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Signal-Based Damage Detection Methods – Algorithms and Applications

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Abstract:-Civil structures are susceptible to damages over their service lives due to aging, environmental loading, fatigue and excessive response. Such deterioration significantly affects the performance and safety of structure. Therefore, it is necessary to monitor the structural performance, detect and assess damages at the earliest possible stage in order to reduce the life-cycle cost of structure and improve its reliability.Recently, signal-based methods have been widely used for structural health monitoring and damage detection. These methods examine changes in the features derived directly from the measured time histories or their corresponding spectra through proper signal processing methods and algorithms to detect damage.Based on different signal processing algorithms for feature extraction, these methods are classified into time-domain methods, frequency-domain methods, and time-frequency (or time-scale)-domain methods.This paper provided an overview of these methods based on two aspects: (1) feature extraction algorithms, and (2) successful applications. Signal-based methods are particularly more effective for structures with complicated nonlinear behaviour and the incomplete, incoherent, and noise-contaminated measurements of structural response.

Keywords:-Damage detection, signal-based methods, features extraction, pattern recognition, algorithms and applications.

I. INTRODUCTION

Deterioration of structures due to aging, cumulative crack growth or excessive response decreases their stiffness and integrity, and therefore significantly affects the performance and safety of structures during their service life. Structural Health Monitoring (SHM) and damage detection denotes the ability to monitor the performance of structure, detect and assess any damage at the earliest stage in order to reduce the life-cycle cost of structure and improve its reliability and safety.Fig. 1 shows a brief classification of different damage detection categories, methods and basic algorithms.

Recent advances in computer, sensors and other electronic technologies make Non-destructive Damage Detection (NDD) techniques far more convenient and cost effective than destructive detection techniques which usually evaluate the safety of a structure by testing samples removed from the structure. NDD techniques can be classified into two categories: (1) local methods; and (2) global methods.

Current highly effective localized NDD methods include acoustic or ultrasonic methods, magnetic field methods, radiograph, microwave/ground penetrating radar, fiber optics, eddy-current methods and thermal field methods. These methods are visual or localized experimental methods that detect damage on or near the surface of the structure by measuring light, sound, electromagnetic field intensity, displacements, or temperature.Some of these methods are particularly effective for a specific application. For example, eddy current is very effective for crack detection at welded joint. But these methods have several limitations when testing large and complex structures. First, the depth of wave penetration is limited. Second, the vicinity of the damage should be known and the portion of the structure being inspected should readily be accessible. However, there is no easy way to determine the global health condition of a structure. Chang and Liu [1] provided detailed information about "local" methods.

Static-based and vibration-based NDD methods provide the opportunity to detect and assess damage on a global basis. Static-based methods rely on the strain or displacement measurements from a structure under known static loads and the finite-element model updating to determine changes in deflection, stiffness, and load-carrying capacity of the structure. These methods are widely used for bridge health monitoring and evaluation. Examples of such work are Barr et al. [2] and Cardinale and Orlando [3]. The drawbacks of static-based NDD methods are: (1) they require a large amount of measured data; (2) they require the finite-element model updating using accurate material properties; (3) they require static-load tests which will interrupt the structure service. These drawbacks will make static-based NDD methods more difficult for online damage detection of an in-service structure. Vibration-based NDD methods rely on the change of vibration characteristics and signals as indication of damage due to the reason that the damage changes the physical properties of a structure, which in turn will cause changes to the vibration characteristics and signals of the structure.Over the last two decades, extensive research has been conducted on Vibration-based detection approach, leading to various experimental techniques, methodologies, and signal processing algorithms. Doebling et al. [4] and Sohn et al. [5] presented comprehensive literature reviews of vibration based damage detection and health monitoring methods for structural and mechanical systems. These methods can be classified into either modal-based or signal-based categories.

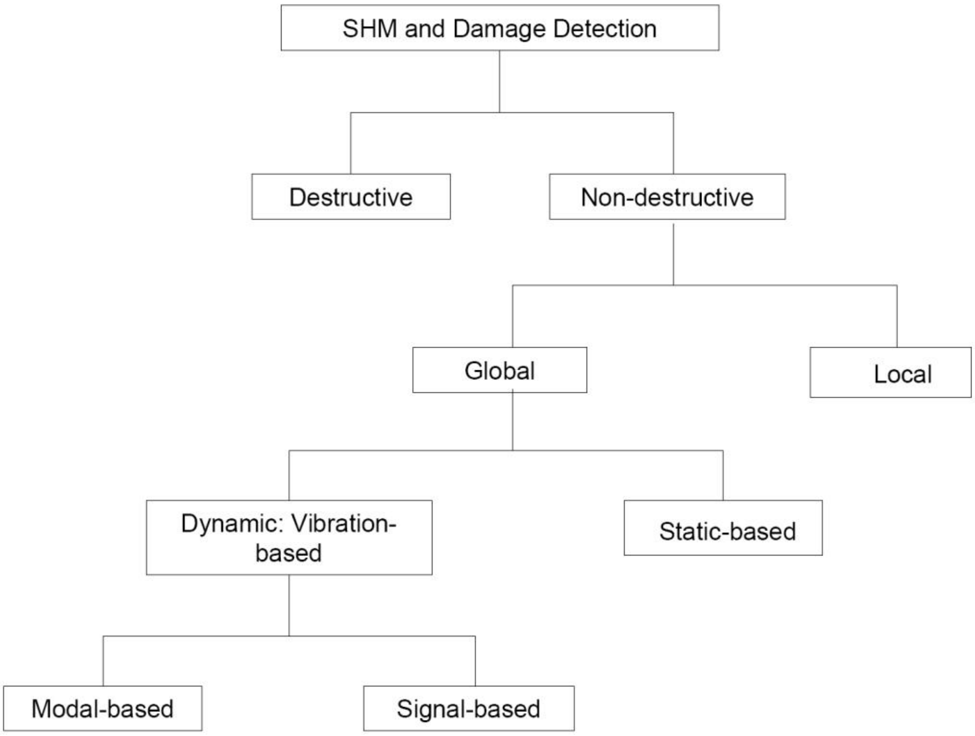

Fig.1:SHM and damage detection categories

Modal-based methods use changes in measured modal parameters (resonant frequencies, modal damping, mode shapes, etc.) or their derivatives as a sign of change in physical-dynamic properties of the structure (stiffness, mass and damping). The basic premise behind the methods is that a change in stiffness leads to a change in natural frequencies and mode shapes. Modal-based methods have been applied successfully to identify the dynamic properties of linearized and time-invariant equivalent structural systems. The methods include mode shape curvature method, the change in flexibility method, the change in stiffness method, modal strain energy, etc. Examples of such work are Kosmatka and Ricles [6], Ren and Roeck [7], Shi et al. [8] and Kim et al. [9]. Recently, wavelet-based and Hilbert-based approaches have been developed as enhanced techniques for parametric identification of non-linear and time-variant systems. Examples of such work are Staszewski [10], Kijewski and Kareem [11], Yang et al. [12], Huang et al. [13], Hou et al. [14], Chen et al. [15] and Yan and Miyamoto [16]. Although modal-based methods are generally applicable for the purpose of damage detection and structural health monitoring, they still have many problems and challenges: (1) damage is a local phenomenon and may not significantly influence modal parameters, particularly for large structures; (2) variation in the mass of the structure or environmental noise may also introduce uncertainties in the measured modal parameters; (3) the number of sensors, the types of sensors, and the coordinates of sensors may have a crucial effect on the accuracy of the damage detection procedure.

Signal-based methods examine changes in the features derived directly from the measured time histories or their corresponding spectra through proper signal processing methods and algorithms to detect damage. Based on different signal processing algorithms for feature extraction, these methods are classified into time-domain methods, frequency-domain methods, and time-frequency (or time-scale)-domain methods. Time-domain methods use linear and nonlinear functions of time histories to extract the signal features. Examples of this category are Auto-Regressive (AR) model, Auto-Regressive Moving Average (ARMA) model, Auto-Regressive with eXogenous input (ARX) model and Extended Kalman Filter (EKF). Frequency-domain methods use Fourier analysis and cepstrum (the inverse Fourier transform of the logarithm of the Fourier spectra magnitude squared) analysis to extract features in a given time window. Examples of this category are Frequency Response Functions (FRFs), frequency spectra, cross power spectra, power spectra, and power spectral density.Time-frequency domain methods employ Wigner-Ville distribution and wavelet analysis to extract the signal features. Examples of this category are spectrogram, continuous wavelet transform coefficients, wavelet packet energies and wavelet entropy.Detailed descriptions of these feature extraction algorithms and successful applications for damage detection were discussed in this paper.

II. SIGNAL-BASED DAMAGE DETECTION

Recently, signal-based damage detection methods have received many attentions. These methods involve two main processes: (1) feature extraction and selection, and (2) pattern recognition. Feature extraction and selection is the process of identifying and selecting damage-sensitive features derived from the measured dynamic response, to quantify the damage state of the structure. A variety of algorithms are employed to improve the feature extraction and selection procedure. Based on different signal processing algorithms for feature extraction, these methods are classified into time-domain methods, frequency-domain methods, and time-frequency methods.

A. Time-Domain Methods

Time-domain methods use linear and nonlinear functions of time histories to extract features. Sohn et al. [17] used an auto-regressive (AR) model to fit the measured time history on a structure. Damage diagnoses using X-bar control chart were performed using AR coefficients as damage-sensitive features. In the$AR(n)$model, the current point in a time series is modeled as a linear combination of the previous n points.

$$x(t)=\sum_{j=1}^{n}\phi_j x(t-j)+e_x(t) \quad (1)$$

where$x(t)$ is the time history at time t; ϕ_j is the unknown AR coefficient; and $e_x(t)$ is the random error with zero mean and constant variance. The value of ϕ_j is estimated by fitting the AR model to the time history data. The AR coefficients of the model fit to subsequent new data were monitored relative to the baseline AR coefficients. The X-bar control chart was used to provide a framework for monitoring the changes in the mean values of the AR coefficients and identifying samples that were inconsistent with the past data sets. A statistically significant number of AR coefficients outside the control limits indicated that the system was transited from a healthy state to a damaged state. Principal component analysis and linear and quadratic projections were applied to transform the time series from multiple measurement points into a single time series in an effort to reduce the dimensionality of the data and enhance the discrimination between features from undamaged and damaged structures. For demonstration, the authors applied the AR model combined with X-bar control chart to determine the existence of damage on a concrete bridge column as the column was progressively damaged. The AR coefficients on the X-bar control chart as detailed in the method indicated the damage existence.

Sohn and Farrar [18] proposed a two-stage time history prediction model, combining auto-regressive (AR) model and an autoregressive with exogenous inputs (ARX) model. The residual error, which was the difference between the actual acceleration measurement for the new signal and the prediction obtained from the AR-ARX model from the reference signal, was defined as the damage-sensitive feature. The increase in residual errors was monitored to detect system anomalies. In this method, the ARX model is expressed as

$$x(t)=\sum_{i=1}^{a}\alpha_i x(t-i)+\sum_{j=1}^{b}\beta_j e_x(t-j)+\varepsilon_x(t) \quad (2)$$

where a and b are the order of the ARX model; α_i and β_j are the coefficients of the AR and the exogenous input, respectively; $\varepsilon_x(t)$ is the residual error after fitting the $ARX(a,b)$ model to the $e_x(t)$ and $x(t)$ pair in the one-stage ahead AR model. If the ARX model obtained from the reference signal block pair $x(t)$ and $e_x(t)$ were not be a good representation of the newly obtained block pair $y(t)$ and $e_y(t)$, there would be a significant change in the residual error, $\varepsilon_y(t)$, compared to $\varepsilon_x(t)$. The standard deviation ratio of the residual errors, $\sigma(\varepsilon_y)/\sigma(\varepsilon_x)$, would reach its maximum value at the sensors instrumented near the actual damage locations. The applicability of this approach was demonstrated by the authors using acceleration time histories obtained from an eight degree-of-freedom mass-spring system. Sohn et al. [19] developed a unique combination of the AR-ARX model, auto-associative neural network, and statistical pattern recognition techniques for damage classification explicitly taking the environmental and operational variations of the system in the consideration. In this method, AR-ARX model is developed to extract damage sensitive features, which are the α_i andβ_j coefficients of the ARX model. An auto-associative neural network is trained to characterize the dependency of the extracted features on the variations caused by environmental and operation conditions. A damage classifier is constructed using a sequential probability ratio test to automatically determine the damage condition of the system. The authors demonstrated the proposed approach using a numerical example of a computer hard disk and an experimental study of an eight degree-of-freedom spring-mass system.

Bodeux and Golinval [20] applied the autoregressive moving average vector (ARMAV) model and statistical tools such as confidence interval and the normal distribution of random variable for damage detection. In the state space, the ARMAV model is expressed as

$$x[n] = Ax[n-1] + W[n] \quad (3)$$

Where x[n] is the observed vibration vector at the nth discrete time point; A is the matrix containing the different coefficients of the autoregressive (AR) part; W[n] is a matrix containing the moving average (MA) terms. The natural eigenfrequenciesf_r and damping ratios ζ_r can be extracted from the eigenvalues τ_r of the AR matrix A as

$$f_r = \frac{\left|\ln(\tau_r)\right|}{2\pi\,\Delta t} \quad (4)$$

$$\zeta_r = \frac{\mathrm{Real}(\ln(\tau_r))}{\left|\ln(\tau_r)\right|} \quad (5)$$

whereΔt is the discrete time interval. The authors used the changes in the frequencies estimated by the ARMAV model to detect the damage on the Steel-Quake structure at the Joint Research Center in Ispra, Italy. The frequencies were assumed to be independently distributed variables and a negative change in frequencies indicated damage caused by structure change. As damage indicator, the probability of negative change $P_{\delta f_i}$ in frequency f_i is given by

$$P_{\delta f_i} = 1 - \Phi\left(\frac{f_i - f_{i0}}{\sigma_i^2 + \sigma_{i0}^2}\right) \quad (6)$$

Where σ_i^2 and σ_{i0}^2 are the variances of the frequencies f_i and f_{i0} corresponding to the damaged and undamaged states. $\Phi$is the unit normal distribution function. The structure was assumed damaged if the probability was close to one. The proposed method was limited to only detecting the damage existence.

Nair et al. [21] applied an Auto-Regressive Moving Average (ARMA) model for damage identification and localization. A damage-sensitive feature, DSF, was defined as a function of the first three auto regressive (AR) components. The mean values of the DSF obtained from the damaged and undamaged signals were significantly different. In this method, the vibration signals obtained from sensors are modeled as ARMA time series as

$$x_{ij} = \sum_{k=1}^{p} \varphi_k x_{ij}(t-k) + \sum_{k=1}^{q} \theta_k \varepsilon_{ij}(t-k) + \varepsilon_{ij}(t) \quad (7)$$

Where $x_{ij}(t)$ is the normalized acceleration signal; φ_k and θ_k are the k-th AR (Auto-Regressive) and MA (Moving Average) coefficients, respectively; p and q are the model orders of the AR and MA processes, respectively; and $\varepsilon_{ij}(t)$ is the residual term. DSF is defined as

$$DSF = \frac{\alpha_1}{\sqrt{{\alpha_1}^2 + {\alpha_2}^2 + {\alpha_3}^3}} \quad (8)$$

where α_1, α_2 and α_3 are the first three AR coefficients. A hypothesis test involving the t-test was used to determine the existence of damages on the structure. Two indices, $LI_1$and LI_2, were introduced based on the AR coefficient space to localize damages. At the sensor locations where damage was introduced, LI_1 and LI_2had comparatively large values.The authors tested the proposed methodologies on the analytical and experimental results of the ASCE benchmark structure. The results of the damage detection indicated that DSF was able to detect the existence of all damage patterns in the ASCE Benchmark simulation experiment. The results of the damage localization indicated that LI_1 and LI_2 were all able to localize minor damages but LI_1 was more robust than LI_2.

Liu et al. [22] presented a damage sensitive feature index for damage detection based on Auto-Regressive Moving Average (ARMA) time series analysis. The acceleration signal was modeled as ARMA models, and a principal component matrix derived from the AR coefficients of these models was utilized to establish the Mahalanobis distance criterion function. The Mahalanobis-distances of m-dimensional vector x_i from the principal component matrix of damaged structure to the ones of undamaged structure were defined as the damage sensitive feature (DSF) index. It is expressed as

$$D_{DSF} = \left[(x-\mu)^T \Sigma^{-1} (x-\mu)\right]^{\frac{1}{2}} \quad (9)$$

Where μ and Σ are mathematics expectation and covariance matrices of the m-dimensional vector from the principal component matrix of undamaged structure, respectively. A hypothesis test involving the t-test method was further applied to make a damage alarming decision by determining the statistical significance in the difference of mean values of D_{DSF} obtained from the damaged and undamaged cases. These methodologies were tested on a numerical three-span-girder beam model containing some subtle damages. The results show that the defined index is sensitive to these subtle structure damages, and the proposed algorithm can be applied to the on-line damage alarming in structural health monitoring.

B. Frequency-Domain Methods

Frequency-domain methods analyze any stationary event localized in time domain. They use Fourier analysis, cepstrum (the inverse Fourier transform of the logarithm of the Fourier spectra magnitude squared) analysis, spectral analysis, frequency response technique, etc to extract features in a given time window. Tang et al. [23] quantitatively diagnosed gear-wear through cepstrum analysis of gear noise signals. The amplitude value of the peak in cepstrum represented gear mesh-harmonics in spectrum. The trend of the change of gear-wear degree was about the same as that of the change of the value of a peak in cepstrum. The value was independent of intensity of gear noise signal and was used as an indicator for quantitatively diagnosing gear-wear. Based on analyzing the results of experiments with gearboxes, the thresholds of the gear wear by cepstrum diagnosis was determined to distinguish normal, moderate and serious wears. The theoretical analysis agreed with the experimental results very well.

Kamarthi and Pittner [24] presented sensor data representation schemes for flank wear estimation in turning processes. The sensor data representation algorithm based on fast Fourier transform (FFT) transformed a time series vector X of the sensor signal from turning experiments into the spectral vector $\hat{x}$, and then formed the vector $\hat{x}_f$ with the set $\{i_1, i_2, \ldots, i_d\}$. The features x_r , the d-dimensional sensor data representation of X, was computed through the relation

$$x_r = S_w^{-1/2} \hat{x}_f \quad (10)$$

The features were used by recurrent neural network architecture to continually compute the flank wear estimates.

Lee and Kim [25] used the frequency analysis to detect and localize damage. A signal anomaly index (SAI) which quantified the change of frequency response was developed as damage feature. The SAI is defined as a Euclidean norm of the difference between two frequency response function (FRFs) of basis and compared state as

$$SAI = \left(\frac{\sum_{f_i=f_1}^{f_n} \left| H^B(f_i) - H^C(f_i) \right|^2}{\sum_{f_i=f_1}^{f_n} \left| H^B(f_i) \right|^2} \right)^{1/2} = \frac{\left\| \mathrm{FRF}^B - \mathrm{FRF}^C \right\|}{\left\| \mathrm{FRF}^B \right\|} \quad (11)$$

where, H( ) and FRF represent the frequency response function in continuous form and discrete form respectively, superscript B and C stand for the state of Basic and Compared. The symbols, f_1 and f_n are the lowest and highest frequency of the considering frequency range, respectively. Changes in the shape of the FRF due to the reason of structural damage caused the increase of SAI value. The presence of damage was identified from the SAI value. All SAI values calculated from different sensors and different frequency ranges formed a SAI matrix which showed variation patterns of the FRF in both the space and the frequency domain. The SAI matrix was used as input for the neural network to identify the location of damage. The authors conducted a series of experimental tests and numerical simulation on an experimental model bridge to demonstrate the feasibility of the proposed algorithm. The results of this example application show that the SAI based pattern recognition approach has the great potential for structural health monitoring on a real bridge.

Fasel et al. [26] used a frequency domain auto-regressive model with exogenous inputs (ARX) to detect joint damage in steel moment-resisting frame structures. Damage sensitive features were extracted from the ARX model in the consideration of non-linear system input/output relationships. A frequency domain ARX model was used to predict the response at a particular frequency based on the input at that frequency, as well as responses at surrounding frequencies. The responses at the surrounding frequencies were included as inputs to the model to account for sub-harmonics and super-harmonics introduced to the system through non-linear feedback. To accounts for non-linearity in the system, first-order ARX model in the frequency domain is built as

$$Y(k) = B(k)U(k) + A_1(k)Y(k-1) + A_{-1}(k)Y(k+1) \quad k = 2,3,\ldots,N_f - 1 \quad (12)$$

where N_f is the highest frequency value examined, Y(k) is the response at the k-th frequency, U(k) is the input at the k-th frequency, and $Y(k-1)$ and $Y(k+1)$ are the responses at the (k-1)th and (k+1)th frequencies, respectively.$A_1(k)$and$A_{-1}(k)$ are the frequency domain auto-regressive coefficients, and B(k) is the exogenous coefficient. The frequency response of one accelerometer was treated as an input and the other accelerometer response was treated as an output. The auto-regressive coefficients in this frequency domain model were used as features. These features were then analyzed using extreme value statistics (EVS) to differentiate between damage and undamaged conditions. The suitability of the ARX model, combined with EVS, to non-linear damage detection was demonstrated on a three-story building model.

Qiao et al. [27, 28] noted that in the Fast Fourier Transform (FFT) spectrums of acceleration signals of the structure under different damage scenarios, the peak magnitude changes were more sensitive than the peak frequency shifts. The authors selected the FFT magnitude vectors in frequency domain as the sensitive features which also preserved the information of frequency shifting, forming a one-dimension pattern, presenting a unique damage condition. In order to separate the feature changes caused by operational and environmental variations of the system from the structure changes of interest, each magnitude vector in a pattern was normalized with respect to the square root of the sum of square of the corresponding pattern. The dynamic response patterns of a damaged structure were compared with a wide range of numerically generated damaged cases stored in a pattern database to detect damage severity and location. To demonstrate the feasibility of the proposed method, numerical and experimental studies were conducted on a simple three-story steel building. The results showed that the FFT patterns were successfully used as sensitive features for damage detection.

C. Time-Frequency (or Scale)-Domain Methods

In contrast to the frequency-domain methods, the time-frequency (or scale) methods can be used to analyze any non-stationary event localized in time domain. Staszewski et al. [29] applied the Wigner-Ville distribution (WVD) to detect local tooth faults in spur gears. The authors showed that the visual observation of the WVD contour plots could be used for fault detection. Dark zones and curved bands in the contour plots were the main features of an impulse produced by the fault in the spur gear. The changes in features of the distribution were used to monitor the progression of a fault. For the sake of automatic fault detection, the authors chose the two-dimensional contour plots of the WVD as patterns, and the amplitude values of the contour plots as features. Pattern recognition procedures based on the statistical and neural approaches were used for classification of different fault conditions.

Biemans et al. [30] employed the orthogonal wavelet analysis of the strain data measured from piezoceramic sensors to detect crack growth in the middle of a rectangular aluminum plate. The strain data measured from the plate under the Gaussian white noise excitation was decomposed into orthogonal wavelet levels. The logarithm of the variance of the orthogonal wavelet coefficients was calculated for all wavelet levels. The mean vector $\bar{\mu}$, of the logarithms for the undamaged plate formed the template for the similarity analysis. A Euclidean distance between the template $\bar{\mu}$ and the logarithms $\bar{x}$, for the damaged plate was used as a damage index. The damage index is denoted as

$$d_{x,\mu}{}^2 = \left(\bar{x}-\bar{\mu}\right)^T \left(\bar{x}-\bar{\mu}\right) \quad (13)$$

The mean and standard deviation of the damage index representing the undamaged condition of the plate were used to establish an alarm level. The damage could be considered existence in the plate if the damage index was above the alarm level. The experimental results on the aluminum plate show that such damage index can be used to successfully detect as small as 6-7mm crack and to monitor the crack growth.

Hou et al. [31] presented the great potential of wavelet analysis for singularity extraction in the signals. Characteristics of four types of representative vibration signals were examined by continuous and discrete wavelet transforms. The singularity in these signals were extracted and best illustrated in the plot of wavelet coefficient in the time-scale plane. The fringe pattern in the continuous wavelet coefficient contour plot indicated the existence of a singularity in the local time and the spike in the discrete wavelet coefficient plot also indicated the existence of a singularity in the local time. The sensitivity of wavelet results to a singularity was effectively used to detect possible structural damage using measured acceleration response data. To demonstrate the feasibility of the proposed method, the authors used both numerical simulation data from a simple structural model with multiple paralleled breakable springs and actual acceleration data recorded on the roof of a building during an earthquake event. The detection results showed that occurrence of damage could be detected by spikes in the detailed of the wavelet decomposition of the response data, and the locations of these spikes could accurately indicate the moments when the damage occurred. The similar work can also be found on Hera and Hou [32], Ovanesova and Suarez [33], Melhem and Kim [34] and Qiao et al. [35].

Kim and Kim [36] used the ratio of the incident wave toward and the reflected wave from the damage as index to assess the damage size. The ratio was estimated by the continuous wavelet transform of the measured signal and the ridge analysis. In the time-frequency plane of the continuous wavelet transform, the ridge was traced to compare the magnitude of the incident wave and the magnitude of the reflected wave from the damage. It was found that the ratio of these magnitudes along the two ridges was the same as the ratio of the magnitude of the incident wave to the magnitude of the reflected wave. Due to the fact that the magnitude and frequency-dependent pattern of the ratio varied with damage size, it was able to correlate the ratio and the damage size except when the damage size was very small. The authors conducted the wave experiments in a cylindrical ferromagnetic beam. Magnetostrictive sensors were used to measure the bending waves in the beam cross section. The continuous Gabor wavelet transform was employed to estimate the crack size in the beam.

Yen and Lin [37] investigated the feasibility of applying the Wavelet Packet Transform (WPT) to detect and classify the mechanical vibration signals. They introduced a wavelet packet component energy index and demonstrated that the wavelet packet component energy had more potential for use in signal classification as compared to the wavelet packet component coefficients alone. The component energy is defined as

$$E_j^i = \int_{-\infty}^{\infty} f_j^i(t)^2 dt \quad (14)$$

where $f_j^i(t)$ is the ith component after j levels of decomposition. Sun and Chang [38] applied the wavelet packet component energy index to assess structural damage. The vibration signals of a structure were decomposed into wavelet packet components. The component energies were calculated and the ones which were both significant in value and sensitive to the change in rigidity were selected as damage indices and then used as inputs into neural network models for damage assessment. The authors performed numerical simulations on a three-span continuous bridge under impact excitation. Various levels of damage assessment including identifying the occurrence, location, and severity of the damage were studied. The results show that the WPT-based component energies are sensitive to structural damage and can be used for various levels of damage assessment.

Sun and Chang [39] also derived two damage indicators from the WPT component energies. The acceleration signals of a structure excited by a pulse load were decomposed into wavelet packet components. The energies of these wavelet packet components were calculated and sorted by their magnitudes. The dominant component energies which were highly sensitive to structural damage were defined as the wave packet signature (WPS). Two damage indicators, SAD (sum of absolute difference) and SSD (square sum of difference), were then formulated to quantify the changes of these WPSs. SAD and SSD are defined as

$$SAD = \sum_{i=1}^{m} \left| E_j^i - \hat{E}_j^i \right| \quad (15)$$

$$SSD = \sum_{i=1}^{m} \left(E_j^i - \hat{E}_j^i \right)^2 \quad (16)$$

where $\hat{E}_j^i$ $(i = 1,2,\ldots,m)$ are termed as the baseline WPS that are used as a reference; and E_j^i $(i = 1,2,\ldots,m)$ are WPS obtained from any subsequent measurement. These two indicators basically quantified the deviations of the WPS from the baseline reference. To monitor the change of these damage indicators, the X-bar control charts were constructed and one-sided confidence limits were set as thresholds for damage alarming. For demonstration, the authors conducted an experimental study on the health monitoring of a steel cantilever I beam. Four damage cases, involving line cuts of different severities in the flanges at one cross section, were introduced. Results show that the health condition of the beam can be accurately monitored by the proposed method; the two damage indicators are sensitive to structural damage and yet insensitive to measured noise.

Yam et al. [40] constructed a non-dimensional damage feature proxy vector for damage detection of composite structures. The damage feature proxy vector was calculated based on energy variation of the wavelet packet components of the structural vibration response before and after the occurrence of structural damage. The damage feature proxy vector, V_d is defined as

$$V_d = \left\{ 1 - \frac{U_{L,1}^d}{U_{L,1}^0}, 1 - \frac{U_{L,2}^d}{U_{L,2}^0}, \ldots 1 - \frac{U_{L,2^{L-1}}^d}{U_{L,2^{L-1}}^0} \right\}^T \quad (17)$$

where $U_{L,j}^0$ and $U_{L,j}^d$ are the energy of the jth order sub-signal of the intact and damaged structures, respectively; L is the layer number of the tree structure of wavelet decomposition. Artificial neural network (ANN) was used to establish the mapping relationship between the damage feature proxy and damage location and severity. The method was applied to crack damage detection of a PVC sandwich plate. The results show that the damage feature proxy exhibits high sensitivity to small damage.

Han et al. [41] proposed a damage detection index called wavelet packet energy rate index (WPERI) for the damage detection. The rate of signal wavelet packet energy $\Delta(E_{j_j})$ at j level is defined as

$$\Delta\left(E_{f_j}\right) = \sum_{i=1}^{2^j} \frac{\left| \left(E_{f_j^i}\right)_b - \left(E_{f_j^i}\right)_a \right|}{\left(E_{f_j^i}\right)_a} \quad (18)$$

where $E_{f_j^i}$ is the energy stored in the component signal $f_j^i(t)$ after j levels of decomposition; $(E_{f_j^i})_a$ is the component signal energy $E_{f_j^i}$ at j level without damage; and $(E_{f_j^i})_b$ is the component signal energy $E_{f_j^i}$ with some damage. It was assumed that structural damage would affect the energies of wavelet packet components and therefore altered this damage indicator. To establish threshold values for damage indexes, WPERIs, X-bar control charts were constructed and one-sided confidence limits were set as thresholds for damage alarming. The proposed method was applied to a simulated simply supported beam and to the steel beams with three damage scenarios in the laboratory. Both simulated and experimental studies demonstrated that the WPT-based energy rate index is a good candidate index that is sensitive to structural local damage.

Diao et al. [42] proposed a two–step structural damage detection approach based on wavelet packet analysis and neural network. The wavelet packet component energy change γ_{si} was selected as an input into probabilistic neural network to determine the location of the damage. The γ_{si} is defined as

$$\gamma_{si} = \frac{E_{si}^{d} - E_{si}^{u}}{E_{si}^{u}} \quad (19)$$

where E_{si}^{u} is the ith component energy at s level without damage, E_{si}^{d} is the ith component energy at s level with damage. The component energy was selected as input into back-propagation network to determine the damage extent. The method was demonstrated by numerical simulation of a tree-dimensional four-layer steel frame.

Chen et al. [15] introduced an improved Hilbert-Huang Transform (HHT) to extract the structural damage information from the response signals of a simulated composite wingbox. The signals was firstly decomposed into sub-signals using Wavelet Packet Transform (WPT). These sub-signals were then decomposed into multiple Intrinsic Mode Function (IMF) components by Empirical Mode Decomposition (EMD). The IMF selection criterion was then applied to eliminate the unrelated IMF components. The retained IMF components were transformed using HHT to obtain instantaneous energy of all sub-signals. By comparing the instantaneous energy corresponding to IMFs of intact wingbox with those of damaged wingbox, it was found that some instantaneous energy was changed obviously. Based on this fact, the authors constructed the variation quantity of instantaneous energy ΔE_t as feature index vector, which is defined as

$$\Delta E_t = \left(E_t / E_t^0 - 1 \right) \times 100\% \quad (20)$$

where E_t^0 and E_t are instantaneous energy of intact and damaged structure respectively at time t. Reduction in Young's modulus was used to characterize damage in wingbox. The detection results show that the feature index vector distinctly reflects the wingbox damage status, and is more sensitive to small damage.

Ding et al. [43] developed a procedure for damage alarming of frame structures based on energy variations of structural dynamic responses decomposed by wavelet packet transform. The damage alarming index ERVD, extracted from the wavelet packet energy spectrum is expressed as

$$ERVD = \sqrt{\sum_{p=1}^{m} \left(ERV_p - \overline{ERV} \right)^2} \quad (21)$$

$$ERV_p = \left| I_{up} - I_{dp} \right| \quad \left(p = 1,2,...,m \right) \quad (22)$$

$$I_p = \frac{E_{i,p}}{\left(\sum_{j=1}^{2^i-1} E_{i,j} \right) / 2^i} \qquad \left(p = 1,2,...,m \right) \quad (23)$$

where I_{up} and I_{dp} are the damage indication vector in the pth dominant frequency band of the intact and damaged structures, respectively. $E_{i,j}$ is the jth component energy at l level. The authors demonstrated the practicability of the damage alarming method for the frame structures by using the ASCE structural benchmark data. The results reveal that the WPT-based damage alarming index ERVD is sensitive to structural local damage affected by the actual measurement noise; the index ERVD constructed under the lower decomposition level and dominant frequency bands is efficient for the detection of the damage occurrence.

Ren and Sun [44] combined wavelet transform with Shannon entropy to detect structural damage from measured vibration signals.Wavelet entropy, relative wavelet entropy and wavelet-time entropy were used as features to detect and locate damage. The wavelet entropy is defined as

$$S_{WT} = S_{WT}\left(p \right) = -\sum_{j<0} p_j \cdot \ln\left[p_j \right] \quad (24)$$

where $\{p_j\}$ is the wavelet energy vector, which represents energy distribution in a time-scale. It gives a suitable tool for detecting and characterizing singular features of a signal in time-frequency domain. For the jth scale, the wavelet energy ratio vector $\{p_j\}$ is defined as

$$p_j = \frac{E_j}{E_{tol}} \quad (25)$$

The relative wavelet entropy (RWE) is defined as

$$S_{WT}\left(p / q \right) = \sum_{j<0} p_j \cdot \ln\left[\frac{p_j}{q_j} \right] \quad (26)$$

which gives a measure of the degree of similarity between two probability distributions. The wavelet-time entropy is defined as

$$S_{WT}^{(i)}\left(p \right) = -\sum_{j<0} p_j^{(i)} \cdot \ln\left[p_j^{(i)} \right] \quad (27)$$

where$p_j^{(i)}$ is the time evolution of relative wavelet energy at a resolution level j in the time interval i

$$p_j^{(i)} = \frac{E_j^{(i)}}{E_{tol}^{(i)}} \quad (28)$$

These features were investigated by numerically simulated harmonic signals and two laboratory test cases. It was demonstrate that wavelet-time entropy is a sensitive damage feature in detecting the abnormality in measured successive vibration signals; relative wavelet entropy is a good damage feature to detect damage occurrence and damage location through the vibration signals measured from the intact and damaged structures; and the relative wavelet entropy method is flexible in choosing the reference signal simultaneously measured from any undamaged location of the target structure.

III. APPLICATIONS TO SPECIAL STRUCTURES

A. Damage Detection on Bridge

Omenzetter et al. [45] identified the unusual events in multi-channel bridge monitoring strain data using wavelet transform and outlier analysis. The strain data was recorded during continuous, long-term operation of a multi-sensor Structural Health Monitoring (SHM) system installed on a full-scale bridge. Outlier detection in multivariate data was applied to find and localize abnormal, sudden events in the strain data and wavelet transform was used to separate the abrupt strain changes from slowly varying ones. The method was successfully tested using known events recorded during construction of the bridge and later effectively used for detection of anomalous post-construction events.

Omenzetter and Brownjohn [46] proposed and examined the application of concepts of time series analysis to the processing of data from a continuously operating SHM system installed in a major bridge structure. The recorded static strain data was modeled using ARIMA models. The coefficients of the ARIMA models were identified on-line using an extended Kalman filter. The method was first applied to strains recorded during bridge construction, when structural changes corresponded to known significant events such as cable tensioning. Then the method was used to analyze signals recorded during the post-construction period when the bridge was in service. The results show that the method can provide information on structural performance under normal environmental and operational conditions.

Ding and Li (47) proposed an online structural health monitoring method for long-term suspension bridge using wavelet packet transform (WPT). The method was based on the wavelet packet energy spectrum (WPES) variation of structural ambient vibration responses. As an example application, the WPES-based health monitoring system was used on the Runyang Suspension Bridge to monitor the responses of the bridge in real-time under various types of environmental conditions and mobile loads. As for the vibration monitoring of the bridge, a total of 27 uni-axial servo type accelerometers were installed at the nine sections of the bridge deck. In each deck section, one lateral accelerometer directly recorded the lateral response, and the vertical acceleration of the deck section was obtained by averaging the accelerations measured by the two vertical accelerometers located in the upriver and downriver cross section, respectively.The analysis showed that changes in environmental temperature had a long-term trend influence on the WPES, and the effect of traffic loadings on the WPES presented instantaneous changes.

Zhang [48] presented a statistical damage identification procedure for bridge health monitoring. The damage features were extracted based on time series analysis combining auto-regressive and auto-regressive with eXogenous input prediction models. The structural condition was evaluated in a statistical way based on the damage possibilities that were derived from a quite large number of data samples to minimize the effect of the variability in data acquisition process and in structural properties on the damage assessment.The proposed damage identification procedure was applied to a numerical 3-span continuous girder bridge model under random ground excitations. Reasonable damage severities for beam structures as well as realistic noise levels were simulated.The results show that the damage identification procedure has great potential to detect structural damage at early stage, in which the structural modal frequency changes are almost imperceptible.

B. Crack Detection on Beam and Plate

Wang and Deng [49] detected the crack on beam and plate structures based on wavelet analysis of spatially distributed structural response measurements.Simulated deflection signals of a beam containing a transverse crack and the displacement response of a plate with a through-thickness crack were used.Wavelet transforms were performed on these signals to obtain the wavelet coefficients along the span of the structures. The crack location was detected by observing a sudden change, such as a spike, in the distribution of the wavelet coefficients. The magnitude of the spike in the wavelet analysis was the maximum when the measurement point was next to the damage location.

Biemans et al. [50] applied the piezoceramic sensors to monitoring crack propagation. The specimens used were two rectangular (400 × 150 × 2 mm) aluminum plate with cracks initiated by spark erosion in the middle of the plates. Each plate was instrumented with 6 piezoceramics bonded in a symmetrical configuration 20 mm below and above the initiated crack. One of the piezoceramics was used as an actuator excited by a sine sweep and Gaussian white noise signals to exploit broadband excitation. The plates were subjected to static and dynamic tensile loading. The growing crack was monitored by two of the remaining piezoceramic sensors. The response strain data was analyzed using a number of time, frequency, and wavelet domain statistical parameters. The results show that low frequency broadband excitation offers a possible means of on-line detection of cracks in metallic structures.

Yan et al. [51] detected the crack damage in a honeycomb sandwich plate by using two structural vibration damage feature indexes: natural frequency and WPT energy index. The finite element dynamic model of a honeycomb sandwich plate was presented using different mesh division for the surface plate and the sandwich plate to accurately express the crack damage status (locations, length and direction) of the plate. In order to acquire the experimental dynamic response of the plate, two piezo-patches with a size of 25×15×0.28 mm were bonded on the surface of the plate. One of them acted as an actuator and the other acted as a sensor. The natural frequencies of the undamaged plate were experimentally measured to verify the numerical model. Based on the dynamic model verified by the experiment, the damage feather indexes for various crack damage status were numerically computed. Then the crack damage status was determined by comparing the damage feature indexes obtained from the numerical and experimental results. The authors found that natural frequency of structure might not be used to detect crack damage less than 10%, even up to 20% of the total size of a plate-like structure; energy spectrum of wavelet transform signals of structural dynamic response was so sensitive to crack damage that it could exhibit a crack length close to 2% of the dimension of a plate-like structure. They also found that high order modes of a structure contain more structural damage information; in order to detect a small damage, more vibration modes should be included in a structural dynamic model.

Chang and Chen [52] detected the locations and sizes of multi-cracks in a beam by spatial wavelet analysis. The crack type was open crack and was represented as a rotational spring.The mode shapes of the multi-cracked beam under free vibration were analyzed by wavelet transformation. The positions of the cracks were observed as a sudden change in the plot of wavelet coefficients. The natural frequencies of the beam were used to predict the depth of the cracks through the characteristic equation. The limitation of this method is that there are two peaks near the boundaries in the wavelet plot and the crack can not be detected when the crack was near the boundaries.

Poudel et al. [53, 54] employed high-resolution images for damage detection on a simply supported prismatic steel beam. A high-speed digital video camera was used to recode the free vibration displacement of the beam which was excited by imposing an initial displacement near the mid-span from the left support. The camera had a Complimentary Metal Oxide Semiconductor (CMOS) sensor with 1280 × 1024 resolution and a 10-bit A/D converter. Its frame rate ranges was from 100 to 2000 frames/s. The displacement data with high spatial resolution were then used to obtain the mode shapes and the mode shape difference function between the reference and damage states of the structure.The spatial signal in terms of mode shape difference function was decomposed by wavelet transformation to display the changes due to cracking damage. The appropriate range of wavelet scale was determined by the spatial frequency bandwidths of the mode shape difference functions. The maximum modulus and sign change of phase angle in the wavelet coefficients indicated the changes at the damage locations.

C. Damage Detection on Mechanical Structures

Staszewski and Tomlinson [55] applied the wavelet transform to the problem of the detection of a broken tooth in a spur gear. The fault detection algorithm was based on pattern recognition analysis. Features of the pattern were the modulus of the wavelet transform. Spectral analysis and an orthogonal transform were used to compress feature elements. The Mahalanobis distance of two patterns obtained from the normal (no fault) condition and not normal (fault) condition was used as a fault detection symptom.Visual inspection of the modulus and phase of the wavelet transform were used to localize the fault.

Wang and McFadden [56, 57] used the wavelet transform to detect abnormal transients generated by gear damage. The early damage to a gear tooth usually caused a variation in the associated vibration signal over a short time, initially less than one tooth meshing period, taking the form of modulated or unmodulated oscillation. In later stages, the duration of the abnormal variation became longer, lasting more than one tooth meshing period. Other distributed faults, such as eccentricity and wear, might cover the most part of the whole revolution of the gear. Changes in the vibration signals therefore could be analyzed to provide an indicator of gear condition. When the size and shape of a wavelet were exactly the same as a section of the signal, the transform gave a maximum absolute value of wavelet coefficients. Therefore, the abnormal signal caused by a gear fault could be displayed by the wavelet transform, which could be regarded as a procedure for comparing the similarity of the signal and the chosen wavelet.

Li et al. [58] applied neural networks to the detection of motor bearing conditions based on the frequency features of bearing vibration. Five basic frequencies related to rolling bearing dynamic movement were extracted by fast Fourier transform (FFT) technique. The basic frequency amplitude vectors were constructed to represent different bearing vibrations. These vectors were created from the power spectrum of the vibration signal and consisted of the five basic frequencies with varying amplitudes based on the defect present. The network consisted of five input measurements corresponding to the amplitudes of the five basic frequencies of interest, ten hidden nodes, and three output fault detectors (bearing looseness, defects on the inner raceway, and defects on the rolling elements). The network was tested using the data generated by MOTORSIM. The results show that neural network can be an effective agent in the detection of various motor bearing faults through the measurement and interpretation of motor bearing vibration signals.

Liao et al. [59] developed a novel technique for monitoring the gearbox condition based on the Self-Organizing Feature Maps (SOFM) network. Seven time-domain features parameters, i.e. standard deviation, Kurtosis, root mean square value, absolute mean value, crest factor, clearance factor and impulse factor were extracted from industrial gearbox vibration signals measured under different operating conditions. Trained with the SOFM network and visualized using the U-matrix method, the feature data were mapped into a two-dimensional space and formed clustering regions, each indicative of a specific gearbox work condition. Therefore the gearbox operating condition with fatigue crack or a broken tooth compared with the normal condition was identified clearly.

Kar and Mohanty [60] applied the multi-resolution Fourier transform (MFT) of vibration and current signals to gearbox health monitoring. One and two teeth were artificially removed in one gear of the gearbox to simulate actual fault condition. When the gearbox was operated under several loads, the vibration signals were acquired from the tail-end bearing of the gearbox, and simultaneously the current drawn by the induction motor is acquired. The vibration and current signals were decomposed into four levels using discrete wavelet transform (DWT) with an orthogonal wavelet of ‘db8’. Then a hanning window with 256 data points and 50% overlap was applied to the scaled signals to find the MFT coefficients.The MFT coefficients of signals were used to classify the types of defects by tracking the energy level possessed by the defect characteristic frequency.

IV. CONCLUSIONS

This paper provided an overview of signal-based methods to detect, locate, and characterize damage in structure and mechanical systems. These methods examine changes in the features derived directly from the measured time histories or their corresponding spectra through proper signal processing methods and algorithms to detect damage.Based on different signal processing algorithms for feature extraction, these methods are classified into time-domain methods, frequency-domain methods, and time-frequency (or time-scale)-domain methods.Features derived by time-domain methods include auto-regressive model, auto-regressive moving average model and auto-regressive with eXogenous input model. Features derived by frequency-domain methods include frequency response functions, frequency spectra, and power spectral density and FFT magnitudes. Features derived by time-frequency-domain methods include spectrogram, continuous wavelet transform coefficients, wavelet packet energies and wavelet entropy.Many successful applications demonstrated that different damage scenarios can be uniquely identified by these signal-based features and pattern recognition techniques can enhance the accuracy and efficiency of damage detection.

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