SHM
Structural Health Monitoring

Damage Detection Using Optical Measurements and Wavelets

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The paper presents an application of the wavelet transform for damage detection based on optical measurements. A number of important issues, that needs to be considered when image sequences are used for vibration analysis, are discussed. These include: correspondence of image features from image to image, image calibration and spatial resolution. The principles of image edge detection are discussed and a comparison between the wavelet approach and the classical method is presented. A novel damage detection method based on optically measured modeshape data is proposed. The method is illustrated using a simple cantilever beam experiment. The major advantage of the method is the significantly increased number of discrete points used to describe modeshapes. This is in contrast to classical techniques where in practice a small number of measurement points are obtained from a limited number of sensors.

Keywords dynamic testing · damage detection · non-contact measurements · optical measurements · image edge detection · wavelets

1 Introduction – Image Sequences and Dynamic Measurements

Vibration tests are widely performed as part of the design and development procedure of almost all engineering systems. In practice modal tests are employed to identify natural frequencies, damping ratios and modeshapes of structures [1,2]. This information can further be used to validate Finite Element results [3].

The traditional approach to vibration testing uses transducers, such as accelerometers, force transducers and strain gauges, that need to be attached to a structure during experiments. However, in many cases this is either not desirable or even not possible, for example when a structure is tested under hazardous conditions or operating at elevated temperatures. Often no interference with a structure is allowed. This problem is particularly relevant to small-scale structures, e.g., Micro-Electro-Mechanical Systems (MEMS). One solution is to employ non-contact instruments such as eddy current probes or optical devices including laser displacement probes and laser Doppler vibrometers. Unfortunately, like traditional accelerometers, all these devices measure single point values. The only exception is when a laser Doppler vibrometer is used in scanning mode resulting in a number of measurements (assuming a non-transient event).

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Different solutions can be proposed when optical measurements are used [4]. Recently, high-speed video systems have become affordable and powerful, making possible the use of optical measurements in a number of applications. Such systems often employ markers so that the process is more robust; in other words the co-called correspondence problem is avoided. This ensures that analysed image features (or markers) can be matched, i.e., their trajectories can be tracked from image to image. However, in practice one would like to avoid markers on structures. This can be achieved using a single camera with motion constrained in a 2D plane and for a known geometry with clearly identified features. It is common for the time step between image sequences to be constant. The sequences are further used to assemble trajectories of the analysed features (or markers). This is preceded by an identification routine that locates the markers' coordinates [5]. The trajectories can then be assembled using a number of techniques, for example the differences between consecutive frames [6–8]. The analysis using image sequences is usually restricted to a limited number of attached markers. Recent application examples include markers used to investigate flutter mode shapes in an aeroelastic wind-tunnel [9].

This paper brings together recent developments in image edge detection and proposes a novel approach by which wavelet coefficients are used to locate or detect damage in a structure. The main objective of the paper is to present a damage detection procedure using image sequences. Edge contours are obtained from image sequences using the classical wavelet-based approach. This provides a number of measurement points that is significantly larger than in the case of classical accelerometer-based measurements. The novelty of the proposed method is that edge contours, that describe the structure's movement, are utilised for further damage detection analysis. The orthogonal wavelet transform is also applied to damage identification. Preliminary results from this work were initially reported in [10] where the presence of seeded damage in a beam was detected. The work presented in this paper extends the previous results in that more sophisticated equipment has been used for optical measurements and hence higher quality modeshape data were obtained. Additionally, the orthogonal wavelet transform is applied to modeshapes for damage identification.

The structure of the paper is as follows: Section 2 briefly describes image-processing principles and introduces the wavelet approach used for image edge detection and terminology and definitions are provided. Section 3 introduces the proposed damage detection method based on the Orthogonal Wavelet Transform of modeshapes. The method is illustrated using a simple cantilever beam experiment in Section 4. This analysis includes a comprehensive discussion related to image sequence processing. Finally, the paper is concluded in Section 5.

2 Image Edge Detection: Classical Methods and the Wavelet Approach

Although image edge detection is well known in the image processing community, the analysis is still a marginal subject of research in engineering applications. Therefore, for the sake of completeness, this section briefly introduces the general concept and the wavelet-based approach to edge detection. The reader is referred to [11] for more detailed analysis.

2.1 Image Edge Detection

Research in image edge detection shows a wide diversity of proposed techniques. The theory of image detection can be traced back to Marr and Hildreth in 1980 [12,13]. In 1986 Canny proposed the method that today is the de-facto technique used in image analysis [14]. The use of the wavelet transform expanded to a wide range of areas and Mallat suggested a wavelet transformation that can be implemented in detecting edges both in one dimensional signals and images [15].

Edges in images often appear where large variations in the intensity exist. An edge can be defined as a step discontinuity in a 2D signal (e.g., an image). The edges can be located by searching for these discontinuities: either as a local maximum of the first derivative or as the zero-crossings of the second derivative of the image. Therefore, for a continuous image $f(x, y)$, its derivative assumes a maximum in the direction of the edge. It can be shown [16] that the direction of the edge of the continuous image shown in Figure 1 is given by,

$$\theta_g = \tan^{-1}\left(\frac{f_y}{f_x}\right) \quad (1)$$

and the magnitude of the edge is given by,

$$M = \sqrt{f_x^2 + f_y^2} \quad (2)$$

where, $f_x = \partial f/\partial x$, $f_y = \partial f/\partial y$, $\partial f/\partial x$ and $\partial f/\partial y$ are the rates of change of the image function f in the two perpendicular directions. Clearly with digital images, the gradient has to be computed using the difference approximations of either the orthogonal gradients f_x, f_y or the directional gradient $\partial f/\partial r$.

Operators that rely on detecting the local maxima include those of Prewitt and of Roberts [16]. It is important to point out that the first derivative operators rely on a single scale, that of the image, whereas Marr and Hildreth [13] proposed a multiscale edge operator. The second derivative is computed through the use of a smoothing filter so robustness is ensured. It has been shown that the Gaussian distribution performs the task adequately [13] and is given below,

$$g(x, y) = e^{-(x^2+y^2/2\sigma^2)} \quad (3)$$

where (x, y) are the image coordinates and σ is the standard deviation of the probability distribution. The standard deviation is the variable that controls the scale at which the Gaussian is operating. The Laplacian of a Gaussian (LoG), which is also called the Marr–Hildreth operator is defined as,

$$\nabla^2(g(x, y, \sigma) * f(x, y)) \quad \text{or} \quad (\nabla^2 g(x, y, \sigma)) * f(x, y) \quad (4)$$

Locating the zero-crossings of the second derivative is easier than locating the maxima of the first derivative. The drawback is the fact that the influence of noise on the second derivative is more profound and hence false edge location is a possibility. This naturally leads to the question of "which is the best edge operator?" Previous research that tackled this issue by comparing first and second derivative approaches concluded that "No one single edge detector was best overall; for any given image it is difficult to predict which detector will be best" [17]. There was however a clear distinction between the better edge quality of the second derivative operators over the first derivative ones.

The classical Canny's operator is in fact a second derivative – multiscale method. Therefore, the use of the wavelet transform in image edge detection is closely related to Canny's operator and for a particular class of wavelets it is equivalent to detecting the wavelet transform maxima [15,18]. The scale parameter in Canny's method is controlled by the standard deviation of the Gaussian, whereas in the wavelet method it is controlled by the scale parameter. The multiscale edges are extracted by locating the local maxima of the second derivative of the smoothed image at various scales [19,20].

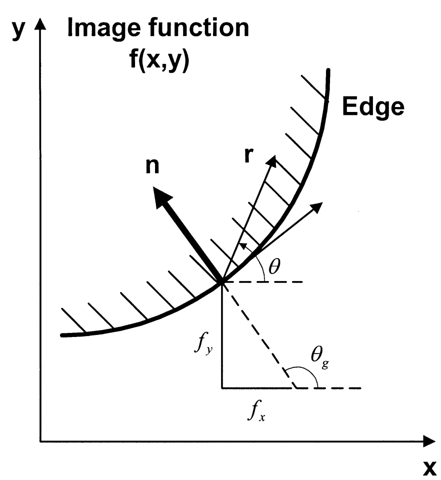

Figure 1 The gradient of the image function along the direction of the edge [16].

Furthermore, the wavelet transform analysis should involve an appropriate wavelet basis function that can be applied in a 3D domain. In this approach one can take image cross sections to identify modeshapes. The modeshape data could then be used for damage detection.

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