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Direct method of damage localization for civil structures via shape comparison of dynamic response measurements

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ABSTRACT

A method of damage localization is introduced which relies on continuous wavelet transformation of the structure's forced dynamic response. Continuous wavelet transforms represent the shape attributes of time series and enhance their delineation in the time-scale domain. As such, they allow identification of localized shape changes of dynamic responses for signal change detection. This change detection capacity enables identifying the damage-affected responses as well as formulating the characteristic effects of individual damaged components on the modeled dynamic response. The results obtained from simulated acceleration of a nine-storey building are 90% and 100% accurate with the steady-state and transient accelerations, respectively.

1. Introduction

The ability to detect damage in civil structures is vital to the safety and livelihood of the society and its economy. Although nondestructive methods based on visual inspection, acoustics, ultrasound, magnetic field, radiography, thermal field and strain-gauges are reasonably effective for detection of near-surface damage, they are impractical for inaccessible components [1]. As an alternative, changes to the modal properties of the structure consisting of resonant frequencies, mode shapes and damping ratios have been used [2]. The modal properties are usually obtained from the ambient or forced dynamic response of the structure, as depicted by acceleration or force measurements at different locations. The basic premise is that damage affects the physical properties (i.e., mass, damping, and/or stiffness) of the structure, therefore, it should be evident from its dynamic response.

Damage identification methods are categorized as inverse and direct [3–5]. Inverse methods update the structural model to duplicate the measured response. They then use this updated model to estimate the physical properties affected by the damage (e.g., reduction of stiffness due to onset of cracks or loosening of a connection) [2]. Inverse methods are generally model-based and computationally demanding. Direct methods, in contrast, estimate the structure's modal properties from the measured response to determine the changes caused by the damage [6]. Even though direct methods are more straightforward than inverse methods they are hampered by the limitations associated with high-frequency modal property estimation. Limitations stem from the high energies required for high-frequency forced excitation of the structure and the numerical errors associate with high-frequency modal property estimates. This paper introduces a direct method that is independent from modal properties, thus, avoids the limitations associated with their estimation.

Considering the four levels of damage identification [3]: detection, localization, quantification, and prognosis, direct methods are usually effective in damage detection from changes to the modal properties [7–15] but they are challenged in damage localization. To localize the damage, direct methods need to associate the detected modal changes with the characteristic pattern of influence by individual damaged components. This is generally performed through pattern classification [16,17] and is contingent upon the availability of distinct characteristic influences by the damaged components. Although considerable effort has been devoted to finding modal properties or features of the response time history that would ensure such distinction [18,19], the modal properties or features that are established are often case-specific and limited in scope. The method introduced in this paper relies solely on the dynamic response time-history, so it obviates feature extraction and makes it broadly applicable to various structures.

The salient feature of the proposed method, that makes it independent of modal analysis or feature extraction, is its effective signal change detection capacity. This capacity which enables the method to focus directly on the dynamic response time history of the structure is provided by continuous wavelet transforms (CWTs). There are two aspects of CWTs that are essential to the method's workings: (1) their representation of various shape

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attributes of dynamic responses, and (2) their delineation of the dynamic responses in the time-scale domain. The representation of shape attributes allows shape comparison of the dynamic responses. Their enhanced delineation allows localization of regions of considerable deviation between them in the time-scale domain. These regions of deviation, which are called *signatures*, have been shown to offer unique advantages in various system identification areas, such as model validation, parameter estimation, and measurement selection [20–23]. This paper extends these results to damage localization of civil structures, through the proposed "damage signature isolation method (DSIM)." It should be noted here that wavelet transforms have been extensively used in fault diagnostic applications, as referenced in [24] and discussed in [25]. However, in all these applications wavelet transforms have been utilized to extract features of the sensory signals – no application, so far as we know, offers a succinct way of contrasting the signals, as provided by the signatures in DSIM.

The basis for defining the characteristic responses of the damaged components in DSIM is the sensitivity of the structure's modeled response to component stiffness values. The underlying assumption is that damage of an individual component is reflected in the corresponding component stiffness, as is also assumed in the indirect approach. Therefore, the sensitivity of the structure's dynamic response to a component stiffness coefficient should provide a blueprint of the characteristic influence of the corresponding component damage. Here, again, sensitivity analysis has been used extensively for damage localization; for example, sensitivity of structural parameters to specific component parameters have been used for damage localization through frequency response functions [26], or the sensitivities of the orthogonality conditions of mode shapes have been considered from damaged and undamaged structures for damage localization [27]. The distinction of DSIM is that by relying on its signal change detection capacity, it can directly use the sensitivities of dynamic response time histories to component stiffness coefficients and does not require any computation associated with frequency response functions or modal properties.

2. Transformation to the time-scale domain

DSIM uses CWTs to represent and enhance various shape attributes of dynamic responses in order to identify the responses that are different in shape. It uses these features to also define the influence matrix that associates these responses with the damaged component. The features of CWTs that are essential to DSIM are described below.

A wavelet transform (WT) is obtained by the convolution of a wavelet function $\psi_s(t)$ with the signal $f(t)$ [28], as

$$W\{f\}(t,s) = f * \psi_s(t) = \int_{-\infty}^{\infty} f(\tau)\psi_s(t-\tau)d\tau \tag{1}$$

where $\psi_s(t) = \frac{1}{s}\psi\left(\frac{t}{s}\right)$ represents the wavelet function, and t and s denote the translation (time) and dilation (scale) parameters, respectively. The wavelet function can be manipulated in two ways, as shown in Fig. 1: (i) it can be moved sideways (translated) to coincide with different segments of the signal, and (ii) it can be widened (dilated) or narrowed (constricted) to align with a larger or smaller segment of the signal at its current location (current time). Dilation in wavelet transforms is analogous to widening or narrowing of the sinusoidal function in Fourier transform according to the frequency. As such, scale, s, in WT is often paralleled to frequency, hence the name "time–frequency" domain.

Numerically, the computation of WTs is significantly facilitated for dyadic time data. We have used 128 data points of each time series for this study and have chosen to obtain the WTs for 72 scales. This results in a time-scale plane of 128 $\times$ 72 pixels, where each pixel has unity time and scale dimensions.

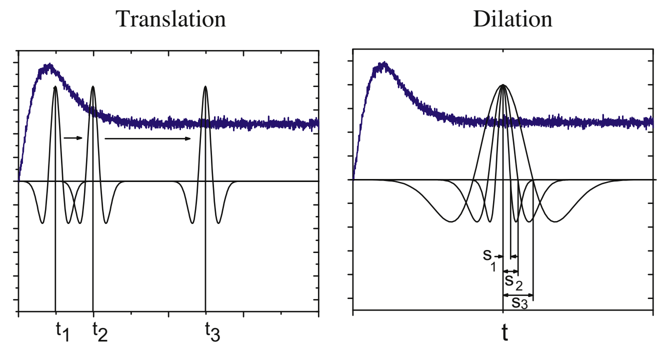

Fig. 1. Translation and dilation of the Sombrero wavelet across a time signal.

2.1. Characterization of shape attributes

Representation of shape attributes of time signals by CWTs stems from their multiscale differential feature [28]. Consider $\psi(t)$ to be the nth order derivative of the smoothing function $\beta(t)$; i.e.,

$$\psi(t) = (-1)^n \frac{d^n(\beta(t))}{dt^n} \tag{2}$$

then this wavelet transform is a multiscale differential operator of the smoothed function $f * \beta_s(t)$ in the time-scale domain [29]; i.e.,

$$W\{f\}(t,s) = s^n \frac{d^n}{dt^n}(f * \beta_s(t)) \tag{3}$$

Using this feature, one can utilize the CWT to represent the first derivative of a time signal to represent its slope, or its second derivative to represent the rate of slope change. For instance, one may consider the smoothing function $\beta(t)$ to be the Gaussian function. In this case, the Gauss wavelet is the first derivative of the Gaussian function, as shown in the left plot of Fig. 2. This results in a wavelet transform that is the first derivative of the signal $f(t)$ smoothed by the Gaussian function, and orthogonal to it. Similarly, the Sombrero wavelet is the second derivative of the Gaussian function, as shown in the right plot of Fig. 2, and produces a wavelet transform that is the second derivative of this smoothed signal in the time-scale domain. The first derivative of a signal is representative of its slope

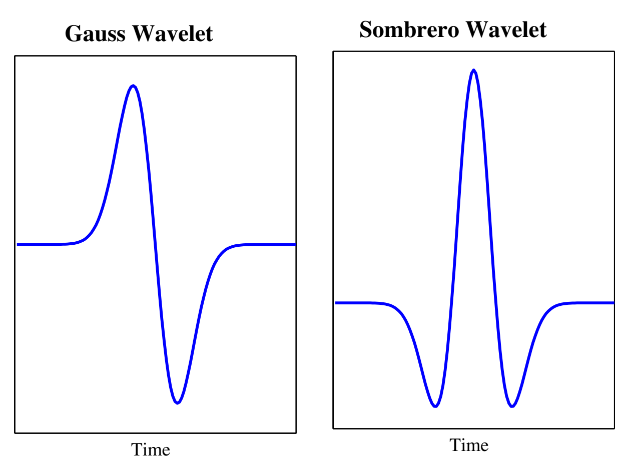

Fig. 2. Gauss wavelet (left) and Sombrero wavelet (right) which are the first and second derivatives of the Gaussian function, respectively.