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A review on recent development of vibration-based structural robust damage detection

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Abstract. The effect of structural uncertainties or measurement errors on damage detection results makes the robustness become one of the most important features during identification. Due to the wide use of vibration signatures on damage detection, the development of vibration-based techniques has attracted a great interest. In this work, a review on vibration-based robust detection techniques is presented, in which the robustness is considerably improved through modeling error compensation, environmental variation reduction, denoising, or proper sensing system design. It is hoped that this study can give help on structural health monitoring or damage mitigation control.

Keywords: robust damage detection; modeling error; environmental variation; denoising; sensing system design; vibration signatures

1. Introduction

Structural damage detection is a typical problem received much attention in engineering over the last decades. Damage in the structure deteriorates its performance and, in turn, reduces structural reliability and safety, leading to the development of various detection techniques summarized in some review papers (Cantwell 1992, Chang 1997, Zhou 2002, Sohn 2003, Worden 2008, Antonino 2008, Ciang 2008, Ostachowicz 2008). As a relatively inexpensive technique with real-time in-situ potential, the vibration-based methods have been well investigated for years, of which the use of different vibration signatures for detection has been systematically reviewed by researchers (Salawu 1997, Doebling 1998, Zou 2000, Carden 2004, Alvandi 2006, Montalvao 2006, Delia 2007, Gandomi 2008, Liu 2009, Li 2010, Annamdas 2010, Fan 2011).

Though considerable progress has been made, in practical applications, however, many challenges still remain. For example, the existence of structural uncertainties might collapse the detection algorithm and consequently lead to suspicious results. Moreover, in many cases, a large amount of data needs to be measured and processed during detection. The uncertainties in data are

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recognized as one of the main barriers against the application of vibration-based techniques in real-life structures (Zhang 2007). As mentioned by Xu *et al.* (2006), although vibration-based damage identification techniques offers several advantages, most of the available damage identification algorithms fail when applied to practical structures due to the effect of measurement errors, need to use incomplete mode shapes, mode truncation, and the non-unique nature of the solutions. To develop robust techniques is therefore critical for improving detection accuracy, under which the advanced algorithms have been explored, and the optimal sensing systems have been designed in recent years. To alleviate the need of reviewing extensive results, Beard *et al.* (2007) draw a sketch on essential elements of design and implementation process for robust damage detection and quantification. In an overview published by Hsieh *et al*. (2006), the robust damage detection scheme can be realized by using the vibrational data in conjunction with other monitoring approaches. Zhou *et al*. (2002) and Wild *et al*. (2008) provided a glance on robust detection from the sensing point of view. Although various techniques have been presented, no comprehensive review of vibration-based robust damage techniques has been made so far.

This paper attempts to retrieve some information through a thorough review on the topic discussed. It is organized in six sections including a brief introduction in section 1. Sections 2 to 5 review the vibration-based detection strategies, in which the robustness is improved by the modeling error compensation, the environmental/operational variance reduction, denoising and the sensing system design. Final, some conclusions are drawn.

2. Robust detection: modeling error compensation

The structural uncertainties are mainly originated from the modeling error due to model discretization or mode truncation. In general, the uncertainty effect on detection results can be compensated by developing vibration-based robust algorithms for model updating. For example, Alvin (1997) developed a sensitivity-based element-by-element method by minimizing the dynamic residual. The robustness for localizing model errors is indicated by embedding the Bayesian estimation to the algorithm. Shi *et al.* (2002) presented a damage quantification algorithm of using the elemental modal strain energy change. The mode truncation error and the finite-element modeling error from the higher modes can be significantly reduced by combining the stiffness information in the algorithm. Xu *et al.* (2007) proposed an iterative algorithm based on the changes of the first several natural frequencies, which takes the advantages of the multiple-parameter perturbation and the generalized inverse methods to improve robustness.

By optimizing an objective function defined as the discrepancy between the experimental and analytical modal parameters, Yu *et al*. (2010) updated the model using the trust-region approach, which makes the optimization process more robust and reliable. A further improvement was investigated by He *et al.* (2010), who modified the trust-region search technique so as to increase the convergence speed.

Revisiting the works done by Yu *et al*. (2010) and He *et al.* (2010), the objective function for optimization is single objective composed of multiple error terms. Different from the single objective cases, the multi-objective approach can simultaneously minimize multiple error terms to enable robust detection with a lower false alarm rate (Jung 2010). Some multi-objective examples are: the eigen-frequency and the modal strain energy residual (Jaishi 2007), the modal flexibility and the frequency/mode shape-dependent damage location criterion (Perera 2008), the coordinate modal assurance criterion and the frequency response assurance criterion (Meo 2008), the modal force errors, and etc.

3. Robust detection: environmental/operational variance reduction

The environmental and operational variances, can in some cases, affect the signals obtained from the sensors, and subsequently detection results. A subtle signal change due to defect can be masked by larger ambient variation of the environmental/operational conditions of an in-service structure. As reported by Carden *et al*. (2008), a primary challenge to implementing structural health monitoring techniques on civil infrastructure is the identification of structural changes in the presence of natural changes in structural response due to environmental variables such as temperature. Zhou *et al.* (2011) showed that, false-positive or false-negative damage may be signaled by vibration-based structural damage detection methods when the environmental effects on the changes of dynamic characteristics of a structure are not accounted for appropriately. Devriendt *et al.* (2010) pointed out that, the use of the transmissibility concept for damage detection is quite promising. However, when using frequency domain transmissibility functions to detect and locate damage, the techniques fail in the case of changing operational conditions.

To better detect damage under variables, Lu *et al.* (2008) proposed a robust decision-making method combining statistical analysis and advanced signal processing. The Hotelling's T^2 statistical analysis is employed to purify the baseline dataset first and then to quantify the deviation of the test data vector from the baseline dataset. By using a time reversal process and a consecutive outlier analysis, Sohn *et al.* (2007) developed an on-line robust diagnosis, which can minimize false-positive indications of damage caused by the undesired operational and environmental variations of the structure. Lin *et al.* (2004) presented an adaptive on-line identification algorithm based on a newly defined variable forgetting factor approach. At each time step, a recursive least-square based algorithm upgrades the adaptation gain matrix using an adaptive forgetting factor that is expressed as the ratio between the minimum value of the diagonal elements of the adaptation gain matrix and a set of pre-defined threshold values. This approach requires only acceleration measurements and is particularly robust to the integration errors.

However, the on-line monitoring leads to an increasing demand for computation time. Care must then be exerted in reducing the computation time, especially when the complicated data processing techniques are adopted for improving the probability of detection with a low false alarm rate. To save time, Clement *et al.* (2011) used the Jacobian feature vector formed by the Jacobian matrix of the dynamics as a damage sensitive feature, which offers a robust alternative to other frequently used but time-consuming features, *e.g.*, the Lyapunov exponents (Casciati 2006). In the work presented by Figueiredo *et al*. (2011), four techniques, *i.e*., Akaike information criterion, partial autocorrelation function, root mean squared error, and singular value decomposition, were adopted to optimize the order of time-series autoregressive model. It was demonstrated that the autoregressive model order range defined by the four techniques provides robust damage detection in the presence of operational and environmental variability.

Evidences show that, the linear approach is not robust with respect to environmental changes and inter-structure variability, whereas the nonlinear one is less sensitive to these effects, as reported by Vanlanduit *et al.* (2005). In their work, the robust singular value decomposition was adopted to determine the threshold, which was defined to decide if the observation comes from the damaged sample or the intact one. Yoder *et al.* (2010) discussed the structural health monitoring of aircraft, which operate in a wide variety of different environmental and boundary conditions. A nonlinear vibro-acoustic modulation technique utilizing a swept probing signal, which is highly sensitivity to the presence of nonlinearities, was presented to facilitate robust crack detection. Thanks to its good nonlinear mapping capability for establishing the relationship between identification signatures and the status of structural damage, the neural network technique has been widely adopted for damage detection (Tsou 1994, Luo 1997). For example, Masri *et al.* (1996, 2000) used vibration measurements from a "healthy" structure and the same structure under different episodes of damage to train a neural network. The robustness is clearly exhibited by identifying damage in structures under different testing states.

4. Robust detection: denoising

Prior to the implementation of detection, one practical issue to be addressed is the effect of noise on data acquisition. In this regard, the robustness can be improved if the developed techniques discriminate noise from signals efficiently (Chen 2008, 2010). For this purpose, Zhang *et al.* (2006) presented an incremental support vector regression training algorithm, a promising statistics technology, for large-scale, structural health monitoring. The approach was demonstrated accurate and robust to data contaminated with different kinds and intensity levels of noise. By mapping features of modal frequency to the statistical damage database, Lin *et al.* (2008) estimated the damage probabilities among various crack depths. The robustness was assessed by imposing noise on the measured frequencies during detection.

As a promising technique, the wavelet analysis has been widely applied for denoising (Deng 1998, Hou 2000, Bakhtazad 2000, Pakrashi 2007). If a suitable wavelet can be selected, the damage information will be extracted from the response signal in a simple and robust way (Ovanesova 2004). With this technique, Wang *et al.* (2010) suggested a wavelet energy spectrum method, which integrates the resulting wavelet energy functions over different frequency bands for robust denoising. A combination of wavelet packet analysis and Bayesian hypothesis testing can avoid the arbitrary selection of wavelet threshold, as discussed by Jiang *et al*. (2007). To identify small damage in a relatively lower signal-to-noise ratio environment, Cao *et al.* (2008) investigated the application of integrated wavelet transforms for damage detection of beams. The robustness and high performance of the proposed method were confirmed in detecting the damage in plate structure and eliminating noise. Fan *et al*. (2009) extended the results to the case of plate-type structures, in which a two-dimensional continuous wavelet transform-based algorithm was presented. The proposed algorithm is superior in noise immunity and robust with limited measurement data. Nicknam *et al*. (2011) developed the curvelet transform via wrapping method for damage detection and denoising in two-dimensional structures.

It is well known that, the genetic algorithm provides a highly efficient and robust search procedure in the entire solution space (Koh 2007, Uhl 2008), and the neural network is with good nonlinearity property. A mixed use of both with other techniques can further enhance the robustness of detection (Wu 2000). In the work reported by Friswell *et al.* (1998), a two-level approach incorporating the advantages of genetic algorithm and eigen-sensitivity analysis was developed. An excellent performance was demonstrated with high levels of experimental noise and inaccurate analytical model. Rus *et al*. (2009) combined genetic algorithms and gradient-based methods to ensure robust search algorithms convergence and maximize the probability of detection against noise effects. Based on modal energy and artificial neural network techniques, Xu *et al.* (2006) proposed a new two-step algorithm, which is quite effective in identifying the location and magnitude of damage, even in the presence of measurement errors in data. Due to the deficiencies of the training algorithms for available wavelet neural network used for structural health monitoring, Zheng *et al.* (2009) combined the hierarchy genetic algorithm and least-square method to improve the learning procedure of wavelet neural network. The simulation demonstrated that the wavelet neural network based on hybrid hierarchy genetic algorithm is robust, promising and converges very fast.

In addition to develop advanced algorithms, an extra concern is the selection of damage sensitive features. For example, using the variation quantity of normalized instantaneous frequency, Chen *et al.* (2007) defined a feature index vector, which is sensitive to small crack and noise-tolerant. However, the frequency-based feature is comparatively less sensitive to detect multiple cracks. The reason is that, the cracks occurring at different locations cause same amount of frequency shift at certain modes. To overcome this problem, Faverjon *et al.* (2008) used the frequency response function-based feature for multi-crack detection. A satisfactory precision on detection results was achieved even if 10% or 20% noise levels were added to simulations. The investigation on the frequency response function-based and the response power spectrum-based features demonstrates the superiority of using the former on robust detection compared with the latter, as done by Lu *et al.* (1998). Instead of using frequency-related features, Reddy *et al.* (2007) formulated a damage index with the Fourier coefficients of mode shapes, which is robust and unique for a given damage size and damage location. It was found that Fourier coefficients provide a useful indication of damage even in the presence of noise. However, higher modes are needed if a small defect is to be detected. Based on the fact that a small defect in the structure can be clearly discerned from the change of strains, the strain-based features, *e.g.*, the curvature mode shape or the strain frequency response function (Pandey 1991, Wang 1997), have been well examined. A review paper presented by Li (2010) shows that, the strain energy-based features perform an excellent anti-noise ability in dealing with noisy signals.

5. Robust detection: sensing system designs

The sensing system design is another way in improving the robustness of identification results, especially when limited sensors or incomplete and noisy measurement signals are used (Bedrossian 2003, Wang 2006, Frazier 2008, Bemont 2009, Wang 2010). As an example, Hong *et al*. (2011) found that, when a structure has cracks and structural variability (*e.g.*, the uncertainty in the geometry or the material properties), the variability affects structural mode shapes, and thus the optimal sensor locations for detecting cracks. A novel sensor placement based on parametric reduced order models and bilinear mode approximation techniques was therefore proposed to minimize this effect.

Recently, advance in sensing technology and computing power stimulates the application of distributed sensor networks, which can enhance the reliability and robustness of monitoring systems through network optimization (Song 2008, Soni 2010). By formulating the noise and uncertainty models as unknown deterministic functions, Savkin *et al*. (2001) solved the optimal robust sensor scheduling problem in terms of the existence of suitable solutions to a Riccati differential equation and a dynamic programming equation. Li *et al*. (2001) determined the optimal sensor locations with the spectral condition number of the Hankel matrix. The effect of noise on the optimal locations was analyzed using the matrix perturbation theory.

Based on an active sensing scheme, Park *et al.* (2007) developed a sensor network system to identify cracks occurring at a welded zone of a steel truss member. In their study, four pairs of pitch-catch Lamb wave signals were utilized from the active sensing network system. A robust wavelet transform was applied to the original response signals to extract damage-sensitive features from the dispersive Lamb waves. As the system is light, cheap, and useful as a built-in system, it offers special potential for real world applications.

Azarbayejani *et al.* (2008) examined the optimal number and locations of sensors using a probabilistic approach, which provides a more robust design of sensor networks compared with the uniform distribution of sensors. A work devoted to this effort was also done by Wang *et al.* (2008), who designed an innovative piezoelectric circuitry network to enhance the detection performance under noise/variances by multivariate statistical analysis.

6. Conclusions

An increasing requirement on the accuracy of structural damage detection calls for the consideration of robustness, especially for the structure subjected to uncertainties or measurement errors. This paper summarized the robust approaches for damage detection, in which the emphasis is focused on the modeling error compensation, the environmental variation reduction, the denosing and the sensing system optimization. Some useful strategies for improving accuracy (*e.g.*, to optimize multi-objective functions, to refine data processing techniques, or to select sensitive vibration signatures) are also reviewed. It is pointed out that, the aim of this paper is not to propose a new method, or to compare the superiority of one approach over the other during robust damage detection. Instead, it tries to address available information and sketch a global picture which might facilitate learning during robust damage detection analysis.

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