2015 IEEE Symposium Series on Computational Intelligence

Computational Intelligence for Structural Identifications

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***Abstract*— Structural health assessment using the structural identification concept using measured dynamic response information in time domain was considered to be not possible in the late seventies. With the help of comprehensive analytical and laboratory investigations, the research team at the University of Arizona conclusively documented that the above statement is not correct. In fact, they showed that the concept has several advantages over other available methods. Considering the implementation potential, the concept appeared to be very desirable. The team proposed several intelligent schemes to address many challenges. They used mathematical concepts used in other disciplines, extensively modified them and proposed few novel concepts. Some of them are briefly presented in this paper and their novelties are described with the help of several informative examples. The concepts presented in the paper cross the disciplinary boundaries and showcase benefits of computational intelligence.**

I. INTRODUCTION

Structural health assessment (SHA) using structural identification (SI) technique has recently become an important research item. In 1979, Maybeck [1] concluded that the SI-based concept cannot be used for SHA using measured response information. There are several reasons for his comments including: (i) no mathematical model to represent a system is perfect, (ii) dynamic systems are not only driven by control inputs, but there are always disturbances that cannot be controlled and modeled deterministically, and (iii) responses observed by sensors do not exhibit the actual perfect system responses, since sensors always introduce their own system dynamics and distortion into measured data. The authors and their team members had to overcome several challenges and proposed several computational intelligence schemes and documented that SI is an ideal option to assess structural health at the local element level. Some of these intelligent schemes are presented in this paper.

Structural identification has three essential components: (1) excitation information, (2) the system to be identified, which can be represented by a series of equations or represented in algorithmic form, e.g., in a finite element (FE) formulation in terms of mass, stiffness, and damping characteristics of each element, and (3) response information. Using input excitation and output response information, the dynamic properties of all the elements can be evaluated using the inverse SI algorithm. Using the information on the identified element properties, it will be straightforward to evaluate the amount or rate of degradation of a particular element with respect to the “as built” or expected properties, or the changes from the previous values if periodic inspections are used or deviations from other similar structural elements for the health assessment purpose.

The SI-based concept appears to be simple. However, to increase its implementation potential, several advanced computational techniques need to be used. It is to be noted that the SI concept has evolved over time from non-model based visual inspections to model-based using static and dynamic response measurements. The most desirable outcomes of an inspection are locating defects at the local element level, their number and severity. To obtain such information, it will be advantageous to represent the structure by finite elements. By tracking the changes in the stiffness properties of all the elements as they age or after a natural and man-made event, the health of a structure can be assessed. Most recently, measured time-domain response information instead of modal properties has attracted a considerable amount of attention and it is emphasized in this paper.

II. CHALLENGES IN SI FOR SHA

A. *Measurement of input excitations*

One of the challenges in implementing the SI concept using time-domain response information is measuring the input excitation. Outside the control laboratory environment, the measurements of excitation information could be very expensive and so error-prone that the SI concept may not be applicable as observed by Maybeck [1]; thus SHA without excitation information will be very desirable. The team initially proposed a procedure, known as Iterative Least-Squares with Unknown Input (ILS-UI) [2]. They used viscous-type structural damping. The efficiency of the numerical algorithm was improved later by introducing Rayleigh-type proportional damping, known as Modified ILS-UI or MILS-UI [3]. Katkhuda et al. [4] improved the concept further and called it Generalized ILS-UI or GILS-UI. Later, Das and Haldar [5] extended the procedure for three dimensional (3D) large structural systems and denoted as 3D GILS-UI.

This study is based on work partly supported by the Iraq’s Ministry of Higher Education and Scientific Research and National Science Foundation under Grant No. CMMI-1403844.

978-1-4799-7560-0/15 $31.00 © 2015 IEEE
DOI 10.1109/SSCI.2015.257

B. Measurement of responses- limited numbers; noise-contamination

The use of Least Squares (LS)-based approach implies that response information must be available at all dynamic degrees of freedoms (DDOFs). For large structural systems, it may not be practical or economical to measure response time histories at all DDOFs. Considering accessibility and other practical issues, only a part of the structure can be instrumented and responses will be measured at a limited number of DDOFs. Thus, considering the implementation potential, the structural health needs to be assessed using only limited number of measured responses in time domain. The research team used accelerometers capable of measuring acceleration time histories at high sampling rates, about 4,000 Hz. Since voltage fluctuations are used to measure acceleration time histories, they are expected to be noise-contaminated with unknown magnitude. To summarize the challenges in SHA for implementing SI discussed so far are the availability of only limited number of measured noise-contaminated responses without using any information on excitation.

C. Computational tools and their limitations

When measured responses are limited and noise-contaminated, generally Kalman filter (KF)-based concept is used. Kalman filter [6, 7] is a set of mathematical equations that provides efficient computational means in a recursive manner to estimate the state of a process, in a way that minimizes the mean of squared error, and calculates the best estimate of states from the noisy sensor responses [8, 9]. It is a time domain filter and is very powerful in several aspects. One of its limitations is that it is applicable for linear systems. For nonlinear SI, extended Kalman filter (EKF) is the most widely used. It extends the linear Kalman filter to handle nonlinear systems based on a first-order linearization of the nonlinear statistical distributions of the variables.

D. Implementation of EKF for SHA

The implementation of EKF concept for SHA may not be simple. The research team proposed several computational intelligent schemes as briefly discussed below. To implement the EKF concept for SHA, the excitation force vector and the initial state vector must be known. The first requirement invalidates the basic intent of SI without input excitation information. To address this challenge, the research team proposed to integrate EKF with the ILS-UI-based concept developed earlier [10]. It will require a two-stage approach. In stage 1, based on the location of excitation and measured response information, a substructure needs to be defined. Then, using the ILS-UI-based algorithm, the stiffness parameters of all the elements in the substructure, the time-history of the unknown excitation and damping information can be extracted. The information on the stiffness parameters of elements in the substructure can be judicially used to generate information on the initial state vector for the whole structure. Thus, both requirements for implementing EKF are now can be satisfied. The concept was initially denoted as ILS-EKF-UI [10]. Later, it was improved and denoted as Modified ILS-EKF-UI or MILS-EKF-UI [11], Generalized ILS-EKF-UI or GILS-EKF-UI [12], and three dimensional GILS-EKF-UI or 3D GILS-EKF-UI [13]. The concept was conclusively verified by conducting extensive analytical and laboratory investigations [14, 15].

E. Nonlinearity in identification

During an inspection, the intensity of dynamic loading is expected to be very low to avoid further damage. In some situations, the defective structure may behave linearly. However, in the presence of major defects, it may not behave linearly. In general, most structural identification problems are nonlinear. This is due to the fact that the identification of the unknown parameters jointly with dynamic responses is a nonlinear identification problem even if the structural system is linear. In other words, the state vector of the system, which needs to be identified, includes system parameters and nonlinear responses and this makes the structural system identification nonlinear. The influence of nonlinearity becomes more severe in the presence of defects. Since the level of severity of defect is unknown at the time of inspection, nonlinear SI-based approach needs to be used.

Although the EKF has been successfully used to assess structural health in many applications, the authors observed that it failed to identify a structure in the presence of high nonlinearity. EKF operates by approximating the state distribution as a Gaussian random variable (GRV) and then propagate it through the first-order linearization for the nonlinear system [16]. The EKF-based approach provides only an approximation to the optimal nonlinear filter due to the truncation of the higher-order terms when linearizing the system. In practice, EKF suffers two well-known drawbacks. First, the derivation of the Jacobian matrices required to implement the filter is nontrivial in most applications and often lead to significant difficulties. Second, the filter can be unstable if the sampling interval or time between two samples is not sufficiently small. There are a threshold of nonlinearities when EKF may not be able to identify a system for SHA. An alternative to EKF is unscented Kalman filter (UKF). UKF was developed with the underlying assumption that approximating a Gaussian distribution is easier than approximating an arbitrary nonlinear transformation [17]. UKF uses deterministic sampling (or so called sigma points) to approximate the state distribution as a GRV. The sigma points are chosen to capture the true mean and covariance of the state distribution. They are propagated through the nonlinear system. The posterior mean and covariance are then calculated from the propagated sigma points. UKF determines the mean and covariance accurately to the second order, while EKF is only able to obtain the first-order accuracy [16]. Therefore, UKF provides better state estimates for nonlinear systems.

F. Implementation of UKF for SHA

The UKF method is a powerful nonlinear estimation technique. However, its applications for SHA are limited to simple and small structural systems [18-21]. It was applied to identify structural system, represented by a shear-type building with a relatively small number of DDOFs and it was not used for structural damage detection. The input excitation is considered to be known and response time histories (acceleration, velocity, or displacement) with relatively long duration were assumed to be available at all DDOFs. Long duration may not be very desirable for SI, since there is a potential for contamination from other sources of excitation. One global iteration was used for the structural identification. The authors [22] also observed that the traditional UKF procedure may not be able to identify large structural systems. These deficiencies prompted the authors to introduce several intelligent computation schemes to improve the UKF algorithm in order to widen its application potential.

The authors [22-24] proposed to use very short duration (fraction of a second) response time histories measured at a very high sampling rates to avoid cross-contamination. However, the algorithm may not converge in most cases; it will require several global iterations not used in UKF. The authors introduced a weighted global iteration (WGI) procedure with an objective function [25] into the UKF algorithm to obtain stable and convergent solutions to identify large structural systems. They proposed to integrate UKF with ILS-UI in order to identify the structure without using excitation information. The procedure is known as unscented Kalman filter with unknown input and weighted global iteration (UKF-UI-WGI).

III. Brief Mathematical concept of UKF-UI-WGI

A. *Implementation stategy of UKF-UI-WGI*

Before presenting the UKF-UI-WGI concept, it may be informative to discuss how it can be implemented for assessing health of real existing structures. Very complicated structural systems will be represented by finite elements. Based on the input excitation information, a substructure will be identified. Assuming the mass is known, the stiffness and damping parameters of all the elements in the substructure will be identified using only limited number of noise-contaminated acceleration response time histories measured at the substructure in stage 1 [2]. Then, the stiffness parameters of all the elements in the structure will be identified in stage 2 using the two-stage UKF-UI-WGI procedure. By tracking changes in the stiffness parameters from the previous, expected or design values or by comparing with other similar elements, the location(s) and the severity of the defects are established.

B. *Stage 1 - Identification of substructure*

A substructure is a small part of a structure that satisfies all the requirements to implement the ILS-UI procedure. Based on the location of input excitation(s) and the available measured response information, substructure(s) are selected, as discussed in [12]. The size of the substructure should be kept to a minimum for economic reason. The defect predictability improves significantly when the defect is located close to the substructure. Using the ILS-UI procedure, the stiffness and damping parameters of all the elements in the substructure can be identified. Information on the time history of input excitation(s) that caused the responses will also be generated [2]. The generated information is then used to implement the UKF-based procedure in stage 2.

C. *Stage 2 – Identification of whole structure*

The identified stiffness parameters of the substructure can be judiciously used to develop the initial state vector of stiffness parameters for the whole frame since they are expected to be similar. The excitation information is also known at this stage. Thus, in stage 2, the health of the whole frame can be assessed using only limited number of noise-contaminated responses using the UKF-UI-WGI procedure.

D. *Mathmatical formulations*

Mathematical formulations of the two stages are discussed very briefly below.

E. *Mathematics of ILS-UI - stage 1*

The governing differential equation of motion using Rayleigh damping for the substructure can be expressed as:

$$\mathbf{M}_{sub}\ddot{\mathbf{X}}_{sub}(t) + (\alpha\mathbf{M}_{sub} + \beta\mathbf{K}_{sub})\dot{\mathbf{X}}_{sub}(t) + \mathbf{K}_{sub}\mathbf{X}_{sub}(t) = \mathbf{f}_{sub}(t) \quad (1)$$

where $\mathbf{M}_{sub}$ is the global mass matrix, generally considered to be known; $\mathbf{K}_{sub}$ is the global stiffness matrix; $\ddot{\mathbf{X}}_{sub}(t)$, $\dot{\mathbf{X}}_{sub}(t)$, and $\mathbf{X}_{sub}(t)$ are the vectors containing the acceleration, velocity, and displacement, respectively, at time t; $\mathbf{f}_{sub}(t)$ is the input excitation vector at time t; and α and β are the mass and stiffness proportional Rayleigh damping coefficients, respectively. The subscript 'sub' is used to denote substructure.

The global mass and stiffness matrix can be formulated using standard procedure [26]. The stiffness parameter for the i^{th} elemnt, k_i is defined as E_iI_i/L_i, where L_i , I_i and E_i are the length, moment of inertia, and modulus of elasticity, respectively. The **P** vector contains all the unknown parameters and can be defined as:

$$\mathbf{P} = \left[k_1\, k_2 \cdots k_{nesub}\ \beta k_1\ \beta k_2 \cdots \beta k_{nesub}\ \alpha\right]^T \quad (2)$$

where *nesub* is the total number of elements in the substructure.

Using the least squares concept, the unknown system parameter vector **P** can be estimated as [2]:

$$\mathbf{P} = \left(\mathbf{A}^T\mathbf{A}\right)^{-1}\mathbf{A}^T\mathbf{F} \quad (3)$$

where **A** matrix contains the measured displacement and velocity responses at time point t; **F** vector contains the unknown input excitations and the inertia forces at time point t; and the responses are measured at equal interval of Δt for q time points. Since the input excitation $\mathbf{f}_{sub}$ is unknown, the force vector **F** in (3) is partially known and the iteration process cannot be initiated. To start the iteration process, the excitation information can be initially assumed to be zero for all the time points as discussed in [4]. The iteration process is continued until the excitation time history converges at all time points, considering two successive iterations, with a predetermined tolerance level, which is set to be 10^{-8} in this study.

It is important to note that only acceleration time histories will be measured during an inspection. However, velocity and displacement time histories are necessary to implement the concept. The acceleration time histories can be successively integrated to generate the velocity and displacement time histories as discussed in more details in [27-29].

F. Mathematics of EKF and UKF- stage 2

In order to implement the EKF or UKF-based procedure, it is necessary to describe the dynamic system by a set of nonlinear differential equations. In the absence of any process noise, it can be expressed in a continuous state vector equation as:

$$\dot{\mathbf{X}}_t = f\left(\mathbf{X}_t, t\right) \tag{4}$$

The discrete time measurements with additive noise at $t = k\Delta t$ can be expressed as:

$$\mathbf{Y}_k = h(\mathbf{X}_k, \mathrm{t}) + \mathbf{V}_k \tag{5}$$

where $\mathbf{X}_t$ is the state vector at time t; $\dot{\mathbf{X}}_t$ is the derivative of the state vector with respect to time t; f is a nonlinear function of the state; $\mathbf{X}_k$ is the state vector at $t = k\Delta t$; Δt is the constant time increment; $\mathbf{Y}_k$ is the measurement vector at $t = k\Delta t$; $\mathbf{V}_k$ is a measurement noise vector of zero mean white noise Gaussian processes with covariance matrix $\mathbf{R}_k$.

To implement these concepts, the acceleration time histories will be measured in the substructure(s). Then the acceleration time histories will be successively integrated to obtain the velocity and displacement time histories. This discrete time measurement model can be expressed in a linear form as:

$$\mathbf{Y}_k = \mathbf{H}\mathbf{X}_k + \mathbf{V}_k \tag{6}$$

where $\mathbf{Y}_k$ is the measurement vector; $\mathbf{H}$ is the measurement matrix.

To implement the filtering process, the initial values of the state vector are necessary. The initial stiffness parameters are generated from the information obtained from stage 1. The initial state vector is assumed to be Gaussian random variable. The next step is to find its mean and covariance at time step (k+1). It is important to note that the corrections of predicted values based on available measurements, i.e., the updating step are the same for both EKF and UKF methods.

1) Mathematics of EKF

The EKF procedure consists of two steps:

a) Prediction step

Predict the state mean vector and its covariance by linearizing the nonlinear dynamic equation as:

$$\hat{\mathbf{X}}_{k+1|k} = \hat{\mathbf{X}}_{k|k} + \int_{k\Delta t}^{(k+1)\Delta t} f(\hat{\mathbf{X}}_{t|k}, t)\,dt \tag{7}$$

and

$$\mathbf{P}_{k+1|k} = \mathbf{\Phi}_{k+1|k}\mathbf{P}_{k|k}\mathbf{\Phi}_{k+1|k}^{\mathrm{T}} \tag{8}$$

where $\mathbf{\Phi}_{k+1|k}$ is the state transition matrix of the system and denoting $\mathbf{I}$ is a unit matrix, it can be written in an approximate form as:

$$\mathbf{\Phi}_{k+1|k} = \mathbf{I} + \Delta \mathrm{t}\left[\frac{\partial \mathrm{f}(\mathbf{X}(\mathrm{t}), \mathrm{t})}{\partial \mathrm{X}(\mathrm{t})}\right]_{\mathbf{X}(\mathrm{t}) = \hat{\mathbf{X}}_{k|k}} \tag{9}$$

The predicted measurement vector is determined as:

$$\mathbf{Y}_{k+1|k} = \mathbf{H}\hat{\mathbf{X}}_{k+1|k} \tag{10}$$

and its error covariance matrix is

$$\mathbf{P}_{k+1}^{YY} = \mathbf{H}\mathbf{P}_{k+1|k}\mathbf{H}^T + \mathbf{R} \tag{11}$$

and the cross correlation matrix is estimated as:

$$\mathbf{P}_{k+1}^{XY} = \mathbf{P}_{k+1|k}\mathbf{H}^T \tag{12}$$

b) Updating step

Since observations are available at time $k+1$, the state vector and the error covariance are updated as follows:

$$\mathbf{K}_{k+1} = \mathbf{P}_{k+1}^{XY}(\mathbf{P}_{k+1}^{YY})^{-1} \tag{13}$$

where $\mathbf{K}_{k+1}$ is the Kalman gain matrix

The updated state mean vector and error covariance matrix are:

$$\hat{\mathbf{X}}_{k+1|k+1} = \hat{\mathbf{X}}_{k+1|k} + \mathbf{K}_{k+1}\left(\mathbf{Y}_{k+1} - \mathbf{Y}_{k+1|k}\right) \tag{14}$$

$$\mathbf{P}_{k+1|k+1} = \mathbf{P}_{k+1|k} - \mathbf{K}_{k+1}\mathbf{P}_{k+1}^{YY}\mathbf{K}_{k+1}^T \tag{15}$$

2) Mathematics of UKF

The UKF procedure consists of three steps:

a) Sigma point calculation step

Sets of 2n+1 sampling points or so-called sigma points are generated around the current state vector based on its covariance as:

$$\boldsymbol{\chi}_0 = \hat{\mathbf{X}}_k \tag{16}$$

$$\boldsymbol{\chi}_i = \hat{\mathbf{X}}_k + \sqrt{(\lambda+n)}\mathbf{A}_{col.i} \qquad i = 1,\ldots,n \tag{17}$$

$$\boldsymbol{\chi}_{i+n} = \hat{\mathbf{X}}_k - \sqrt{(\lambda+n)}\mathbf{A}_{col.i} \qquad i = 1,\ldots,n \tag{18}$$

where

$$\lambda = \alpha^2 (n+\kappa) - n \tag{19}$$

$\mathbf{A}$ is a square root of the covariance matrix such that $\mathbf{P}_k = \mathbf{A}\mathbf{A}^\mathbf{T}$. $\mathbf{A}_{col,i}$ is the ith column of $\mathbf{A}$'s matrix and n is the dimension of the state vector. α and κ are scaling parameters.

b) Prediction step

Transform the sigma points through the nonlinear dynamic equation as:

$$\chi_{i,k+1|k} = \boldsymbol{\chi}_{i,k|k} + \int_{k\Delta t}^{(k+1)\Delta t} f\left(\mathbf{X}(t),t\right) dt \qquad i = 1,\ldots,n \tag{20}$$

The predicted state mean vector and error covariance matrix are:

$$\hat{\mathbf{X}}_{k+1|k} = \sum_{i=0}^{2n} W_i \chi_{i,k+1|k} \tag{21}$$

$$\mathbf{P}_{k+1|k} = \sum_{i=0}^{2n} W_i \left(\chi_{i,k+1|k} - \hat{\mathbf{X}}_{k+1|k}\right)\left(\chi_{i,k+1|k} - \hat{\mathbf{X}}_{k+1|k}\right)^T + \left(1-\alpha^2+\beta\right)\left(\chi_0 - \hat{\mathbf{X}}_{k+1|k}\right)\left(\chi_0 - \hat{\mathbf{X}}_{k+1|k}\right)^T \tag{22}$$

where β is a parameter added to the weight on the zeroth sigma point of the calculation of the covariance. W_i is the weight given by:

$$W_0 = \frac{\lambda}{\lambda+n} \tag{23}$$

$$W_i = \frac{1}{2(\lambda+n)} \qquad i = 1,\ldots,n \tag{24}$$

Since the measurement model is linear, KF will be used instead of using the sigma points to compute the predicted measurement, its error covariance and cross correlation matrix. i.e. (10) to (12) can be used.

Once the process model and measurement of the EKF or UKF is set up, prediction and correction are performed at each time point. The correction is performed with the help of Kalman gain operated on the discrepancy between the predicted and measured values of the variables. Prediction and updating operations performed at each time point is generally known as local iteration. Completion of local iterations covering all time points in the entire time-history of responses is known as first global iteration. A weighted global iteration procedure with an objective function is incorporated after the first global iteration to obtain convergence in an efficient way. The weight factor along with the initial covariance matrix may accelerate the EKF and UKF procedures; however, in some cases the stability might be sacrificed to some extent. The weight factor leads to great fluctuation of the state in the initial stage due to the amplification of the initial covariance. The weight plays an important role in accelerating the convergence process [22].

IV. Illustrative Example

Suppose, a nonlinear function $y = x^4$ and x is a Gaussian random variable with a mean of 2.5 and a standard deviation of 0.3. The true mean and variance of y along with values obtained by UKF and EKF are shown in Table I.

The propagations of uncertainties using UKF and EKF are shown in Fig. 1. It can be observed that the UKF approximates the propagation of the uncertainty in terms of the probability density function in the presence of large nonlinearity more accurately than the EKF, as discussed in more detail in [23,30].

V. Verifications of Computational Schemes for SHA

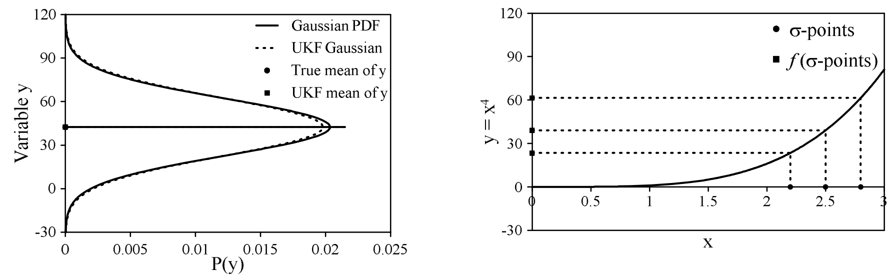
The intelligent aspects of several computational schemes presented in this paper need verification. As mentioned earlier, the team conducted extensive analytical and experimental investigations to validate some of the concepts. The authors used experience gained from the previous studies to highlight some of the intelligent computational schemes using analytical response information in this paper.

A. Description of the structure

A two-dimensional frame with a bay width of 9.14 m and story height of 3.66 m, as shown in Fig. 2, is considered. The frame has a total of 15 members; 5 beams and 10 columns. The beams and columns are made of W21×68 and W14×61 sections, respectively, of Grade 50 steel. The frame is modeled by 12 nodes in the FE representation. Each node has three DDOFs; two translational and one rotational. The support condition at the base (nodes 11 and 12) of the frame is considered to be fixed. The total number of DDOFs for the frame is 30. The actual theoretical stiffness parameter values k_i evaluated in terms of $(E_i I_i/L_i)$ are calculated to be 13,476 kN-m and 14,552 kN-m for a typical beam and column, respectively.

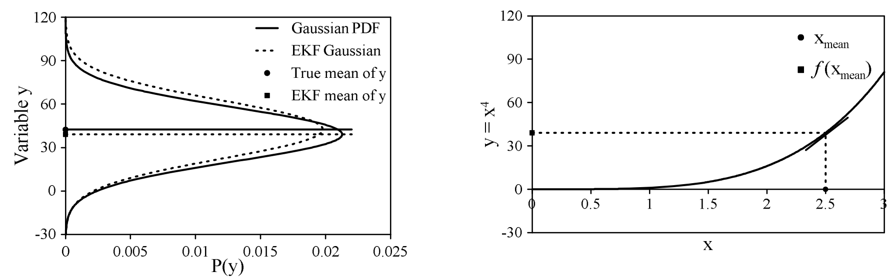
TABLE I. Comparison between True and Predicted Mean and Variance

	True	UKF	EKF
Mean of y	42.46	42.45	39.06
Variance of y	406.47	384.65	351.56



(i) Gaussian probability distribution function of *y*　　(ii) Function relationship

(a) Propagation of uncertainty using UKF



(i) Gaussian probability distribution function of *y*　　(ii) Function relationship

(b) Propagation of uncertainty using EKF

Fig. 1. Propagation of uncertainties using UKF and EKF.

First two natural frequencies of the defect-free frame are estimated to be f_1 = 3.6973 Hz and f_2 = 11.715 Hz, respectively. Following the procedure described in Clough and Penzien [31], Rayleigh damping coefficient α and β are calculated to be 1.0594748 and 0.000619589, respectively, for an equivalent modal damping of 3% of the critical for the first two modes. The frame is excited by two forces; a sinusoidal load, f(t) = 8 sin(20 t) kN, is applied at node 1 and a triangular impulsive load is applied at node 3, as shown in Fig. 3.

The information on responses are numerically generated at 0.00025 s time interval using a commercially available computer program ANSYS [32]. After the responses are simulated, the information on input excitations is completely ignored. Responses between 0.02 s and 0.32 s providing 1201 time points are used in the subsequent health assessment process.

B. SHA of defect-free frame

SHA of defect-free frame is considered in this section. The substructure required to identify the two excitation loads are shown in double lines in Fig. 2. Using responses at five nodes in the substructure, the stiffness and damping parameters and the time-history of unknown input forces are identified using the ILS-UI procedure in stage 1. The errors in identified stiffness parameters are shown in column 2 of Table II. As commonly used in the literature, the errors are defined as the percentage deviation of identified values (at the current state) with respect to the initial theoretical values. The errors in the stiffness parameter identification of the four members in the substructure are very small. The excitation time history and damping coefficients were also identified very accurately.

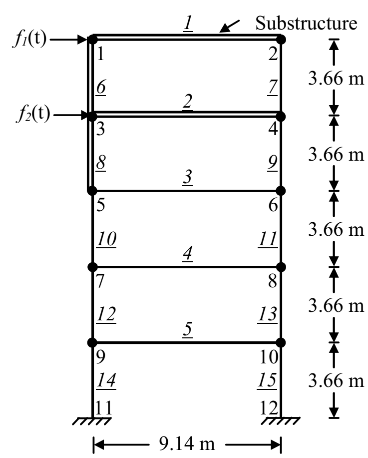
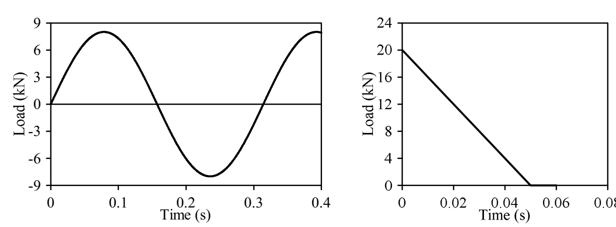


Fig. 2. Finite representation of a five-story frame.



a. sinusoidal　　b. impulse

Fig. 3. Excitation forces

TABLE II. STAGE 1: IDENTIFICATION OF SUBSTRUCTURE

Member	Defect-Free	Defect 1	Defect 2
(1)	(2)	(3)	(4)
k_1	0.001	0.021	0.011
k_2	0.010	0.021	0.016
k_6	0.020	0.023	0.022
k_8	0.020	0.023	0.022

The stiffness parameters of all 15 elements of the frame are then estimated using the EKF and UKF-based procedures in stage 2 using only responses at the substructure. The errors in identification of stiffness parameters are shown in columns 2 and 3 of Table III. The maximum error in the identification using EKF-based procedure is 1.2%, but it is only 0.2% using UKF-based procedure. From the results, it can be noticed the magnitude of error using EKF is higher than that of UKF-based procedure.

TABLE III. STAGE 2: IDENTIFICATION OF WHOLE STRUCTURE

Member	Defect-Free		Defect 1		Defect 2	
	EKF	UKF	EKF	UKF	EKF	UKF
(1)	(2)	(3)	(4)	(5)	(6)	(7)
k_1	-0.1	0.0	-0.4	0.0	-0.2	0.0
k_2	0.0	0.0	0.0	-0.1	-0.1	-0.2
k_3	-0.1	0.1	-0.6	0.0	**-60.2**	**-59.9**
k_4	-0.1	-0.1	0.2	-0.5	**-40.6**	**-39.9**
k_5	0.4	0.0	0.8	0.5	**-18.3**	**-20.4**
k_6	-0.1	0.0	-0.2	-0.1	0.3	-0.1
k_7	-0.2	0.0	**-9.4**	**-9.9**	-0.7	-0.1
k_8	0.2	***0.2***	0.6	0.3	0.0	0.3
k_9	0.3	0.2	1.1	0.4	-0.2	0.2
k_{10}	-1.1	0.1	***-2.7***	***0.8***	-0.3	0.9
k_{11}	***1.2***	0.1	2.6	0.7	***12.4***	***-2.1***
k_{12}	-0.9	0.1	-2.3	0.4	-2.3	-1.0
k_{13}	0.5	0.1	1.5	0.6	4.7	-0.1
k_{14}	-0.2	-0.1	-1.0	-0.6	-4.4	1.8
k_{15}	0.1	-0.1	0.3	-0.8	-2.4	-0.2

C. SHA of defective frame

Two defective states of the frame are considered. In Defect 1, the moment of inertia of the member 7 (column) over the entire length is reduced by 10% of the defect-free value. In Defect 2, the moment of inertia of three members (beams), over their entire length is reduced by 60%, 40%, and 20% of their corresponding defect-free values. Obviously, the location and the severity of defects will be unknown at the time of inspection, but the measured responses should reflect their presence. As mentioned earlier, for this illustrative example, the responses are numerically generated using ANSYS by appropriately modeling the location, nature, and extent of defects. In real inspections, they will be measured. The substructure required in stage 1 is considered to be the same as used previously. Using responses at 15 DDOFs, the substructure is identified and the results of defect cases 1 and 2 are summarized in columns 3 and 4 of Table II, . Then, using the results obtained in stage 1, the whole frame is identified. The results of Defect 1 using EKF and UKF-based procedure are presented in columns 4 and 5 of Table III, respectively, and the results of Defect 2 are presented in columns 6 and 7 of Table III, respectively. The reduction in the the stiffness parameter of defective members is indicated by bold values and the maximum error in the identification is indicated by italic bold values in the table. It can be clearly seen that the errors in identification using EKF is higher than that of UKF-based procedure. For an example, the maximum error in identification of Defect 2 using EKF is 12.4%; however, it is only 2.1% using UKF-based procedure. The acceptable error in the identification process was reported to be about 10%. [33, 34]. The results clearly show the superiority of the UKF-UI-WGI procedure over the EKF-based procedure.

D. Importance of weight factor

In this section, the effectiveness of the weighted global iteration (WGI) on the UKF algorithm for SHA is studied. To do so, the convergence of defective member 7 in Defect 1 is considered. To implement UKF-based procedure, the initial value of the stiffness parameter of member 7 is considered to be 14,556 kN-m and this value is assigned based on the identified stiffness in stage 1, as discussed earlier. The convergence behavior for identified stiffness parameter of member 7 using UKF-UI-WGI is shown in Fig. 4. After first global iteration, the result of identified stiffness is equal to 14,314 kN-m and corresponding reduction in stiffness with respect to theoretical defect-free value is 1.64%; however, the actual reduction must be 10%. This represents the result of traditional UKF procedure. It is clearly shown that it failed to identify the state of large structural system. After incorporating weight factor in the UKF algorithm in the second and subsequent global iterations, the algorithm converges at 4^{th} global iteration. The identified stiffness parameter is 13,109 kN-m, which corresponds to 9.9% reduction from defect-free value. This example demonstrates the superiority of the UKF-UI-WGI over traditional UKF procedure.

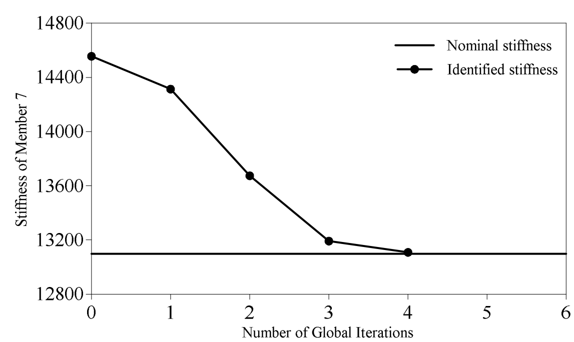


Fig. 4. Convergence behavior of stiffness of member 7 for Defect 1

VI. CONCLUSIONS

The authors and their research team at the University of Arizona conclusively established that the structural identification-based concept can be used for the health assessment of large realistic structural systems. In the process, the team re-defined the SI concept by not using the excitation information and used very short duration (fraction of a second) noise-contaminated limited number of response information. Multiple global iterations with weight factor were also introduced. Health of defect-free and defective states of a frame was assessed to demonstrate the application potential of the proposed method. The team intelligently modified and used some of signal processing concepts used in Electrical Engineering for Civil Engineering applications of structural health assessment; an upcoming research topic. The concepts presented in the paper cross the disciplinary boundaries.

ACKNOWLEDGMENT

This study is based on work partly supported by the Iraq's Ministry of Higher Education and Scientific Research. The financial supports from the National Science Foundation; most recently under Grant No. CMMI-1403844 is also appreciated. Any opinions, findings, conclusions, or recommendations expressed in this paper are those of the writers and do not necessarily reflect the views of the sponsors.

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