Past, Resent, and Future of Structural Health Assessment

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Abstract Past, present, and future of structural health assessment (SHA) concepts and related areas, as envisioned by the authors, are briefly reviewed in this chapter. The growth in the related areas has been exponential covering several engineering disciplines. After presenting the basic concept, the authors discussed its growth from infancy, that is, hitting something with a hammer and listening to sound, to the use of most recent development of wireless sensors and the associated advanced signal processing algorithms. Available SHA methods are summarized in the first part of this chapter. The works conducted by the research team of the authors are emphasized. Later, some of the future challenges in SHA areas are identified. Since it is a relatively new multidisciplinary area, the education component is also highlighted at the end.

Keywords Structural health assessment • Kalman filter • Substructure • System identification • Uncertainty analysis • Sensors

1 Introduction

The nature and quality of infrastructure have always been one of the indicators of sophistication of a civilization. There is no doubt that we are now at a historical peak. However, keeping the infrastructure at its present level has been a major challenge due to recent financial strain suffered by the global community. We do not have adequate resources to build new infrastructure or replace the aged ones that are over their design lives. The most economical alternative is found to be extending the life of existing infrastructure without compromising our way of living

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and without exposing public to increased risk. This has been one of the major challenges to the engineering profession and attracted multidisciplinary research interests. The main thrust has been to locate defects in structures at the local element level and then repair them or replace the defective elements, instead of replacing the whole structure. Several advanced theoretical concepts required to detect defects have been proposed. At the same time, improved and smart sensing technologies, high-resolution data acquisition systems, digital communications, and high-performance computational technologies have been developed for implementing these concepts. The general area is now commonly known as structural health assessment (SHA) or structural health monitoring (SHM). In spite of these developments in analytical and sensor technologies, the implementations of these concepts in assessing structural health have been limited due to several reasons. An attempt has been made here to identify some of the major works (emphasizing analytical), their merits and demerits, contributions made by the research team of the authors, and future challenges.

2 Concept of Structural Health Assessment

All civil engineering structures, new and old, may not totally satisfy the intents of the designers. Minor temperature cracks in concrete or lack of proper amount of pretension in bolts cannot completely be eliminated. In that sense, all structures can be assessed as defective. Our past experiences indicate that presence of minor defects that do not alter the structural behavior may not be of interest to engineers. Considering only major defects, all of them are not equally important. Their locations, numbers, and severities will affect the structural behavior. Thus, the concept behind SHA can be briefly summarized as locating major defects, their numbers, and severities in a structure at the local element level. For the sake of completeness of this discussion, available SHA procedures are classified into four levels as suggested by Rytter [39]. They are as follows: level 1 – determination if damage is present in a structure, level 2 – determination of geometric location of the damage, level 3 – assessment of severity of the damage, and level 4 – prediction of remaining life of the structure.

3 Structural Health Assessment: Past

Structural health assessment has been practiced for centuries. Ever since pottery was invented, cracks and cavities in them were detected by listening to the sound generated when tapped by fingers. A similar sonic technique was used by blacksmiths to establish the soundness of the metals they were shaping. Even today, it is not uncommon to observe that inspectors assess structural health by hitting structures with a hammer and listening to the sounds they produce. These types of inspections, with various levels of sophistication, can be broadly termed as nondestructive evaluation (NDE) of health of a structure.

3.1 Early Developments in SHA

Although the awareness of the scientific concepts of many NDE technologies began during 1920s, they experienced major growth during and after the Second World War. However, there had been always problems in the flow of NDE research to everyday use [4]. Besides the use of visual testing (VT), early developments of instrument-based nondestructive detection of defects include penetrate testing (PT), magnetic particle testing (MPT), radiographic testing (RT), ultrasonic testing (UT), Eddy current testing (ET), thermal infrared testing (TIR), and acoustic emission testing (AE). Many of them required the damage/irregularity to be exposed to the surface or within small depth from the open surface. Some of them required direct contact of sensors with the test surface [22]. They mainly focussed on the "hot spot" areas or objects readily available for testing. For instance, RT has been routinely used for detection of internal physical imperfections such as voids, cracks, flaws, segregations, porosities, and inclusions in material at selective location(s). Most of these methods are non-model based, that is, the structure need not be mathematically modeled to identify location and severity of defects.

3.2 Transition from Past to Present: New Challenges

For most large civil infrastructure, the location(s), numbers, and severity of defect(s) may not be known in advance, although sometimes they can be anticipated using past experiences. Also, sometimes, defects may be hidden behind obstructions, for example, cracks in steel members hidden behind fire-proofing materials. Thus, instrument-based nondestructive testing (NDT) may not be practical if the inspector does not know what to inspect or the location of defect is not known *a priori*. During 1970s, detection of cracks was a major thrust. Subsequently, determination of crack size in order to compare with the critical crack size added another level of challenge to the engineering profession. In any case, inspection of "hot spot" areas limited their application potential. Subsequently, a consensus started developing about the use of measured responses to assess current structural health, as discussed next.

3.3 Model-Based SHA

Some of the deficiencies in non-model-based approaches can be removed by using model-based techniques. The aim of this approach is to predict the parameters of the assumed mathematical model of a physical system; that is, the system is considered to behave in predetermined manner represented in algorithmic form using the governing differential equations, finite element (FE) discretization, etc.

The changes in the parameters should indicate the presence of defects. To implement the concept, responses need to be measured by exciting the structure statically or dynamically.

3.3.1 SHA Using Static Responses

Because of its simplicity, initially SHA using static responses were attempted. Static responses are generally measured in terms of displacements, rotations, or strains, and the damage detection problems are generally formulated in an optimization framework employing minimization of error between the analytical and measured quantities. They mostly use FE model for structural representation. Three classes of error functions are reported in the literature: displacement equation error function, output error function, and strain output error function [41]. Recently, Bernal [3] proposed flexibility-based damage localization method, denoted as the damage locating vector (DLV) method. The basic approach is the determination of a set of vectors (i.e., the DLVs), which when applied as static forces at the sensor locations, no stress will be induced in the damaged elements. The method can be a promising damage detection tool as it allows locating damages using limited number of sensor responses. It was verified for truss elements, where axial force remains constant through its length. However, the verification of the procedure for real structures using noise-contaminated responses has yet to be completed.

There are several advantages of SHA using static responses including that the amount of data needed to be stored is relatively small and simple, and no assumption on the mass or damping characteristics is required. Thus, less errors and uncertainties are introduced into the model. However, there are several disadvantages including that the number of measurement points should be larger than the number of unknown parameters to assure a proper solution. Civil engineering structures are generally large and complex with extremely high overall stiffness. It may require extremely large static load to obtain measurable deflections. Fixed reference locations are required to measure deflections which might be impractical to implement for bridges, offshore platforms, etc. Also, static response-based methods are sensitive to measurement errors [1, 2].

3.3.2 SHA Using Dynamic Responses

Recent developments in SHA are mostly based on dynamic responses. There are several advantages of this approach. It is possible to excite structures by dynamic loadings of small amplitude relative to static loadings. In some cases, ambient responses caused by natural sources, for example, wind, earthquake, and moving vehicle, can be used. If acceleration responses are measured, they eliminate the need for fixed physical reference locations. They perform well in presence of high measurement errors [14].

Earlier works on SHA using dynamic responses are mostly modal information based [5, 15, 16, 38, 42]. Changes in modal properties, that is, natural frequencies, damping, and mode shape vectors, or properties derived from these quantities are used as damage indicators. Doebling et al. [15] presented various methods for damage identification including methods based on changes in frequency, mode shapes, mode shape curvature, and modal strain energy. Sohn et al. [42] updated the above report and discussed procedures based on damping, antiresonance, Ritz vectors, a family of autoregressive moving average (ARMA) models, canonical variate analysis, nonlinear features, time-frequency analysis, empirical mode decomposition, Hilbert transform, singular value decomposition, wave propagation, autocorrelation functions, etc. More complete information on them can be found in the literature cited above.

Natural frequency-based methods use change in the natural frequency as the primary feature for damage identification. They are generally categorized as forward problem or inverse problem. The forward problems deal with determination of changes in frequency based on location and severity of damage, whereas the inverse problems deal with determination of damage location and size based on natural frequency measurement. Among the mode shape-based procedures for damage detection, the mode shape/curvature methods generally use two approaches: traditional analysis of mode shape or curvature and modern signal processing methods using mode shapes or curvature. Modal strain energy-based procedures consider fractal modal energy for damage detection [16]. Methods based on damping have the advantage that a larger change in damping can be observed due to small cracks. Also, it is possible to trace nonlinear, dissipative effects produced by the cracks. However, damping properties have not been studied as extensively as natural frequencies and mode shapes [42]. Methods based on dynamically measured flexibility detect damages by comparing flexibility matrix synthesized using the modes of damaged structure to that of undamaged structure or flexibility matrix from FE analysis. The flexibility matrix is most sensitive to changes in the lower frequencies [15].

Modal-based approaches have many desirable features. Instead of using enormous amount of data, the modal information can be expressed in countable form in terms of frequencies and mode shape vectors. Since structural global properties are evaluated, there may be an averaging effect, reducing the effect of noise in the measurements. However, the general consensus is that modal-based approaches fail to evaluate the health of individual structural elements; they indicate overall effect, that is, whether the structure is defective or not [18, 26, 37]. For complicated structural systems, the higher-order calculated modes are unreliable, and the minimum numbers of required modes to identify the system parameters is problem dependent, limiting their applicability. The mode shape vectors may be more sensitive to defects than the frequencies, but the fact remains that they will be unable to predict which element(s) caused the changes. It was reported that even when a member breaks, the natural frequency may not change more than 5%. This type of change can be caused by the noises in the measured responses. A time-domain approach will be preferable.

3.3.3 Damages Initiated During Observations

A considerable amount of work also reported is on damages initiation time, commonly known as time-frequency methods for damage identification. The time-frequency localization capability has been applied for damage feature extractions from sudden changes, breakdown points, discontinuity in higher derivatives of responses, etc. They circumvent the modeling difficulty as they do not require the system to be identified, and the health assessment strategy often reduces to the evaluation of symptoms reflecting the presence and nature of defect [6]. Extensive study on short-time Fourier transform (STFT), Wigner-Ville distribution (WVD), pseudo Wigner-Ville distribution (PWVD), Choi-Williams distribution (CWD), wavelet transform (WT), Hilbert transform (HT), and Hilbert-Huang transform (HHT) for analyzing any nonstationary events localized in time domain has been reported in the literature. STFT is an extension of the Fourier transform allowing for the analysis of nonstationary signals by dividing it into small-time windows and analyzing each using the fast Fourier transform (FFT). The formulation provides localization in time as well as capturing frequency information simultaneously. WT has greater flexibility than STFT in terms of choosing different basis functions or mother wavelets. The wavelets have finite duration, and their energy is localized around a point in time. The WVD gives the energy distribution of a signal as a function of time and frequency; however, it has major shortcoming for multicomponent signals in terms of cross-terms. The CWD provides filtered/smoothed version of the WVD by removing the cross-terms [40].

These studies are very interesting, but there is no general consensus about the most suitable technique. Recently, Yadav et al. [48] studied some of the time-frequency procedures for defect characterization in a wave-propagation problem. However, the fundamental limitation of STFT, WVD, PWVD, CWD, and CWT is due to the fact that they are based on Fourier analysis and can accommodate only nonstationary phenomena in the data driven from linear systems; they are not suitable to capture nonlinear distortion. In this context, the HT and HHT are suitable for nonlinear and nonstationary data. Application of Hilbert transform to nonlinear data requires the signal to be decomposed to "mono-component" condition without any smaller, riding waves. The real advantage of HT is implemented in HHT proposed by Huang et al. [25]. The procedure consists of empirical mode decomposition (EMD) and Hilbert spectral analysis (HSA). HHT clearly define nonlinearly deformed waveforms; this definition can be the first indication of the existence of damage [24]. They applied the concept for bridge health monitoring using two criteria: nonlinear characteristics of the intra-wave frequency modulations of the bridge response and frequency downshift as an indication of structural yield. Yang et al. [51] proposed two HHT-based procedures for identifying damage time instances, damage locations, and natural frequencies and damping ratios before and after occurrence of damage.

4 Structural Health Assessment: Present

In an attempt to develop an ideal SHA technique for the rapid assessment of structural health, the research team at the University of Arizona identified several desirable features considering theoretical as well as implementation issues. The team concluded that a system identification (SI)-based approach using measured dynamic response information in time domain will have the most desirable attributes. A basic SI-based approach has three essential components: (a) the excitation force(s); (b) the system to be identified, generally represented by some equations in algorithmic form such as by FEs; and (c) the output response information measured by sensors. Using the excitation and response information, the third component, that is, the system, can be identified. The basic concept is that the dynamic responses will change as the structure degrades. Since the structure is represented by FEs, by tracking the changes in the stiffness parameter of the elements, the location and severity of defects can be established.

For a structure with N dynamic degrees of freedom (DDOF), the dynamic governing equation can be written as

$$\mathbf{M}\ddot{\mathbf{x}}(t) + \mathbf{C}\dot{\mathbf{x}}(t) + \mathbf{K}\mathbf{x}(t) = \mathbf{f}(t) \tag{1}$$

where $\mathbf{K}$, $\mathbf{M}$, and $\mathbf{C}$ are $N \times N$ stiffness, mass, and damping matrix, respectively; $\mathbf{x}(t)$, $\dot{\mathbf{x}}(t)$, $\ddot{\mathbf{x}}(t)$, and $\mathbf{f}(t)$ are $N \times 1$ displacement, velocity, acceleration, and load vector, respectively, at time t. The acceleration time histories at the FE node points are expected to be measured by accelerometers. The velocity and displacement time histories can be generated by successively integrating the acceleration time histories, as suggested by Vo and Haldar [44]. Assuming mass is known, $\mathbf{K}$ matrix at the time of inspection can be evaluated. Using the information on the current elements' stiffness properties and comparing them with the "as built" or expected properties or deviation from the previous values if periodic inspections were conducted**,** the structural health can be assessed.

4.1 General Challenges in Time-Domain SHA

Referring to the SI concept discussed earlier, structural stiffness parameters will be estimated by using information on excitation and measured responses. It is interesting to point out that according to Maybeck [36], deterministic mathematical model and control theories do not appropriately represent the behavior of a physical system, and thus, the SI-based method may not be appropriate for SHA. He correctly pointed out three basic reasons: (a) a mathematical model is incapable of incorporating various sources of uncertainties and thus does not represent true behavior of a system, (b) dynamic systems are driven not only by controlled inputs but also by disturbances that can neither be controlled nor modeled using deterministic formulations, and (c) sensors used for data measurements cannot be perfectly devised to provide complete and perfect data about a system. These concerns and other implementation issues must be addressed before developing a SI-based SHA procedure.

Outside the controlled laboratory environment, measuring input excitation force(s) can be very expensive and problematic during health assessment of an existing structure. In the context of a SI-based approach, it will be desirable if a system can be identified using only measured response information and completely ignoring the excitation information. This task is expected to be challenging since two of the three basic components of SI process will be unknown. Responses, even measured by smart sensors, are expected to be noise contaminated. Depending on the amount of noise, the SI-based approach may be inapplicable. The basic concept also assumes that responses will be available at all DDOFs. For large structural systems, it may be practically impossible or uneconomical to instrument the whole structure; only a part can be instrumented. Thus, the basic challenge is to identify stiffness parameters of a large structural system using limited noise-contaminated response information measured at a small part of the structure. The research team successfully developed such a method in steps, as discussed next.

4.2 SHA Using Responses at All DDOFs

Using noisy responses measured at all DDOFs, Wang and Haldar [46] proposed a procedure, popularly known as iterative least squares with unknown input (ILS-UI). They used viscous damping and verified it for shear buildings. The efficiency of the numerical algorithm was improved later by introducing Rayleigh-type proportional damping, known as modified ILS-UI or MILS-UI [32]. Later, Katkhuda et al. [29] improved the concept further and called it generalized ILS-UI or GILS-UI. All these are least-squares procedures. They were extensively verified using computer-generated response information for shear buildings, two-dimensional trusses, and frames. They added artificially generated white noises in the computer-generated noise-free responses and showed that the methods could assess health of defect-free and defective structures. Recently, the concept has been verified for three-dimensional (3D) structures, denoted as 3D-GILS-UI [11, 12].

For the sake of completeness, other recently proposed least-squares-based SHA procedures need a brief review. Yang et al. [54] proposed a recursive least-squares estimation procedure with unknown inputs (RLSE-UI) for the identification of stiffness, damping, and other nonlinear parameters, and the unmeasured excitations. They implemented an adaptive technique [52] in RLSE-UI to track the variations of structural parameters due to damages. Then, Yang et al. [50, 53] proposed a new data analysis method, denoted as the sequential nonlinear least-square (SNLSE) approach, for the on-line identification of structural parameters. Later, Yang and Huang [49] extended the procedure for unknown excitations and reduce number of sensors (SNLSE-UI-UO). They verified the procedures for simple linear and nonlinear structures. Several other methods based on least squares can be found in Choi et al. [10], Chase et al. [8, 9], and Garrido and Rivero-Angeles [17].

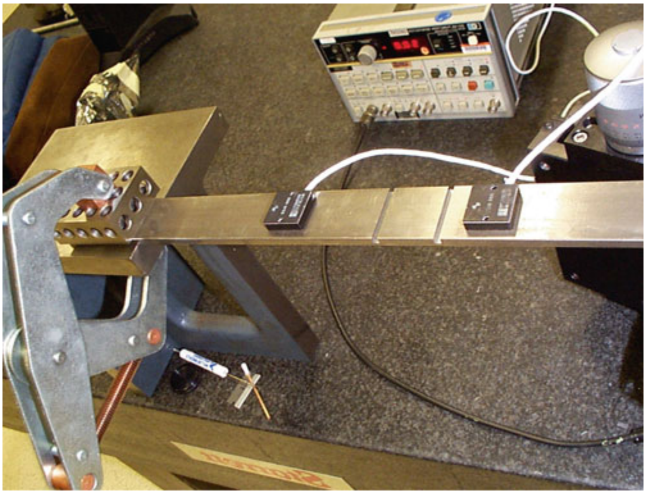

Fig. 1 Laboratory test of defective beams

After analytically establishing the concept that a structure can be identified using only noise-contaminated response information, completely ignoring the excitation information, the research team at the University of Arizona tested a one-dimensional beam [45] and a two-dimensional frame built to one-third scale in the laboratory [34, 35]. The test setups for the two studies are shown in Figs. 1 and 2, respectively. Both studies conclusively confirmed the validity of the basic SI concept without excitation information.

4.3 SHA Using Limited Response Information: Measured at a Small Part of the Structure

It is now established that least-squares concept can be used for SHA without using excitation information, but response information must be available at all DDOFs. This led the team to study cases when response information is available only at a part of the structure. Kalman filter-based algorithm is commonly used when the system is uncertain and the responses are noise-contaminated and not available at all DDOFs.

4.3.1 Kalman Filter

Application of Kalman filter (KF) for assessing health for civil engineering structures is relatively recent. Various forms of Kalman filter can be found in the literature including extended Kalman filter (EKF), unscented Kalman filter (UKF),

Fig. 2 Experimental verification of a scaled 2D frame

particle filter, and ensemble Kalman filter (EnKF). In mathematical sense, the basic KF is a nondeterministic, recursive computational procedure to provide best estimate of the states by minimizing the mean of squared error for a process governed by linear stochastic differential equation expressed as [47]

$$\mathbf{x}(k+1) = \mathbf{F}(k)\mathbf{x}(k) + \mathbf{G}(k)\mathbf{u}(k) + \mathbf{w}(k) \tag{4}$$

with the measurement model of the form:

$$\mathbf{z}(k+1) = \mathbf{H}(k+1)\mathbf{x}(k+1) + \mathbf{v}(k+1) \tag{5}$$

where $\mathbf{x}(k+1)$ and $\mathbf{x}(k)$ are the state vectors at time instant $k + 1$ and k, respectively; vectors $\mathbf{w}(k)$ and $\mathbf{v}(k)$ represent the process and measurement noises, respectively; $\mathbf{F}(k)$ relates the two state vectors in absence of either a driving function or process noise; $\mathbf{G}(k)$ relates the optimal control input $\mathbf{u}(k)$ to the state; and $\mathbf{H}(k + 1)$ in the measurement model relates the state vector to the measurement vector $\mathbf{z}(k + 1)$. $\mathbf{w}(k)$ and $\mathbf{v}(k)$ are considered to be independent, zero-mean, white random vectors with normal probability distributions. Kalman filter is very powerful in several ways. It incorporates the (1) knowledge of the system, (2) statistical description of the system noises, measurement errors and uncertainty in the dynamic models, and (3) any available information on the initial conditions of the variables of interest [36].

The basic KF is essentially applicable for linear structural behavior. For SHA of civil engineering structures, the behavior may not be linear. Moderate to high level of excitation may force the structure to behave nonlinearly. Presence of defects may also cause nonlinearity, even when the excitation is at the low level. This leads to the development of the extended Kalman filter (EKF) concept. For EKF, Eq. (4) is expressed in the following form [47]:

$$\mathbf{x}(k+1) = f[\mathbf{x}(k), \mathbf{u}(k), \mathbf{w}(k)] \tag{6}$$

and the measurement equation, Eq. (5), is modified as

$$\mathbf{z}(k+1) = h[\mathbf{x}(k+1), \mathbf{v}(k+1)] \tag{7}$$

where nonlinear function f relates the states at time k to the current states at time $k + 1$, and it includes the state vector $\mathbf{x}(k)$, driving force $\mathbf{u}(k)$, and process noise $\mathbf{w}(k)$. The nonlinear function h relates the state vector $\mathbf{x}(k + 1)$ to the measurement vector $\mathbf{z}(k + 1)$. Again, $\mathbf{w}(k)$ and $\mathbf{v}(k)$ are the independent, zero-mean, white random vectors with normal distribution, representing the process and measurement noises, respectively. The EKF estimates the state by linearizing the process and measurement equations about the current states and covariances. KF or EKF attempts to predict responses and the model parameters and then updates them at each time point using current measurements. The procedure involving prediction and updating at each time point is generally known as *local iteration*. Completion of local iteration processes covering all time instances in the entire time-history of responses is generally known as first *global iteration*. The global iterations need to be repeated to satisfy the preselected convergence criterion of system parameters. Hoshiya and Saito [23] proposed a weighted global iteration (WGI) procedure with an objective function after the first global iteration to obtain convergence in an efficient way. The entire procedure is denoted as EKF-WGI. Recently, several researchers have improved computational aspects of EKF-WGI [14]. Koh and See [31] proposed an adaptive EKF (AEKF) to estimate both the parameter values and associated uncertainties in the identification. Yang et al. [50, 53] proposed an adaptive tracking technique based on EKF to identify structural parameters and their variation during damage events. Ghosh et al. [19] developed two novel forms of EKF-based parameter identification techniques; these are based on variants of the derivative-free locally transversal linearization (LTL) and multistep transverse linearization (MTrL) procedures. Liu et al. [33] proposed multiple model adaptive estimators (MMAE) that consist of bank of EKF designed in the modal domain (MOKF) and incorporated fuzzy logic-based block in EKF to estimate variance of measurement noise.

When KF or EKF is used to identify a structure using dynamic response information satisfying the governing equation represented by Eq. (1), it requires that the excitation information and the initial values of unknown state vector. As mentioned earlier, to improve implementation potential, the proposed approach needs to identify a structure without using excitation information, and the information on the state vector will be available only at the completion of the identification, not at the beginning. The discussions clearly indicate that the basic KF or EKF cannot be used to identify a structure. To overcome these challenges, the research team proposed a two-stage approach by combining GILS-UI and EKF-WGI procedures. Based on the available measured responses, a substructure can be selected that will satisfy all the requirements to implement the GILS-UI procedure in stage 1. At the completion of stage 1, the information on the unknown excitation and the damping and stiffness parameters of all the elements in the substructure will be available. The identified damping can be assumed to be applicable for the whole structure. Structural members in a structure are expected to have similar cross-sectional properties. Suppose the substructure consists of one beam and one column. The identified stiffness parameters of the beam in the substructure can be assigned to all the beams in the structure. Similarly, the identified stiffness parameters of the column can be assigned to all the columns. This will give information on the initial state vector. With the information on initial state vector and excitation information, the EKF-WGI procedure can be initiated to identify the whole structure in stage 2. This novel concept was developed in stages; they are known as ILS-EKF-UI [47], MILS-EKF-UI [32], and GILS-EKF-UI [28]. These procedures were successfully verified using analytically generated responses, primarily for two-dimensional structures [21, 27]. Martinez-Flores et al. [35] then successfully verified GILS-EKF-UI in the laboratory for a two-dimensional frame shown in Fig. 2. They considered defect-free and several defective states with different levels of severities, including broken members, loss of cross-sectional area over the entire length of members, loss of area over small length of a member, and presence of one or multiple cracks in a member; Das and Haldar [13] recently extended the method to assess structural health for 3D structures.

5 Future of Structural Health Assessment

Future directions of the SHA area, as foreseen by the authors, are presented in the following sections. In the previous sections, the authors emphasized analytical concepts used for SHA and their contributions. In developing their methods, they observed many challenges yet to be resolved. Some issues are related to explicit consideration of uncertainty in describing the system and noises in the measured responses. Selection of initial state vector for large structure is also expected to be challenging. Although EKF can be used in presence of nonlinearity, the threshold nonlinearity is not known, that is, when it will fail to identify a structure. The methods proposed by the authors can identify structures with less information, but the absolute minimum number of required responses for acceptable identification needs further study. Issues related to the stability, convergence, and acceptable error in prediction need further works. Although the information of excitation is not required, characteristics of excitations need some attentions.

At the beginning of this chapter, the authors mentioned that SHA is a multidisciplinary research area. This chapter will not be complete without the discussions on sensors, intelligent sensing technologies and signal processing, next generation structural health monitoring strategies, etc. Since SHA is a relatively new area and not covered in the existing curriculum of major branches of engineering, it is necessary to emphasize education aspect of SHA. The authors are not expert in some of these areas; however, they expect that the discussions will prompt future engineers to explore them. The first author is in the process of editing a book with contributions from experts covering all these areas [20].

5.1 Transition from Present to Future: Local Level SHA Using Global Responses

SHA procedures are developed generally assuming that measured responses will be altered in presence of defects. Obviously, minor defects may not alter the responses and thus cannot be detected. A structure is expected to be inspected several times during its lifetime. Minor defects such as initiation and development of cracks and corrosion of reinforcements in concrete are expected to grow over time. The basic assumption is that when they become major, they will be detected during the periodic inspections. Environmental influences on structural behavior, for example, effect of temperature on measured responses, are not completely understood at this time. Similar comments can be made for exposure to chemicals or high-pressure gradients. Smart sensors are now being developed to detect damage for various applications. Not all sensors are equally sensitive, and noises in the measurements cannot be avoided. Depending upon to noise to signal ratios, the output of a sensor can be misleading. The discussions clearly indicate that besides analytical developments, industrial research is also going to be critical in implementing a particular health assessment strategy. Hopefully, advances in technologies, digital computing, and data processing will remove some of these hurdles.

5.2 SHA in Presence of Nonlinearity

One major assumption in most SI-based SHA procedures is that the responses are linear or mildly nonlinear. Major nonlinearities are not expected to show up in the responses during ambient excitation or when the level of excitation is relatively small. However, in real situations, the nonlinearity in the responses cannot be avoided. To understand and develop robust mathematical model of the dynamical system, the distinct effects of nonlinearities must be realistically accounted for. At the same time, it will be important to use the available resources in a very systematic manner for successful implementation of the SHA procedures. To identify a highly nonlinear structure, it is important first to identify the level of nonlinearity and establish whether available methods are appropriate or not.

Next, it will be important to determine the location, type, and form of nonlinearity and how to model them in the optimum way. Another important task will be the selection of parameters/coefficients that need to be tracked for damage assessment. The area of nonlinear system identification is still in its infancy. An extensive discussion on the related areas and future directions in nonlinear SI is discussed by Kerschen et al. [30].

5.3 Intelligent Sensing Technologies and Signal Processing

Development of new sensor technologies for various applications is expanding in an exponential scale. Use of smart wireless sensors is becoming very common. The placements of sensors, density, sources of power for their operation, calibration for maintaining them in good operating condition, acquisition of signals, advanced signal processing algorithms considering increased signal-to-noise ratio, well-developed numerical procedure for post-processing of signal, integration of software and hardware, realistic mathematical model for structures and their components, etc., are being actively studied by various researchers. Smart sensors are wireless and equipped with on-board microprocessors; they are small in size and can be procured at a lower cost. However, there are several hardware aspects such as efficient data acquisition, synchronization, limited memory, encryption and secured data transmission, and limited bandwidth that need further attention. They should be operational throughout the life of the structure, if continuous-time SHA is performed [7]. It is expected that distributed computational framework and use of agents-based architecture will expand the possibility of intelligent infrastructure maintenance in future [43].

5.4 Next Generation Structural Health Monitoring Strategy

Structural systems always change due to inevitable deterioration processes. Assessment of current state of a structure cannot be complete without taking into account the uncertainties at every step of the assessment process. Even ignoring uncertainties, monitoring a structure continuously throughout its life may not be an optimum use of available resources. Next generation structural health monitoring research needs to be performance based. Using information from the most recent assessment, mathematical model to represent the structure, placement of sensors, data collection, and interpretation methods need to be modified or updated. The integration of past and present information on structural health needs to be carried out for the cost-efficient assessment. Risk-based nondestructive evaluation concept is expected to optimize the frequency of inspection.

5.5 SHA Curriculum in Education

The authors sincerely hope that the previous discussions provided a flavor of multidisciplinary nature of SHA areas. Both authors are civil engineers. Their formal education in civil engineering did not train them to undertake the research discussed here. Most engineering colleges do not offer courses related to SHA. NDE mostly belongs to mechanical engineering, whereas sensors and signal processing belong to electrical engineering. So far, the SHA/SHM education for professional engineers is limited to web-based resources or short course modules. Recently, several universities in Europe are collaboratively offering an Advanced Master's in Structural Analysis of Monuments and Historical Constructions (SAMHC) funded by the European Commission. In the USA, University of California, San Diego, has started M.S. program with specialization in SHM.

There is no doubt that the SHA/SHM areas will grow exponentially in near future all over the world. Trained engineers will be essential to carry out the necessary works. A severe shortage of trained professionals is expected. It will be highly desirable if we introduce a multidisciplinary engineering discipline in SHA/SHM by integrating civil, electrical, material, and mechanical engineering departments.

6 Conclusions

Structural health assessment has become an important research topic and attracted multidisciplinary research interests. Its growth has been exponential in the recent past. Past and present developments in the related areas are briefly reviewed in this chapter. Because of their academic background, the authors emphasized the structural health assessment for civil infrastructures. Some of the future challenges are also identified. Advancements in sensor technology and signal processing techniques are also reviewed briefly. An upcoming edited book on the subject by the first author is expected to provide more information on the related areas. Because of the newness of the area, there is a major gap in current engineering curriculum. In the near future, a severe shortage is expected for experts with proper training in SHA/SHM. The authors advocate for a new multidisciplinary engineering discipline in SHA/SHM by integrating, civil, electrical, material, and mechanical engineering departments.

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