A Comparison of Unscented and Extended Kalman Filtering for Nonlinear System Identification

Abdullah Al-Hussein
Graduate Student, Dept. of Civil Engineering and Engineering Mechanics, University of Arizona, Tucson, USA

Achintya Haldar
Professor, Dept. of Civil Engineering and Engineering Mechanics, University of Arizona, Tucson, USA

ABSTRACT: A nonlinear system identification-based structural health assessment procedure is presented in this paper. The procedure uses the unscented Kalman filter (UKF) concept. The weighted global iteration with an objective function is incorporated with the UKF algorithm to obtain stable, convergent, and optimal solution. An iterative least squares technique is also integrated with the UKF algorithm. The procedure is capable of assessing health of any type of structures, represented by finite elements. It can identify the structure using limited noise-contaminated dynamic responses, measured at a small part of large structural systems and without using input excitation information. In order to demonstrate its effectiveness, the proposed procedure is compared with the extended Kalman filter (EKF)-based procedure. For numerical verification, a two-dimensional five-story two-bay steel frame is considered. Defect-free and two defective states with small and severe defects are considered. The study shows that the proposed UKF-based procedure can assess structural health more accurately and efficiently than the EKF-based procedures for nonlinear system identification.

1. INTRODUCTION

Civil structural systems are expected to deteriorate with time during their normal use. They also suffer damages when exposed to natural events like large earthquakes or high winds. Man-made events like impacts or explosions can also cause different levels of damages to them. To maintain the intended use of the structures and economic activities of the region, it is important to detect the location and severity of defects as early as possible so that required remedial actions can be promptly initiated. Replacing them may not be the best option.

Structural health assessment based on nonlinear system identification (SI) in the presence of many sources of uncertainties in the state of the system is the main objective of this paper. To obtain the optimal solution to the nonlinear filtering problem, a complete description of the conditional probability density function is necessary. Unfortunately, a large number of parameters are required for its description. In the past decades, many techniques of suboptimal approximation have been developed for nonlinear structural SI (Kerschen et al. 2006).

For civil engineering applications, several methods are available for nonlinear SI using the extended Kalman filter (EKF) and the unscented Kalman filter (UKF) concepts. The EKF concept has been widely used for nonlinear system identification through linearizing nonlinear models. However, the derivation of the Jacobian matrices and the linearization approximations to the nonlinear functions can be nontrivial and can lead to implementation difficulties, particularly when the nonlinearities are severe. Furthermore, the level of severity will be unknown at the time of inspection. The linearization process can also introduce large errors which may lead to poor performance and divergence of the filter for highly nonlinear problems.

A recently developed filtering technique called unscented Kalman filter (Julier et al. 1995), which attempts to remove some of the shortcomings of EKF in the estimation of nonlinear systems. UKF was developed with the underlying assumption that approximating a Gaussian distribution is easier than approximating an arbitrary nonlinear function. Unlike EKF, UKF does not approximate nonlinear equations of the system. Instead, it approximates the posterior probability density by a Gaussian density function, which is represented by a set of deterministically selected sample points. When sample points are propagated through a nonlinear transformation, they capture the true mean and covariance up to the second-order of any nonlinearity. If the priori random variable is Gaussian, the posterior mean and covariance are accurate to the third-order for any nonlinearity. UKF has been successfully applied to numerous practical problems and it has been shown to outperform EKF in many cases. Although UKF has been applied to a wide range of estimation problems, it has not been applied widely in the field of civil engineering. To the best knowledge of the authors, most of the applications of UKF in civil engineering were considered for simple structures represented by shear buildings with very few, not more than three, dynamic degrees of freedom (DDOFs). In addition, at least one of dynamic responses (displacement, velocity or acceleration) was assumed to be measured at all DDOFs. It makes the procedure difficult to implement for large structural systems.

The authors addressed these deficiencies and introduced a weighted global iteration (WGI) procedure with an objective function into the UKF algorithm to obtain stable and convergent solutions. The integrated procedure is denoted as unscented Kalman filter with weighted global iteration (UKF-WGI). The WGI procedure with an objective function was first introduced by Hoshiya and Saito (1984) in the EKF algorithm and denoted as extended Kalman filter with weighted global iteration (EKF-WGI).

Furthermore, in all applications of UKF, the input excitation is assumed to be known. Measuring excitation information accurately is a major challenge even in the controlled laboratory environment. To overcome this shortcoming, UKF-WGI is integrated with the iterative least-squares concept (Al-Hussein and Haldar 2014). A substructure approach is also incorporated in the proposed procedure since dynamic response information will only be measured at parts of a large structural system. The integrated procedure is denoted as unscented Kalman filter with unknown input and weighted global iteration (UKF-UI-WGI).

2. THE CONCEPT OF UKF-UI-WGI

To meet the basic objective of the novel SHA technique discussed in the previous section, a two stage approach is proposed. In Stage 1, using the information on the locations of the measured responses, substructure(s) can be defined. The substructure(s) can be identified without using excitation information by using a procedure developed by Katkhuda and Haldar (2008). When Stage 1 is implemented properly, it will generate excitation information. The identified stiffness properties of all the elements in the substructure, if used judicially, can provide information on the initial state vector for the whole structure. The information on the excitation time history and the initial state vector is required for the implementation of the UKF concept. With the information generated in Stage 1, the stiffness parameters for the whole structure can be identified using the proposed UKF-WGI concept in Stage 2. Combining Stages 1 and 2 will result a novel SHA method, denoted as UKF-UI-WGI. By comparing the identified stiffness parameters with expected or previous values if inspected previously, the locations of defects and their severity can be assessed. The mathematical concepts behind these two stages are discussed very briefly next.

3. MATHEMATICAL FORMULATION OF UKF-UI-WGI

a. Stage 1 - Concept of ILS-UI procedure

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 procedures (Cook et al. 2002). The global stiffness matrix corresponding to the ith element, $\mathbf{K}_i$, can be expressed as:

$$\mathbf{K}_i = k_i\mathbf{S}_i \quad (2)$$

where k_i is E_iI_i/L_i; L_i, I_i and E_i are the length, moment of inertia, modulus of elasticity, respectively, of the i^{th} element. $\mathbf{S}_i$ is the global stiffness coefficient matrix.

Using Eq. (2), Eq. (1) can be rearranged in the matrix form as:

$$\mathbf{A}(t)\,\mathbf{P} = \mathbf{F}(t) \quad (3)$$

where $\mathbf{A}$ matrix contains the measured displacement and velocity responses at time point t; $\mathbf{F}$ vector contains the unknown input excitations and the inertia forces at time point t; $\mathbf{P}$ vector contains all the unknown parameters and can be defined as:

$$\mathbf{P} = [k_1\ \ k_2 \ldots k_{nesub}\ \ \beta k_1\ \ \beta k_2\ \ldots\ \beta k_{nesub}\ \ \alpha]^T \quad (4)$$

Considering that the responses are measured at equal interval of Δt for q time points, Eq. (3) can be rewritten as:

$$\mathbf{A}\,\mathbf{P} = \mathbf{F} \quad (5)$$

A least-squares-based procedure proposed by Wang and Haldar (1994) is used for the solution of unknown system parameters $\mathbf{P}$ using the following expression:

$$\mathbf{P} = (\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T\mathbf{F} \quad (6)$$

Since the input excitation $\mathbf{f}_{sub}$ is unknown, the force vector $\mathbf{F}$ in Eq. (6) 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 by Katkhuda et al. (2005). The iteration process is continued until the excitation time history converges at all time points, considering two successive iterations, with a predetermined tolerance level. A tolerance level 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 (Vo and Haldar 2003; Das et al. 2013; Haldar et al. 2013).

b. Stage 2 - Concept of the UKF-WGI procedure

In order to implement the UKF-WGI concept, the dynamic system is expressed in the state-space form by a set of first-order nonlinear differential equations as:

$$\dot{\mathbf{X}}_t = f(\mathbf{X}_t, \mathbf{t}) \quad (7)$$

where $f(\mathbf{X}_t, t)$ is the nonlinear function of the state and $\mathbf{X}_t$ can be mathematically expressed as:

$$\mathbf{X}_t = \begin{bmatrix} \mathbf{X}(t) \\ \dot{\mathbf{X}}(t) \\ \widetilde{\mathbf{K}} \end{bmatrix} \quad (8)$$

where the vectors $\mathbf{X}(t)$ and $\dot{\mathbf{X}}(t)$ contain displacement and velocity responses of the system, respectively, and vector $\widetilde{\mathbf{K}}$ contains the unknown system parameters.

Equation (7) can be rewritten as:

$$\dot{\mathbf{X}}_t = \begin{bmatrix} \dot{\mathbf{X}}(t) \\ \ddot{\mathbf{X}}(t) \\ 0 \end{bmatrix} = \begin{bmatrix} \dot{\mathbf{X}}(t) \\ -\mathbf{M}^{-1}\left[\mathbf{K}\mathbf{X}(t) + (\alpha\mathbf{M} + \beta\mathbf{K})\dot{\mathbf{X}}(t) - \mathbf{f}(t)\right] \\ 0 \end{bmatrix} \quad (9)$$

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

$$\mathbf{Y}_k = h(\mathbf{X}_k, \mathrm{t}) + \mathbf{V}_k \quad (10)$$

where h is the function that relates the state to the measurement; $\mathbf{X}_k$ is the state vector at $t = k\Delta t$; Δt is the constant time increment; and $\mathbf{V}_k$ is a measurement noise vector of zero mean white noise Gaussian processes with covariance matrix $\mathbf{R}_k$. The noise covariance matrix is generally assumed to be diagonal and it remains constant with time. In this study it is assumed to be of the magnitude of the order of 10^{-4} for all responses.

To start the filtering process, the initial state vector and its error covariance matrix need to be assigned first. The basic filtering process in UKF-WGI is first generating $2n$+1 vectors (sigma points) around current state (k), then propagating the sigma vectors in the governing differential equation of motion to get the mean and covariance at time k+1 and finally updating them using available measurement response at time k+1. Mathematically, the steps can be expressed as (Al-Hussein and Haldar 2014):

i. Sigma vector calculation step

As discussed earlier, sets of $2n$+1 sigma vectors need to be generated around the current state vector based on its covariance as:

$$\begin{aligned} \boldsymbol{\chi}_{0,k|k} &= \hat{\mathbf{X}}_{k|k} \\ \boldsymbol{\chi}_{i,k|k} &= \hat{\mathbf{X}}_{k|k} + \sqrt{(\lambda+n)}\,\mathbf{C}_{col.i} \quad i = 1,\ldots,n \\ \boldsymbol{\chi}_{i+n,k|k} &= \hat{\mathbf{X}}_{k|k} - \sqrt{(\lambda+n)}\,\mathbf{C}_{col.i} \quad i = 1,\ldots,n \end{aligned} \quad (11)$$

where $\lambda = \alpha^2(n+\kappa) - n$; n is the dimension of the state vector; φ and γ are tuning parameters; and $\mathbf{C}$ is a square root of the covariance matrix such that $\mathbf{P}_k = \mathbf{C}\mathbf{C}^{\mathbf{T}}$; $\mathbf{C}_{col.i}$ is the i^{th} column of $\mathbf{C}$'s matrix.

ii. Prediction step

In the prediction step, it is necessary to transform the sigma vectors through the nonlinear dynamic equation as:

$$\boldsymbol{\chi}_{i,k+1|k} = \boldsymbol{\chi}_{i,k|k} + \int_{k\Delta t}^{(k+1)\Delta t} f(\mathbf{X}_t, t)\,dt \quad i = 0,\ldots,2n \quad (12)$$

The predicted state vector can be shown to be:

$$\hat{\mathbf{X}}_{k+1|k} = \sum_{i=0}^{2n} W_i\,\boldsymbol{\chi}_{i,k+1|k} \quad (13)$$

and its predicted error covariance matrix is:

$$\mathbf{P}_{k+1|k} = \sum_{i=0}^{2n} W_i\left(\boldsymbol{\chi}_{i,k+1|k} - \hat{\mathbf{X}}_{k+1|k}\right)\left(\boldsymbol{\chi}_{i,k+1|k} - \hat{\mathbf{X}}_{k+1|k}\right)^T + (1-\varphi^2+\delta)\left(\boldsymbol{\chi}_{0,k+1|k} - \hat{\mathbf{X}}_{k+1|k}\right)\left(\boldsymbol{\chi}_{0,k+1|k} - \hat{\mathbf{X}}_{k+1|k}\right)^T \quad (14)$$

where δ is a parameter added to the weight on the zeroth sigma point of the calculation of the covariance. The weight factor W_i can be shown to be:

$$\begin{aligned} W_0 &= \frac{\lambda}{\lambda+n} \qquad i = 0 \\ W_i &= \frac{1}{2(\lambda+n)} \qquad i = 1,\ldots,2n \end{aligned} \quad (15)$$

The predicted measurement vector $\hat{\mathbf{Y}}_{k+1|k}$ can be expressed as:

$$\hat{\mathbf{Y}}_{k+1|k} = \mathbf{H}\hat{\mathbf{X}}_{k+1|k} \quad (16)$$

and its error covariance matrix $\mathbf{P}_{k+1}^{\mathrm{YY}}$ as:

$$\mathbf{P}_{k+1}^{YY} = \mathbf{H}\mathbf{P}_{k+1|k}\mathbf{H}^T + \mathbf{R}_{k+1} \quad (17)$$

and the cross correlation matrix $\mathbf{P}_{k+1}^{\mathrm{XY}}$ can be estimated as:

$$\mathbf{P}_{k+1}^{XY} = \mathbf{P}_{k+1|k}\mathbf{H}^T \quad (18)$$

iii. Updating step:

The state vector and the error covariance matrix are updated as follows:

$$\mathbf{K}_{k+1} = \mathbf{P}_{k+1}^{XY}(\mathbf{P}_{k+1}^{YY})^{-1} \quad (19)$$

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

$$\hat{\mathbf{X}}_{k+1|k+1} = \hat{\mathbf{X}}_{k+1|k} + \mathbf{K}_{k+1}\left(\mathbf{Y}_{k+1} - \hat{\mathbf{Y}}_{k+1|k}\right) \quad (20)$$

$$\mathbf{P}_{k+1|k+1} = \mathbf{P}_{k+1|k} - \mathbf{K}_{k+1}\mathbf{P}_{k+1}^{YY}\mathbf{K}_{k+1}^{T} \tag{21}$$

where $\widehat{\mathbf{X}}_{k+1|k+1}$ is the updated state vector and $\mathbf{P}_{k+1|k+1}$ is the updated error covariance matrix.

The three steps in the UKF (generating sigma vectors, prediction and updating processes) are successively carried out for each of the q time points for the entire time history used for the identification. To implement the next global iterations, the authors incorporated the weighted global iteration with objective function in the UKF algorithm to obtain a stable and fast convergent solution. In the second global iteration process, the initial value of the stiffness parameters is the same as that obtained at the completion of first global iteration. A weight factor w is introduced in the stiffness covariance matrix obtained at the completion of the first global iteration process to amplify it and then used as initial stiffness covariance in the second global iteration. The same processes of local iterations are carried out for all the time points and a new set of state vector and error covariance matrix are obtained at the completion of second global iteration. The global iteration processes are continued until the estimated error in identified stiffness parameters at the end of two consecutive global iterations becomes smaller than a predetermined convergence criterion (ε). If they diverge, the best estimated values are considered based on minimum objective function θ, as discussed elsewhere by Hoshiya and Saito (1984).

4. NUMERICAL EXAMPLE: HEALTH ASSESSMENT OF A FRAME

a. Description of the frame

A two-dimensional frame with a bay width of 9.14 m and story height of 3.66 m, as shown in Figure 1, is considered. The frame has a total of 25 members; 10 beams and 15 columns. The beams and columns are made of W21×68 and W14×61 sections, respectively, of Grade 50 steel. The frame is modeled by 18 nodes in the finite element (FE) representation. Each node has three dynamic degrees of freedom (DDOFs); two translational and one rotational. The support condition at the base (nodes 16, 17, and 18) of the frame is considered to be fixed. The total number of DDOFs for the frame is 45. The actual theoretical stiffness parameter values k_i evaluated in terms of (E_iI_i/L_i) are calculated to be 13476 kN-m and 14553 kN-m for a typical beam and column, respectively. First two natural frequencies of the frame are estimated to be f_1 = 3.598 Hz and f_2 = 11.231 Hz, respectively. Following the procedure described in Clough and Penzien (2003), Rayleigh damping coefficient α and β are calculated to be 1.7122088 and 0.00107326, respectively, for an equivalent modal damping of 5% (commonly used in model codes in the US) of the critical for the first two modes.

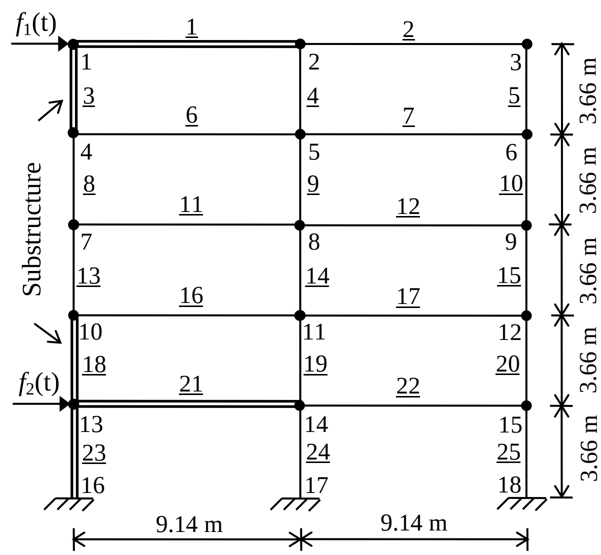

Figure 1: Finite element representation of a frame.

The frame is excited simultaneously by two sinusoidal loadings. The first loading, $f_1(t)$ = 3 sin(18t) kN is applied horizontally at node 1, and the second loading, $f_2(t)$ = 2 sin(22t) kN is applied horizontally at node 13, as shown in Figure 1. Instead of conducting the experiments and following the general practices, the information on responses are numerically generated using a commercially available software ANSYS (ver. 15.0). The responses are obtained at 0.0001 s time interval. After the responses are simulated, the information on input excitations is completely ignored. Responses between 0.02 s and 0.32 s providing 3001 time points are used in the subsequent health assessment process.

b. Structural health assessment of a frame

To demonstrate the effectiveness of the proposed procedure, the following three cases are considered:

(i) Defect-free frame
(ii) Defect 1 - loss of cross sectional area over a finite length of member 17
(iii) Defect 2 - stiffness of member 17 is reduced by 90%

In order to establish the superiority of the proposed UKF-UI-WGI procedure over EKF-based procedure developed earlier by the research team, the identified results are compared.

c. Substructure identification using the ILS-UI procedure

The substructure for all three cases is shown in Figure 1 with double lines. Using responses at 18 DDOFs in the substructure, the stiffness and damping parameters and the time history of unknown input force are identified using the ILS-UI procedure in Stage 1. The errors in identification of the stiffness parameters are shown in Table 1 for all cases. As commonly used in the literature, the errors are defined as the percentage deviation of identified values, representing the current state, with respect to the initial theoretical values. From the results, it can be observed that the errors in the identified stiffness parameter of the five members in the substructure are very small. The damping coefficients and excitation time history are also identified very accurately for all three cases.

d. Complete structure identification using the UKF-WGI and EKF-WGI procedure

The information of Stage 1 is used to initiate UKF-WGI and EKF-WGI. Then, the stiffness parameters of all 25 elements of the frame for all three cases are estimated in Stage 2.

First, the stiffness parameters of all members in the frame are identified for the defect-free state and the results of UKF-WGI and EKF-WGI are summarized in Table 2, Columns 3 and 4, respectively. For both methods, since the identified stiffness parameter did not vary significantly from the expected values, the methods correctly identified the defect-free state of the frame. The acceptable error in the identification process was reported to be about 10% (Das et al. 2012). The results of EKF-WGI are still within the acceptable level but not as good as the proposed UKF-WGI method. However, it can be concluded that both filters identified the defect-free state of the frame.
After assessing structural health of the defect-free frame, the defective cases with different levels of severity are considered. In less severe Defect 1, the cross-sectional area of member 17 is considered to be corroded over a length of 30 cm, located at a distance of 30 cm from node 12. In Defect 2, the stiffness parameter of member 17 is reduced by 90% from defect-free value. The results of UKF-WGI and EKF-WGI for Defect 1 are summarized in Table 2, Columns 5 and 6, respectively and for Defect 2 are summarized in Columns 7 and 8, respectively. The results clearly indicate that the UKF- WGI procedure is capable of identifying the location and severity of defect for two defective cases. The identification of defect location using the EKF-WGI procedure for Defect 1 is not straightforward. Both the proposed and EKF-based procedures identified the reductions of the stiffness parameter of defective member 17 as 8.39% and 7.54%, respectively. However, the results of EKF-based procedure show that the stiffness parameter of defect-free member 5 is increased by 11.23%, which is more than acceptable error. The same observation can be made for Defect 2 also. Therefore, it can be concluded that EKF-WGI failed to assess the health of the frame for both defective states.

Table 1: Stiffness parameter (EI/L) identification of the substructure.

Member	Theoretical (kN-m)	Defect Free		Defect 1		Defect 2	
		Identified	Change %	Identified	Change %	Identified	Change %
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
k_1	13476	13476	0.001	13476	0.001	13476	0.001
k_3	14553	14553	0.001	14553	0.001	14553	0.001
k_{18}	14553	14553	0.004	14553	0.003	14553	0.003
k_{21}	13476	13477	0.003	13477	0.003	13477	0.003
k_{23}	14553	14553	0.004	14553	0.003	14553	0.003

Table 2: Change (%) in stiffness parameter (EI/L) identification of whole structure.

Member	Theoretical (kN-m)	Defect Free		Defect 1		Defect 2	
		UKF	EKF	UKF	EKF	UKF	EKF
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
k_1	13476	-0.07	-0.05	-0.06	-0.07	-0.02	-0.07
k_2	13476	0.37	-0.37	0.87	-6.84	2.73	-8.45
k_3	14553	-0.05	-0.03	-0.05	-0.07	-0.02	-0.06
k_4	14553	0.17	0.03	0.20	-1.96	0.75	-2.49
k_5	14553	-0.13	0.76	-1.00	11.23	-3.34	15.13
k_6	13476	-0.02	-0.06	-0.02	0.73	-0.21	1.36
k_7	13476	-0.21	-0.04	0.06	1.90	-0.65	1.27
k_8	14553	0.67	0.41	0.62	-0.12	0.76	-0.15
k_9	14553	0.57	0.38	0.37	-2.88	1.21	-5.69
k_{10}	14553	0.22	0.69	1.37	7.31	-1.34	7.46
k_{11}	13476	0.09	0.51	0.25	2.43	-0.60	3.61
k_{12}	13476	0.01	-0.25	-0.71	-2.06	0.45	1.42
k_{13}	14553	-0.55	-0.68	-0.57	-1.07	-0.15	-0.91
k_{14}	14553	-0.81	-1.57	-1.69	-4.68	0.20	-6.83
k_{15}	14553	-1.17	0.07	-0.13	4.42	-3.16	13.95
k_{16}	13476	0.26	0.40	-0.09	0.56	0.05	0.90
k_{17}	13476	1.01	1.24	**-8.39**	**-7.54**	**-89.75**	**-89.57**
k_{18}	14553	0.02	0.01	0.05	0.17	-0.02	0.23
k_{19}	14553	-0.45	-0.69	-0.42	-1.07	-0.13	-1.77
k_{20}	14553	0.02	0.26	-1.16	-1.25	0.12	-3.33
k_{21}	13476	0.04	0.07	0.05	0.18	-0.03	0.15
k_{22}	13476	-0.45	-0.52	-0.97	-1.34	-0.22	-2.52
k_{23}	14553	0.06	0.14	0.05	0.18	-0.08	-0.18
k_{24}	14553	0.00	0.09	0.05	0.02	-0.06	-0.97
k_{25}	14553	0.34	0.15	0.62	0.67	0.51	3.17

These examples clearly demonstrate the superiority of the proposed UKF-UI-WGI procedure over the EKF-based procedure developed earlier by the research team.

5. CONCLUSIONS

A novel nonlinear system identification-based structural health assessment procedure is presented in this paper. The procedure is developed in two stages. First, weighted global iteration with an objective function is incorporated with the UKF algorithm. Then, an iterative least squares technique is integrated with the UKF algorithm. The procedure is capable of identifying health of large structural systems using limited number of noise-contaminated responses and without using input excitation information. In order to demonstrate its superiority, the proposed procedure is compared with the extended Kalman filter-based procedure. For numerical verification, a two-dimensional five-story two-bay steel frame is considered. Defect-free and two defective states with small and severe defect are considered. The study shows that the proposed procedure can provide more accurate and efficient assessment of structural health than the EKF-based procedure for nonlinear system identification.

6. ACKNOWLEDGMENTS

This study is based on work partly supported by the Iraq's Ministry of Higher Education and Scientific Research. Any opinions, findings, conclusions, or recommendations expressed in this paper are those of the writers and do not necessarily reflect the views of the sponsor.

7. REFERENCES

Al-Hussein, A., and Haldar, A. (2014). "A new extension of unscented Kalman filter for structural health assessment with unknown input." *Proceedings of SPIE Vol. 9061, 90612Y*.

ANSYS version 15.0, (2013). *The Engineering Solutions Company*.

Clough, R. W., and Penzien, J. (2003). *Dynamics of structures*, Third Edition, Computers and Structures, CA, USA.

Cook, R. D., Malkus, D. S., Plesha, M. E., and Witt, R. J. (2002). *Concepts and applications of finite element analysis*, Fourth Edition, John Wiley and Sons, NJ.

Das, A. K., Al-Hussein, A., and Haldar, A. (2013). "Algorithmic and computing technologies for health assessment of real structures in the presence of large nonlinearity." *2013 ASCE International Workshop on Computing in Civil Engineering*, University of Southern California, June 23-25.

Das, A. K., Haldar, A., and Chakraborty, S. (2012). "Health assessment of large two dimensional structures using minimum information - recent advances." *Advances in Civil Engineering*, 2012, Article ID 582472.

Haldar, A., Das, A. K., and Al-Hussein, A. (2013). "Data analysis challenges in structural health assessment using measured dynamic responses." *Advances in Adaptive Data Analysis*, 5(4), 1-22.

Hoshiya, M., and Saito, E. (1984). "Structural identification by extended Kalman filter." *Journal of the Engineering Mechanics, ASCE*, 110(12), 1757-1770.

Julier, S. J., Uhlmann, J. K., and Durrant-Whyte, H. (1995). "A new approach for filtering nonlinear systems." *In Proceedings of the American Control Conference*, 1628-1632.

Katkhuda, H., and Haldar, A. (2008). "A novel health assessment technique with minimum information." *Structural Control and Health Monitoring*, 15(6), 821-838.

Katkhuda, H., Martinez-Flores, R., and Haldar, A. (2005). "Health assessment at local level with unknown input excitation." *Journal of Structural Engineering, ASCE*, 131(6), 956-965.

Kerschen, G., Worden, K., Vakakis, A. F., Golinval, J. C. (2006). "Past, present and future of nonlinear system identification in structural dynamics." *Mechanical Systems and Signal Processing*, 20(3), 505-592.

Vo, P. H., and Haldar, A. (2003). "Post processing of linear accelerometer data in system identification." *Journal of Structural Engineering*, 30(2), 123-130.

Wang, D., and Haldar, A. (1994). "Element-level system identification with unknown input." *Journal of Engineering Mechanics, ASCE*, 120(1), 159-176.