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Detection of Local Damage in Large Size Structures Based on Substructure and Distributed Computing Strategy

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ABSTRACT: Damage in structures is an intrinsically local phenomenon. Thus, the detection of local damage in large size structures by the conventional structural identification approach is challenging. In this paper, a novel technique is proposed to detect structural local damage in large size structures subject to some unknown excitation based on substructure and distributed computing strategy. A large size structure is decomposed into smaller substructures in finite element formulation. Interaction effect between adjacent substructures is taken into account by considering the interaction forces at substructural interfaces as 'unknown inputs' to substructures. Two cases that measurements at the substructure interfaces are available or not available are considered. Element level structural parameters and the 'unknown inputs' in the substructures are identified by an algorithm based on the classical extended Kalman estimator and recursive least squares estimation. Performance of proposed technique is illustrated by a numerical example of detecting local damage in a multi-story frame building. It is shown that the proposed technique provides an efficient tool for the detection of structural local damage。 This technique can be embedded into the on-board computational core of intelligent wireless sensor network for automated detection of civil infrastructures.

1 INTRODUCTION

Detection of local damage in large size structures is an important but challenging task as damage in structures is an intrinsically local phenomenon. Various damage detection techniques have been developed. System identification (SI) of structural system, or structural identification, based structural damage detection techniques have received great attention in recent years (Chang, 2005, 2007, Ou et al., 2005). It is straightforward to identify structural local damage based on tracking the changes in the identified values of structural dynamic parameters at element level, e.g., the degrading of stiffness parameters. However, as an inverse problem, damage detection by the conventional structural identification is challenging, especially when the system involves a larges number of unknown parameters due to ill-condition and computation convergence problems. In addition, as the size of a structure increase, its computational efforts increase tremendously. It also requires a dense array of sensors to be deployed in structures in order to obtain reasonably accurate results of damage detection.

The modeling of large-size structures involves a large number of degrees of freedom (DOFs). For a large-size structure, there may be only limited number of critical parts where damage may likely to occur, and hence the detection can be restricted to such critical parts of the structures. Consequently, a large-size structure can be decomposed into substructures, each with less DOFs and unknown parameters. (Natke, 1997, Link, 1997). Then, different substructure can be identified almost independently, or even concurrently with parallel computing. Interaction effects between adjacent structures are accounted by interaction forces at the interfaces between substructures. Substructure identification approaches have been proposed (e.g., Koh et al., 2003, Tee et al., 2005, Yang et al., 2007b). However, in their substructural identification approaches, not only the external excitations to the substructure but also the responses at the interface between substructures are needed. The measured signals at the interface DOFs are treated as inputs to the substructures concerned. Nerveless, it is not always possible or even cost-effective to measure interface DOFs.

On the other hand, it is often difficult to accurately measure all excitation inputs to the structures. Identification of structural parameters without excitation information has been attempted in the past (Kathuda, et al. 2005, Tee et al. 2005). However, these approaches require that information about structural displacement and velocity responses are available or they are obtained through integration of measured acceleration responses. It is impractical to measure displacement, velocity and acceleration responses at all DOFs due to the high cost of deploying a dense array of different kinds of sensors in large size structures. Usually only a limited number of accelerometers are deployed to measure acceleration responses at some DOFs of the structures. Velocity and displacement responses directly obtained by integrating the measured acceleration responses usually result in errors. Therefore, it is essential to develop a technique which can detect structural local damage utilizing only limited observations of acceleration responses of structures under unknown excitations. Recently, Yang et al proposed an algorithm of extended Kalman filter for structural damage identification under unknown inputs (Yang et al. 2007a) and a sequential nonlinear least square estimation with unknown inputs and outputs (Yang et al 2006, 2007). The authors also proposed an algorithm for element level structural damage detection with limited observations and with unknown inputs (Lei et al. 2006, 2008). However, these approaches involve relatively complicated mathematical derivations and computations. Moreover, it is necessary to have the measurements of all the DOFS at the interface between substructures (Yang et al. 2007b, Lei et al. 2008).

In this paper, a technique for the distributed detection of local damage in large-size linear structures is proposed based on substructure and distributed computing strategy. Based on its finite element model, a large-scale linear structure is divided into a set of smaller substructures. Interaction effect between adjacent substructures is taken into account by considering the interaction forces at substructural interfaces as the ‘unknown inputs’ to the substructures. Two cases that measurements at the substructure interfaces are available or not available are considered. Structural dynamic parameters at element level, the unknown external excitation and the ‘unknown inputs’ of interaction forces to the substructures are estimated sequentially by the extended Kalman estimation and the recursive least squares estimation. A numerical example of detecting several types of structural damage at element level in an 8-story shear-type building is studied to illustrate the efficiency of the proposed technique.

2 DAMAGE DETECTION BASED ON SUBSTRUCTURE APPROACH

2.1 *Finite element model of a large size linear structure*

Based on the finite-element model of the structure, the equation of motion of a large-scale linear structure under external excitation can be written as

$$\boldsymbol{M}\ddot{\boldsymbol{x}}(t)+\boldsymbol{C}\dot{\boldsymbol{x}}(t)+\boldsymbol{K}\boldsymbol{x}(t)=\boldsymbol{B}\boldsymbol{f}(t)+\boldsymbol{B}^u\boldsymbol{f}^u(t) \tag{1}$$

where $\boldsymbol{x}$, $\dot{\boldsymbol{x}}$ and $\ddot{\boldsymbol{x}}$ are vectors of displacements, velocity and acceleration response of the structure, respectively; $\boldsymbol{M}$, $\boldsymbol{C}$ and $\boldsymbol{K}$ are mass, damping, and stiffness matrices of the structure, respectively; $\boldsymbol{f}(t)$ is a p-measured external excitation vector, $\boldsymbol{f}^u(t)$ is a q-unmeasured external excitation vector, and $\boldsymbol{B}$ and $\boldsymbol{B}^u$ are the influence matrices associated with $\boldsymbol{f}(t)$ and $\boldsymbol{f}^u(t)$, respectively. Usually, mass of a structure can be estimated with accuracy based on its geometry and material information. It is often assumed that mass matrix $\boldsymbol{M}$ is a diagonal matrix.

A large-size structure involves a large number of DOFs. To reduce computational burdens and the difficulty in obtaining reasonably accurate results of damage detection, it is reasonable to apply substructural approach for a large-size structure.

2.2 *Substructure approach*

In order to reduce the numbers of DOFs and the unknown parameters. A large-scale structure can be divided into a set of substructures based on its finite-element model. The equation of motion of a substructure concerned can be extracted from the equation of motion of the whole structure, Eq.(1), to yield

$$\boldsymbol{M}_{rr}\ddot{\boldsymbol{x}}_r(t)+[\boldsymbol{C}_{rr}\ \ \boldsymbol{C}_{rs}]\begin{bmatrix}\dot{\boldsymbol{x}}_r(t)\\ \dot{\boldsymbol{x}}_s(t)\end{bmatrix}+[\boldsymbol{K}_{rr}\ \ \boldsymbol{K}_{rs}]\begin{bmatrix}\boldsymbol{x}_r(t)\\ \boldsymbol{x}_s(t)\end{bmatrix}=\boldsymbol{B}_r\boldsymbol{f}_r(t)+\boldsymbol{B}_r^u\boldsymbol{f}_r^u(t) \tag{2}$$

where subscript 'r' denotes internal DOFs of the substructure concerned, subscript 's' denotes interface DOFs. Mass matrix of the large-scale linear structure in Eq.(1) is assumed to be diagonal.

Then, the above equation can be re-arranged as

$$\boldsymbol{M}_{rr}\ddot{\boldsymbol{x}}_r(t)+\boldsymbol{C}_{rr}\dot{\boldsymbol{x}}_r(t)+\boldsymbol{K}_{rr}\boldsymbol{x}_r(t)=\boldsymbol{B}_r\boldsymbol{f}_r(t)+\boldsymbol{B}_r^u\boldsymbol{f}_r^u(t)-\boldsymbol{C}_{rs}\dot{\boldsymbol{x}}_s(t)-\boldsymbol{K}_{rs}\boldsymbol{x}_s(t) \tag{3}$$

Treating the interaction effects as 'unknown inputs' to the substructure concerned, Eq.(3) can be expressed as

$$\boldsymbol{M}_{rr}\ddot{\boldsymbol{x}}_r(t)+\boldsymbol{C}_{rr}\dot{\boldsymbol{x}}_r(t)+\boldsymbol{K}_{rr}\boldsymbol{x}_r(t)=\boldsymbol{B}_r\boldsymbol{f}_r(t)+\boldsymbol{B}_r^u\boldsymbol{f}_r^u(t)+\boldsymbol{B}_r^*\boldsymbol{f}_r^*(t) \tag{4}$$

where $\boldsymbol{f}_r^*(t)$ is the s-'unknown input' vector at the substructure interface, $\boldsymbol{B}_r^*$ is the influence matrix associated with the 'unknown inputs' $\boldsymbol{f}_r^*(t)$, and

$$\boldsymbol{B}_r^*\boldsymbol{f}_r^*(t)=-\boldsymbol{C}_{rs}\dot{\boldsymbol{x}}_s(t)-\boldsymbol{K}_{rs}\boldsymbol{x}_s(t) \tag{5}$$

Therefore, the substructure is excited by the measured and unmeasured external excitations and the additional the 'unknown inputs' due to substructure interaction at the substructural interfaces. It is required to explore an algorithm to identify the dynamic parameters of the substructure under unknown inputs.

2.3 *Identification of structural parameters in a substructure under unknown inputs*

Identification of structural parameters without input information has been attempted in the past. Some algorithms have been developed under the condition that information about structural displacement and velocity responses are available. Recently, Yang *et al.* proposed the algorithms of extended Kalman filter for structural damage identification under unknown inputs (Yang et al. 2007a) and the sequential nonlinear least square estimation with unknown inputs and outputs (Yang et al 2006, 2007b). Lei et al. also developed an algorithm for element level structural damage detection with limited observations and with unknown inputs (Lei et al. 2006, 2008). However, these approaches involve relatively complicated mathematical derivations and computations. Moreover, it is necessary to have the measurements at the DOFS where unknown inputs act on.

In this paper, an algorithm is proposed to identify structural parameters of a substructure without input information based on sequential estimation of the extended state vector by the extended Kalman estimation and the unknown inputs by the recursive least squares estimation.

2.3.1 Estimation of the extended state vector of a substructure by the extended Kalman estimator

Consider an extended state vector of the substructure defined as

$$\boldsymbol{Z}_r = [\,\boldsymbol{Z}_{1r}^T, \boldsymbol{Z}_{2r}^T, \boldsymbol{Z}_{3r}^T, \boldsymbol{Z}_{4r}^T\,]^T \tag{6}$$

in which

$$\boldsymbol{Z}_{1r} = \boldsymbol{x}_r^T \;;\; \boldsymbol{Z}_{2r} = \dot{\boldsymbol{x}}_r^T \;;\; \boldsymbol{Z}_{3r} = [k_{r1}, k_{r2}, \ldots, k_{rm}\,]^T \;;\; \boldsymbol{Z}_{4r} = [c_{r1}, c_{r2}, \ldots, c_{rm}\,]^T \tag{7}$$

i.e., $[\,\boldsymbol{Z}_{1r}^T, \boldsymbol{Z}_{2r}^T\,]^T$ are the state vector of the substructure concerned, $\boldsymbol{Z}_{3r}^T$ and $\boldsymbol{Z}_{4r}^T$ are two m-unknown parameter vectors consisting of the unknown stiffness k_{ri} (i=1,2,…, m) and damping parameter c_{ri} (i=1,2,…, m) of the substructure, respectively.

Considering the unknown stiffness and damping parameters are constant, .i.e., $\dot{\theta}_{ri} = 0$, $\dot{c}_{ri} = 0$, Eq. (4) can be written into the following extended state equation for the extended state vector as,

$$\begin{Bmatrix} \dot{\boldsymbol{Z}}_{1r} \\ \dot{\boldsymbol{Z}}_{2r} \\ \dot{\boldsymbol{Z}}_{3r} \\ \dot{\boldsymbol{Z}}_{4r} \end{Bmatrix} = \begin{Bmatrix} \boldsymbol{Z}_{2r} \\ \boldsymbol{M}_{rr}^{-1}[\,\boldsymbol{B}_r \boldsymbol{f}_r(t) + \boldsymbol{B}_r^u \boldsymbol{f}_r^u(t) + \boldsymbol{B}_r^* \boldsymbol{f}_r^*(t) - (\,C_{rr}\,)_{Z_{4r}} \boldsymbol{Z}_{2r} - (\,K_{rr}\,)_{Z_{3r}} \boldsymbol{Z}_{1r}\,] \\ 0 \\ 0 \end{Bmatrix} \tag{8}$$

where $(\,C_{rr}\,)_{Z_{4r}}$ represents that elements in the damping matrix C_{rr} of the substructure are composed by unknown damming vector $\boldsymbol{Z}_{4r}$, $(\,K_{rr}\,)_{Z_{3r}}$ represents the constitution of the elements in the stiffness matrix K_{rr} of the substructure analogously.

As observed from Eq.(8), the extended state equation is a nonlinear equation of the extended state vector. Therefore, Eq.(8) can be rewritten in the following general nonlinear differential state equation as

$$\dot{\boldsymbol{Z}}_r = f(\boldsymbol{Z}_r, \boldsymbol{f}_r, \boldsymbol{f}_r^u, \boldsymbol{f}_r^*, t) \tag{9}$$

Usually, only a limited number of accelerometers are deployed in structures to measure the acceleration responses at some DOFs of the substructure. Therefore, the discretized observation vector (measured acceleration responses) can be expressed as

$$\begin{aligned} \boldsymbol{Y}_r[k] &= \boldsymbol{D}_r \dot{\boldsymbol{Z}}_{2r}[k] + \boldsymbol{v}_r[k] \\ &= \boldsymbol{D}_r\left\{-(\mathrm{C}_{rr})_{Z4r} \boldsymbol{Z}_{2r}[k] - (\mathrm{K}_{rr})_{Z3r} \boldsymbol{Z}_{1r}[k]\right\} + \boldsymbol{G}_r \boldsymbol{f}_r[k] + \boldsymbol{G}_r^u \boldsymbol{f}_r^u[k] + \boldsymbol{G}_r^* \boldsymbol{f}_r^*[k] + \boldsymbol{v}_r[k] \end{aligned} \tag{10}$$

in which $\boldsymbol{G}_r = \boldsymbol{D}_r \times B_r$, $\boldsymbol{G}_r^u = \boldsymbol{D}_r \times B_r^u$, $\boldsymbol{G}_r^* = \boldsymbol{D}_r \times B_r^*$

$\boldsymbol{Y}_r[k]$ is an l-observation vector at $t = k\times\Delta t$ with Δt being the sampling time step, i.e., $\boldsymbol{Y}_r[k] = \boldsymbol{Y}_r[k\times\Delta t]$, $\boldsymbol{Z}_{1r}[k] = \boldsymbol{Z}_{1r}[t = k\times\Delta t]$, , $\boldsymbol{Z}_{2r}[k] = \boldsymbol{Z}_{2r}[t = k\times\Delta t]$, $\boldsymbol{f}_r[k] = \boldsymbol{f}_r[t = k\times\Delta t]$, $\boldsymbol{f}_r^u[k] = \boldsymbol{f}_r^u[t = k\times\Delta t]$, $\boldsymbol{f}_r^*[k] = \boldsymbol{f}_r^*[t = k\times\Delta t]$, $\boldsymbol{D}_r$ is the matrix associated with the locations of accelerometers, and $\boldsymbol{v}[k]$ is the measured noise vector assumed to be a Gaussian white noise vector with zero mean and a covariance matrix $\boldsymbol{E}[\boldsymbol{v}_{ir}\boldsymbol{v}_{jr}^T] = \boldsymbol{R}_{ij}\delta_{ij}$, where δ_{ij} is the Kroneker delta.

As observed from Eq.(10), the observation vector (measured acceleration responses) is a nonlinear function of the extended state vector. Thus, the discretized observation vector can be expressed by the nonlinear equation as follows:

$$\boldsymbol{Y}_r[k] = h\big(Z_r[k],t[k]\big) + \boldsymbol{G}_r\boldsymbol{f}_r[k] + \boldsymbol{G}_r^u\boldsymbol{f}_r^u[k] + \boldsymbol{G}_r^*\boldsymbol{f}_r^*[k] + \boldsymbol{v}_r[k] \tag{11}$$

where $\boldsymbol{Z}_r[k] = \boldsymbol{Z}_r[t = k\times\Delta t]$.

Based on the classic extended Kalman estimator, the extended state vector at time $t = (k+1)\times\Delta t$ can be estimated as follows,

$$\hat{\boldsymbol{Z}}_r[k+1|k] = \tilde{\boldsymbol{Z}}_r[k+1|k] + K_r[k]\Big\{\boldsymbol{Y}_r[k] - h\Big(\boldsymbol{Z}_r[k],\boldsymbol{f}_r[k],\boldsymbol{f}_r^u[k],\boldsymbol{f}_r^*[k],t[k]\Big)\Big\} \tag{12}$$

in which,

$$\tilde{\boldsymbol{Z}}_r[k+1|k] = \hat{\boldsymbol{Z}}_r[k|k-1] + \int_{t[k]}^{t[k+1]} f(\boldsymbol{Z}_r,\boldsymbol{f}_r,\boldsymbol{f}_r^u,\boldsymbol{f}_r^*,t)\,dt \tag{13}$$

where $\hat{\boldsymbol{Z}}_r[k+1|k]$ is the estimation of $\boldsymbol{Z}_r[k+1]$ given the observation of $\big(\boldsymbol{Y}_r[1],\boldsymbol{Y}_r[2],\ldots,\boldsymbol{Y}_r[k]\big)$. $K_r[k]$ is the Kalman gain matrix at time $t = k\times\Delta t$.

However, since $\boldsymbol{f}_r^u, \boldsymbol{f}_r^*$ are "unknown inputs" to the substructure concerned, it's impossible to obtain recursive solution for the extended state vector by the classical extended Kalman estimator alone.

2.3.2 Recursive estimation of the unknown inputs when measurements at the substructure interface are available

For the case that measurements (sensors) are available at both the substructure interface and the DOFs where the external excitation act, both the matrix $\boldsymbol{G}_r^u$ and matrix $\boldsymbol{G}_r^*$ in Eq.(11) are non-zero matrices. Therefore, given the observation of $\big(\boldsymbol{Y}_r[1],\boldsymbol{Y}_r[2],\ldots,\boldsymbol{Y}_r[k+1]\big)$, the unknown external excitations $\boldsymbol{f}_r^u[k+1]$ and the 'unknown inputs' $\boldsymbol{f}_r^*[k+1]$, can be estimated from Eq.(12) by the recursive least square estimation as

$$\Big\{\hat{\boldsymbol{f}}_r^u[k+1],\hat{\boldsymbol{f}}_r^*[k+1]\Big\}^T = \boldsymbol{\Phi}^T\boldsymbol{R}^{-1}\boldsymbol{\Phi}\boldsymbol{\Phi}^T\Big\{\boldsymbol{Y}_r[k+1] - h\Big(\hat{Z}_r[k+1|k],t[k+1]\Big) - \boldsymbol{G}_r\boldsymbol{f}_r[k+1]\Big\} \tag{14}$$

in which, $\hat{\boldsymbol{f}}_r^u[k+1]$ and $\hat{\boldsymbol{f}}_r^*[k+1]$ are the estimation of $\boldsymbol{f}_r^u[k+1]$ and $\boldsymbol{f}_r^*[k+1]$, respectively, and matrix $\boldsymbol{\Phi}$ is defined as $\boldsymbol{\Phi} = [\boldsymbol{G}_r^u,\boldsymbol{G}_r^*]$.

From sect. 2.3.1 and 2.3.2, it is noted that when measurements are available at both the substructure interface and the DOFs where the external excitation act, structural parameters of the substructure can be identified independently without transformation of information with the adjacent substructures. Then, different substructure can be identified independently.

2.4 Recursive estimation of the unknown inputs when measurements at the substructure interface are not available

For the case that measurements (sensors) are not available at the DOFs at the substructure interface, the unknown input $\boldsymbol{f}_r^*$ does not presents itself in the observation equation, Eq.(11). Therefore, it can not be identified as shown in sect. 2.3.2. However, since the extended state vector at time $t=(k+1)\times\Delta t$ have been estimated as shown in sect. 2.3.1, it is possible to estimate the 'unknown input' $\boldsymbol{f}_r^*$ at time $t=(k+1)\times\Delta t$ based on its expression in Eq.(5), i.e.,

$$\boldsymbol{B}\boldsymbol{f}_r^*[k+1|k] = -\boldsymbol{C}_{rs}[k+1|k]\dot{\boldsymbol{x}}_s[k+1|k] - \boldsymbol{K}_{rs}[k+1|k]\boldsymbol{x}_s[k+1|k] \tag{15}$$

in which $\hat{\boldsymbol{f}}_r^*[k+1|k]$ is the estimation of $\boldsymbol{f}_r^*[k+1]$ given the estimated values of extended state vector in different substructure at time at time $t=(k+1)\times\Delta t$. With the estimated value of the 'unknown input' $\hat{\boldsymbol{f}}_r^*[k+1|k]$, the unknown external excitations at time $t=(k+1)\times\Delta t$, $\boldsymbol{f}_r^u[k+1]$ can be estimated from Eq.(11) by the recursive least square estimation as

$$\begin{aligned}\hat{\boldsymbol{f}}_r^u[k+1] = [\boldsymbol{G}^u]^T\boldsymbol{R}^{-1}\boldsymbol{G}^u[\boldsymbol{G}^u]^T\Big\{&\boldsymbol{Y}_r[k+1] - h\big(\hat{Z}_r[k+1|k], t[k+1]\big)\\ &-\boldsymbol{G}_r\boldsymbol{f}_r[k+1] - \boldsymbol{G}_r^*\hat{\boldsymbol{f}}_r^*[k+1|k]\Big\}\end{aligned} \tag{16}$$

It is noted that when measurements at the substructure interface are not available, the 'unknown input' $\boldsymbol{f}_r^*[k+1]$ can be determined based on its expression once the extended state vector at time at time $t=(k+1)\times\Delta t$ have been estimated. However, transformation of information with the adjacent substructures is needed to in order to determine the 'unknown input' $\boldsymbol{f}_r^*[k+1]$ .Therefore, in the case, different substructure can not be identified independently, but can be identified concurrently with parallel computing.

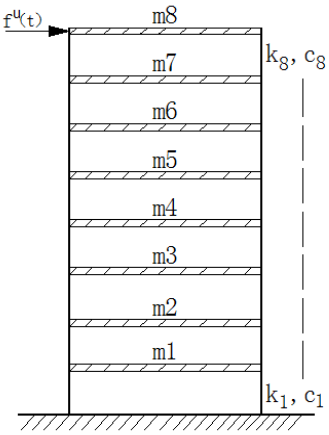
3 NUMERICAL EXAMPLE

Detection of local damage in 8-story shear-type frame with lump masses under a unknown white noise excitation, as shown in Fig.1, is taken as an numerical example to illustrate the proposed technique and investigate its damage detection feasibility. The following parametric values are used in the numerical study: mass of each floor $\mathrm{m_1 = m_2 = ..., = m_8 = 120kg}$; story stiffness $\mathrm{k_1 = k_2 = ..., = k_8 = 60kN/m}$, and damping coefficients $\mathrm{c_1 = c_2 = ..., = c_8 = 0.7kN\ s/m}$. As an example, the building is divided into two substructures. The 1-4 story part of the building is the substructure one and rest part of the building is the substructure two, as shown in Fig. 2. Interaction effect between each two adjacent substructures is considered by interaction forces $\boldsymbol{f}_1^*(t)$ and $\boldsymbol{f}_2^*(t)$ at the substructural interfaces. The interaction forces are treated as unknown inputs to the substructures. Two cases for the deployment of accelerometers are considered.

Case I: accelerometers are employed at the 2nd, 3rd, 4th, 5th, 7th and the 8th floors, i.e., measurements are available at all DOFs of the substructure interface and the external excitation

Case II: accelerometers are employed at the 1st, 2nd, 3rd, 6th, 7th and the 8th floors. Thus, measurements at the substructure interface are not available.

Two damage patterns are considered. For damage pattern 1(DP1), a damage in the 4th story occurs with k_4 being reduced to 50kN/m. For damage pattern 2 (DP2), damage occurs in both the 3rd and 6th stories, which leads to k_3 being reduced to 50kN/m and k_6 being reduced to 40kN/m. The identified stiffness parameters by the proposed method for the two damage patterns and the two cases are shown in table 1. From the comparison of the identified results with their true values, it is shown that the proposed technique can detect structural element stiffness with good accuracy based on degrading of element stiffness parameters.



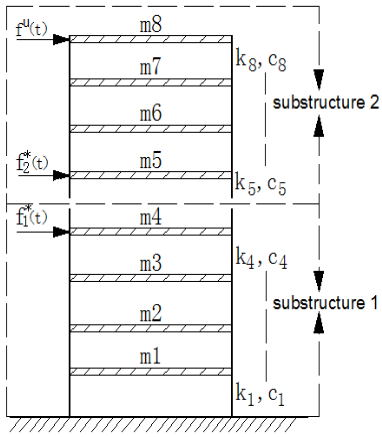


Figure 1. A shear building under unknown excitation; Figure 2. Two substructure with "unknown input'

Table 1. Identified results of story stiffness parameters of the building

Story No.	Story stiffness k_i (kN/m)					
	Undamaged		Case I		Case II	
	Case I	Case II	DP 1	DP 2	DP 1	DP 2
3	60.2	59.6	59.7	50.4	59.5	49.3
4	59.7	60.4	50.3	59.5	49.4	60.5
6	60.3	60.5	60.2	39.5	60.7	40.6

Compared with other damage detection techniques, the technique proposed in this paper allows for distributed identification of local damage in large-size structures. It provides an efficient distributed computing strategy for detecting structural local damage with less amount of data transformation. Therefore, the technique is very suitable to be embedded into the wireless intelligent sensing network for automated detection of structural damage (Lynch et al. 2006)

Conclusions

In this paper, a technique is proposed for detecting local damage in large-size structures subject to some unknown external excitation utilizing the substructure and distributed computing strategy. Interaction effect between adjacent substructures is accounted by considering the interaction forces at substructural interfaces as the 'unknown inputs' to the substructures. Two cases that measurements at the substructure interfaces are available or not available are considered. Under the condition that the number of response measurement is more than that of the unknown external excitation, structural parameters at element level, the unknown external excitation and the 'unknown inputs' to substructures can be estimated sequentially based on the extended Kalman estimation and recursive least squares estimation. Compared with other techniques, the proposed technique not only considers the unknown external excitation and the un-measured DOFs at substructure interface, but also requires less mathematical computations as it is straight forward. A numerical example demonstrates that the technique is capable of detecting local damage in large-size structures with satisfactory accuracy.

The proposed technique also provides a distributed computing strategy which is suitable for automated damage detection implemented by the wireless intelligent sensor network based on the distributed computing capacity. Relevant research work is undertaken by the authors.

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