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Decentralized damage identification using wavelet signal analysis embedded on wireless smart sensors

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ABSTRACT

In this paper, a decentralized damage identification method using wavelet signal analysis tools embedded on wireless smart sensors (Imote2) has been proposed and experimentally validated. The damage identification analysis is decentralized by calculating discrete wavelet coefficients for acceleration in Imote2 sensors and transmitting the wavelet coefficients to a base station for damage identification through wavelet entropy indices. The wavelet entropy is modified to serve as a damage-sensitive signature that can be obtained both at different spatial locations and time stations to indicate existence of damage. It is known that wavelet-based approaches have clear advantages over Fourier transform-based ones for damage identification, since the wavelet transform allows for a wider choice of basis functions. This flexibility allows the wavelet transform to isolate changes in a signal that may be difficult to detect using other transform methods. To assess the reliability of the measurement signals, the wireless sensors have been compared with reference wired sensors. The proposed decentralized method for damage identification is verified via experimental tests using two laboratory structures: a three-story shear building structure and a three-dimensional truss bridge structure.

1. Introduction

Recent advances in wireless smart sensor technologies have opened up numerous applications in the dynamics-based health monitoring of civil engineering structures [1–3]. Wireless sensors still have some limitations, most notably less reliable data transmission than wired sensing systems, a relatively short communication range, and operational constraints due to limited power; however, numerous field studies have demonstrated that wireless smart sensors can be used to build a reliable and accurate structural health monitoring system [4–6].

Fundamentally, a wireless smart sensor has three capabilities: (1) Sensing, (2) Computing and (3) Communicating. The advent of micro-electro-mechanical system (MEMS) has facilitated the integration of various on-board MEMS-based sensors (e.g. for acceleration, temperature, and humidity) with built-in signal conditioning circuitry on sensor boards. Wireless smart sensors, with their integrated high-speed computing and communication technologies, enable quick and accurate measurement of structural response (e.g. ambient and forced-vibration response) and assessment of structural integrity. The use of wireless smart sensors in structural health monitoring systems is highly cost-effective, since the wires that would ordinarily be required to connect the sensors to a central data acquisition system are eliminated. This is one of the intriguing benefits of using wireless smart sensors for large-scale civil engineering structures.

During the past several decades, FFT-based natural frequencies and mode shapes have been the dominant parameters used in damage detection and assessment of structural integrity. It is notable that a robust and efficient method using the mode shape can detect and quantify severity of damage [7]. The wavelet and wavelet packet transforms have been recognized as newly emerging signal analysis methods [8]. Compared to the Fourier transform, which uses simple harmonic functions (sine and cosine) as a basis, the wavelet transform allows for a wider choice of basis functions. This flexibility allows the wavelet transform to isolate changes in a signal that may be difficult to detect using other transform methods. This advantage of the wavelet transform is naturally inherited by wavelet-based measures of energy and entropy, and leads to better damage identification. Particularly, wavelets have advantages when the structural dynamic responses are complex and non-stationary. Numerous studies have used wavelet and wavelet packet transforms to detect cracks or structural damage [9–11]. In particular, Ren et al. suggested the use of information entropy [12] as a damage-sensitive feature for detecting damage in structures [13]. They proposed the

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new damage signatures of wavelet entropy, time evolution of wavelet entropy and relative wavelet entropy, and experimentally demonstrated each one's sensitivity to damage detection. Poudel et al. proposed a damage detection process that uses a wavelet transformation of a mode shape difference function comparing the reference and damaged case [14]. Important factors to be considered in developing any wavelet transform-based method are the particular wavelet basis function to be used, the model of damage, and the effects of windowing and masking due to noise. Pakrashi et al. considered all of these factors, testing with four kinds of wavelets and three different damage models for beam structures [15].

Although the advantages of wavelet signal analysis for damage detection have been well recognized, there has been no attempt to use wavelets in a wireless smart sensor network for damage diagnosis. As relevant research, the Damage Location Assurance Criterion (DLAC) proposed by Messina was validated using Imote2 wireless sensors on a cantilever beam [16] and a 3D truss structure [17]. In this paper, a new damage detection system using wireless smart sensors, built on Imote2 platforms, with an embedded wavelet signal-based damage detection algorithm is suggested. The damage metric adopted in this paper, relative wavelet entropy, is a proven metric; in [13], the effects of noise on a damage detection method based on relative wavelet entropy were studied, and a test with real damage was conducted. In this paper, we focus on a new decentralized damage detection approach that computes the wavelet transform coefficients on wireless smart sensors, and perform additional in-depth studies of the use of wavelet entropy metrics in damage detection. Wavelet entropy values are employed as a damage signature to interrogate local damage occurrence and locations.

Experimental studies were conducted using a bench-scale three-story shear building and a three-dimensional truss bridge structure to investigate damage detection methods using wavelet entropy values. Different damage scenarios are simulated for the three-story shear building structure by adding dummy masses, either to an individual story or to a combination of stories. To simulate realistic damage to the three-dimensional truss bridge structure, specially designed bolted joints are loosened. The natural frequencies of a test structure are considered in selecting the specific energy ratios computed from the measured acceleration data, and in suggesting a method to increase specificity for damage detection. Finally, damage detection capabilities of the proposed approach have been demonstrated through hammer impact response testing and ambient vibration testing. Results have been discussed.

2. Wavelet entropy based damage detection

2.1. Overview of wavelet transform for structural health monitoring

A variety of transforms could be considered for processing vibration signals. A fast Fourier transform (FFT) resolves the original time domain signal into its frequency components. Note that the FFT provides no time resolution; based on the FFT, it is not possible to determine when a component at a particular frequency appeared unless moving window FFT analysis is applied. The ability of the discrete wavelet transform (DWT) to provide both frequency and time resolution makes the DWT an interesting choice for structural health monitoring. With the DWT, it is possible to see not only what frequency components are present, but also when in time those components appear. This gives the DWT a particular advantage when signals are non-stationary, which is often the case in on-line structural health monitoring.

The discrete wavelet transform operates by repeated application of a pair of decomposition filters to the original time domain signal. The decomposition filters, one lowpass (LPF) and one high-pass (HPF), are designed so that no information is lost in the process of transformation to the wavelet domain. Fig. 1 shows the structure of the discrete wavelet transform computation. For a single scale of decomposition, the wavelet decomposition filters are applied to the original time domain signal $x(t)$, and the outputs of the filters are decimated by two (i.e., every other output sample is discarded). This divides the signal into an approximations band $\boldsymbol{A}$, which contains the low frequency components of the original signal, and a details band $\boldsymbol{D}$, which contains the high frequency information. Note that the approximations and details bands are time domain signals; because of the decimation by two, these signals have half as many samples as the original data, and have an effective sample rate of half that of the original signal. Additional scales of discrete wavelet transformation can be done by repeated application of the filters on the approximations band of previous scale. The outputs of later scales represent increasingly narrow and lower frequency bands. The final output of the DWT is the approximations sub-band of the final scale ($\boldsymbol{A}_3$ in our three-scale example), and the details sub-bands of all the scales ($\boldsymbol{D}_3$, $\boldsymbol{D}_2$, and $\boldsymbol{D}_1$ here).

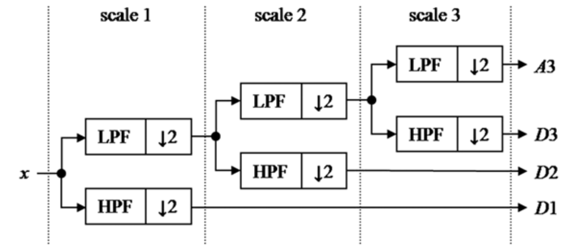

Fig. 1. Structure of a discrete wavelet transform (DWT) computation.

There are many possible choices of wavelets, or sets of lowpass and highpass filters. Applying the DWT requires choosing an appropriate wavelet and an appropriate number of scales. The accelerometer signals used in structural health monitoring have most of their energy at the natural frequencies of the structure; decomposition should be done such that the energies at these natural frequencies are confined to specific sub-bands. Then, if damage to a structure causes a natural frequency of the structure to shift, that damage will be seen clearly as a change in the energy in the corresponding sub-band. The number of scales is an important consideration, as the decimation in each additional scale further subdivides the frequency range of that scale's input approximations into two output sub-bands, one approximations and one detail.

The FFT can also be used to pinpoint the energy of a signal within a particular frequency band. The DWT actually offers significantly less frequency resolution than the FFT; for example, the top half of the frequency spectrum is represented in the DWT by one single sub-band ($\boldsymbol{D}_1$), whereas in the FFT the information from the top half of the frequency spectrum is further subdivided among half of the FFT coefficients. However, the DWT also provides time resolution; each sub-band is a time domain signal, allowing for changes in frequency content over time to be detected. This property is important for the real-time monitoring of structures to detect damage as it happens. In addition, the DWT has advantages when the signals being processed are not comprised of pure sinusoids; it is possible to pick a wavelet that matches the shape of the signal well, in a way that better compacts the energy into particular sub-bands. We expect this property to be important for complex, non-laboratory structures.

2.2. Wavelet energy and entropy

As noted in the previous section, the wavelet coefficients produced by applying a N-scale DWT to an original time domain