DWT) and the empirical mode decomposition (EMD), are briefly reviewed. The soft thresholds of these decompositions are also calculated. As an illustration, the soft-thresholding process is applied to a measured Lamb wave signal, which is blended with the white Gaussian noise.

2.1. Soft-thresholding by the DWT

The wavelet transform, gaining burgeoning popularity, has been well documented as an indispensable signal processing method. It provides a multi-resolution analysis from another perspective: in the time-scale domain. Based on the continuous or discrete selection of the operation scales, the wavelet transform can be classified as the continuous wavelet transform (CWT) and the discrete wavelet transform (DWT). For the CWT, a wavelet, with an effectively limited duration and an average value of zero, is selected and compared with a section at the start of the signal of interest. A wavelet coefficient can be calculated to depict how closely correlated the wavelet is with that section of the signal:

$$\gamma(j,k) = \int x(t)\psi^*_{j,k}(t)dt \tag{1}$$

where j is the scale and k is the translation; * denotes the complex conjugate; and $\psi_{j,k}(t)$ is a wavelet series based on the mother wavelet. By shifting the wavelet over the signal of interest, a series of wavelet coefficients can be calculated for a specific scale. Then, the same procedure is repeated by a stretched or compressed wavelet according to a higher or lower scale:

$$\psi_{j,k}(t) = \frac{1}{\sqrt{j}}\psi\left(\frac{t-k}{j}\right) \tag{2}$$

The coefficients calculated from all the performed scales constitute a three dimensional spectrum on which the x-axis represents the position along the signal, the y-axis represents the wavelet scale, and the z-axis represents the value of the wavelet coefficient. The low scale, which compresses the wavelet, can characterize rapidly the changing details with high frequency; whereas the high scale, which stretches the wavelet, can characterize the coarse features with low frequency.

However, operating the CWT at every scale is a fair amount of work generating a significant amount of data. The DWT, choosing the scale and position based on powers of two (the dyadic scale and position), has been proven much more efficient and just as accurate. The signal of