A technique for autonomous structural damage detection with smart wireless sensor network

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ABSTRACT

In this paper, a distributed structural damage detection approach is proposed for large size structures under limited input and output measurements. A large size structure is decomposed into small size substructures based on its finite element formulation. Interaction effect between adjacent substructures is considered as 'additional unknown inputs' to each substructure. By sequentially utilizing the extended Kalman estimator for the extended state vector and the least squares estimation for the unmeasured inputs, the approach can not only estimate the 'additional unknown inputs' based on their formulations but also identify structural dynamic parameters, such as the stiffness and damping of each substructure. Local structural damage in the large size structure can be detected by tracking the changes in the identified values of structural dynamic parameters at element level, e.g., the degrading of stiffness parameters. Numerical example of detecting structural local damages in a large-size plane truss bridge illustrates the efficiency of the proposed approach. A new smart wireless sensor network is developed by the authors to combine with the proposed approach for autonomous structural damage detection of large size structures. The distributed structural damage detection approach can be embedded into the smart wireless sensor network based on its two-level cluster-tree topology architecture and the distributed computation capacity of each cluster head.

Keywords: Structural damage detection, system identification, substructure approach, unknown inputs, extended Kalman estimator, least-square estimation, wireless sensor network, distributed computation

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 on structural damage detection techniques has received great attention in recent years [1-2]. 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 large numbers 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.

On the other hand, it's often difficult to accurately measure all excitation inputs of the structure. Identification of structural parameters without excitation information has been attempted in the past [3-4]. However, these approaches require information of structural displacement and velocity 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 structure. 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 and a sequential nonlinear least square estimation with unknown inputs and outputs [5-6]. The authors also proposed

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an algorithm for element level structural damage detection with limited observations and unknown inputs [7]. 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 [7-8].

In this paper, a technique for distributed detection of local damage in large-size structures with smart wireless sensor network is proposed. Based on its finite element model, a large size structure is decomposed 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 'additional unknown inputs' to the substructures. The extended state vector containing the structural parameters at element level and unknown external excitation of the substructures are estimated sequentially by the extended Kalman estimation and the recursive least squares estimation, respectively. A numerical example of detecting structural damages at element level in a large size plane truss bridge is studied to illustrate the efficiency of the proposed technique. Then, a new smart wireless sensor network recently developed by the authors is introduced. The distributed structural damage detection approach can be embedded into smart wireless sensor network for autonomous structural damage detection based on its two-level cluster-tree topology architecture and the distributed computation capacity of each cluster head.

2. DAMAGE DETECTION BASED ON SUBSTRUCTURE APPROACH

2.1 Finite element model of a large size linear structure

Based on finite-element analysis, the equation of motion of a large size 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 displacement, 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, $\boldsymbol{B}$ 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. The Rayleigh damping is usually assumed and the damping matrix $\boldsymbol{C}$ is ex-pressed as

$$\boldsymbol{C} = \alpha \boldsymbol{M} + \beta \boldsymbol{K} \tag{2}$$

in which α is the mass-proportional damping coefficient and β is the stiffness-proportional damping coefficient. A large size structure involves a large number of DOFs; it's difficult to directly identify its large numbers of structural parameters such as all the element stiffness and the Rayleigh damping coefficients α and β . 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 number of DOFs and the unknown parameters ,the large scale structure can be divided into a set of small size 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

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

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

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

Treating the interaction effects as 'unknown inputs' to the substructure concerned, Eq. (4) can be expressed as

$$\boldsymbol{M}_{rr}\ddot{\boldsymbol{x}}_r(t)+\boldsymbol{C}_{rr}\dot{\boldsymbol{x}}_r(t)+\boldsymbol{K}_{rr}\boldsymbol{x}_r(t)=\boldsymbol{B}_r\boldsymbol{f}_r(t)+\boldsymbol{B}_r^u\boldsymbol{f}_r^u(t)+\boldsymbol{B}_r^*\boldsymbol{f}_r^*\left(t\right) \tag{5}$$

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

$$\boldsymbol{B}_r^*\boldsymbol{f}_r^*\left(t\right)=-\boldsymbol{M}_{rs}\ddot{\boldsymbol{x}}_s(t)-\boldsymbol{C}_{rs}\dot{\boldsymbol{x}}_s(t)-\boldsymbol{K}_{rs}\boldsymbol{x}_s(t) \tag{6}$$

Therefore, the substructure is excited by limited unmeasured external excitations and the 'additional 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 unavailable. Recently, Yang et al. proposed the algorithms of extended Kalman filter for structural damage identification under unknown inputs and the sequential nonlinear least square estimation with unknown inputs and outputs [5-6]. Lei et al. also developed an algorithm for element level structural damage detection with limited observations and with unknown inputs [7]. 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-square 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

$$\boldsymbol{Z}_r=[\boldsymbol{Z}_{1r}^T,\boldsymbol{Z}_{2r}^T,\boldsymbol{Z}_{3r}^T]^T \tag{7}$$

in which

$$\boldsymbol{Z}_{1r}=\boldsymbol{x}_r^T\ ;\ \boldsymbol{Z}_{2r}=\dot{\boldsymbol{x}}_r^T\ ;\ \boldsymbol{Z}_{3r}=[k_{r1},k_{r2},...,k_{rm},a,\ \beta]^T \tag{8}$$

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

Considering the unknown stiffness and damping parameters are constant, .i.e., $\dot{k}_{ri}=0$, $\dot{\alpha}=0$, $\dot{\beta}=0$, Eq. (5) can be written into the following extended state equation for the extended state vector as,

$$\dot{\boldsymbol{Z}}_r=\begin{Bmatrix}\dot{\boldsymbol{Z}}_{1r}\\ \dot{\boldsymbol{Z}}_{2r}\\ \dot{\boldsymbol{Z}}_{3r}\end{Bmatrix}=\begin{Bmatrix}\boldsymbol{Z}_{2r}\\ \boldsymbol{M}_{rr}^{-1}[\boldsymbol{B}_r\boldsymbol{f}_r(t)+\boldsymbol{B}_r^u\boldsymbol{f}_r^u(t)+\boldsymbol{B}_r^*\boldsymbol{f}_r^*\left(t\right)-(\boldsymbol{C}_{rr})_{Z_{3r}}\boldsymbol{Z}_{2r}-(\boldsymbol{K}_{rr})_{Z_{3r}}\boldsymbol{Z}_{1r}]\\ 0\end{Bmatrix} \tag{9}$$

where $(\boldsymbol{C}_{rr})_{Z_{3r}}$ and $(\boldsymbol{K}_{rr})_{Z_{3r}}$ represents that elements in the damping matrix $\boldsymbol{C}_{rr}$ and stiffness matrix $\boldsymbol{K}_{rr}$ of the substructure are composed by unknown parameter vector $\boldsymbol{Z}_{3r}$, respectively.

As observed from Eq. (9), the extended state equation is a nonlinear equation of the extended state vector. Therefore, Eq.(9) can be rewritten in the following general nonlinear differential state equation as

$$\dot{\boldsymbol{Z}}_r = f(\boldsymbol{Z}_r, \boldsymbol{f}_r, \boldsymbol{f}_r^u, \boldsymbol{f}_r^*, t) \tag{10}$$

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

$$\begin{aligned} \boldsymbol{Y}_r[k] = \boldsymbol{D}_r \dot{\boldsymbol{Z}}_{2r}[k] + \boldsymbol{v}_r[k] = \boldsymbol{D}_r \left\{ -(\boldsymbol{C}_{rr})_{Z_{3r}} \boldsymbol{Z}_{2r}[k] - (\boldsymbol{K}_{rr})_{Z_{3r}} \boldsymbol{Z}_{1r}[k] \right\} \\ + \boldsymbol{G}_r \boldsymbol{f}_r[k] + \boldsymbol{G}_r^u \boldsymbol{f}_r^u[k] + \boldsymbol{G}_r^* \boldsymbol{f}_r^*[k] + \boldsymbol{v}_r[k] \end{aligned} \tag{11}$$

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, $\boldsymbol{D}_r$ 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. (11), 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:

$$\boldsymbol{Y}_r[k] = h\left(Z_r[k], t[k]\right) + \boldsymbol{G}_r \boldsymbol{f}_r[k] + \boldsymbol{G}_r^u \boldsymbol{f}_r^u[k] + \boldsymbol{G}_r^* \boldsymbol{f}_r^*[k] + \boldsymbol{v}_r[k] \tag{12}$$

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,

$$\hat{\boldsymbol{Z}}_r[k+1|k] = \tilde{\boldsymbol{Z}}_r[k+1|k] + \boldsymbol{K}_r[k] \left\{ \boldsymbol{Y}_r[k] - \boldsymbol{h}\left(\boldsymbol{Z}_r[k], \boldsymbol{f}_r[k], \boldsymbol{f}_r^u[k], \boldsymbol{f}_r^*[k], t[k] \right) \right\} \tag{13}$$

in which,

$$\tilde{\boldsymbol{Z}}_r[k+1|k] = \hat{\boldsymbol{Z}}_r[k|k-1] + \int_{t[k]}^{t[k+1]} f(\boldsymbol{Z}_r, \boldsymbol{f}_r, \boldsymbol{f}_r^u, \boldsymbol{f}_r^*, t)\, dt \tag{14}$$

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

However, since $\boldsymbol{f}_r^u$ and $\boldsymbol{f}_r^*$ are unknown inputs of 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 Estimation of the unknown external excitation and the additional unknown inputs to the substructure

For a large size structure, it's impossible to employ so many sensors at all the DOFs of the substructure interfaces. Therefore, the unknown input $\boldsymbol{f}_r^*$ does not present itself in the observation equation, Eq. (12). However, since the extended state vector at time $t = (k+1) \times \Delta t$ have been estimated, 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. (6), i.e.,

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

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 $t=(k+1)\times\Delta t$. $\ddot{x}_S[k+1|k]$ can be estimated by numerical differentiation.

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. (12) by the recursive least square estimation as

$$\hat{\boldsymbol{f}}_r^u[k+1]=[\boldsymbol{G}^u]^T\boldsymbol{R}^{-1}\boldsymbol{G}^u[\boldsymbol{G}^u]^T\left\{\boldsymbol{Y}_r[k+1]-h\left(\hat{Z}_r[k+1|k],t[k+1]\right)-\boldsymbol{G}_r\boldsymbol{f}_r[k+1]-\boldsymbol{G}_r^*\hat{\boldsymbol{f}}_r^*[k+1|k]\right\} \quad (16)$$

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, in the case, different substructure can not be identified independently, but can be identified concurrently with parallel computing.

3. NUMERICAL EXAMPLE OF A PLANE TRUSS BRIDGE

As show in Figure1, detection of structural local damage in a simply supported plane truss bridge with 23 bars subject to one unknown external excitation is taken as a numerical example to illustrate the aforementioned distributed damage detection approach. There are two DOFs, i.e. horizontal and vertical directions, at each node of the plane truss. In this numerical example, lumped mass is adopted; the mass of each bar is concentrated on its two ends. The following values for the structural element parameters are used in the numerical simulation study: cross section of bar $A=8.947\times10^{-5}\,m^2$; density of bar $\rho_i=7850kg/m^3$; Yong's module $E_i=2\times10^7\,N/m^2$, and the length of bar $l_i=2m$ and $l_i=\sqrt{2}m$, respectively. Rayleigh damping coefficients are selected as $\alpha=0.0226$ and $\beta=0.0035$.

Only 16 accelerometers are installed at each degree of freedom of nodes except those at node 2, 6 and 10. Therefore, only limited acceleration responses at some nodes are measured. The external excitation is assumed to be a white noise, but it is also not measured.

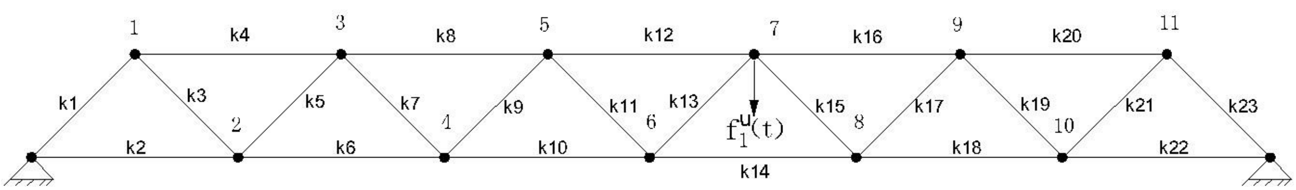

Fig.1 A large size simply supported plan truss with 23 bars

The global mass matrix $\boldsymbol{M}$ is diagonal as the mass is concentrated at the nodes. The global stiffness matrix $\boldsymbol{K}$ can be formulated as the summation of the element stiffness matrices. The local stiffness matrix of the i-th element is given by

$$\tilde{\boldsymbol{k}}_i=k_i\begin{bmatrix}1&0&-1&0\\0&0&0&0\\-1&0&1&0\\0&0&0&0\end{bmatrix} \quad (17)$$

in which, $k_i=E_iA_i/l_i$. The local element stiffness is first transformed into the element matrix $\boldsymbol{k}_i$ in the global coordinate system, using the transformation matrix $\boldsymbol{T}$, i.e.

$$\boldsymbol{k}_i = \boldsymbol{T}^T \tilde{\boldsymbol{k}}_i \boldsymbol{T} \quad ; \qquad \boldsymbol{T} = \begin{bmatrix} cos\theta & sin\theta & 0 & 0 \\ -sin\theta & cos\theta & 0 & 0 \\ 0 & 0 & cos\theta & sin\theta \\ 0 & 0 & -sin\theta & cos\theta \end{bmatrix} \tag{18}$$

where θ = the angle between the local and global coordinate systems. Then, the element stiffness matrix $\boldsymbol{k}_i$ is expanded to the size of the global stiffness matrix denoted by $\overline{\boldsymbol{k}}_i$ based on its nodal number. The global stiffness matrix **K** is obtained by summing up and for all the elements,

$$\boldsymbol{K} = \sum_{i=1}^{p} \overline{\boldsymbol{k}}_i \tag{19}$$

in which p is the total number of elements (members).

In the substructure approach for this large size truss bridge, the original large truss is divided into three sub-trusses as shown in Figure2. Interaction effect between adjacent substructures is taken into account by considering the interaction forces at substructural interfaces. These interaction forces are treated as the 'additional unknown inputs' to the substructure concerned, .e.g., $\boldsymbol{f}_1^*, \boldsymbol{f}_2^*$ and $\boldsymbol{f}_3^*$ are treated as the "additional unknown inputs" to substructure 1.

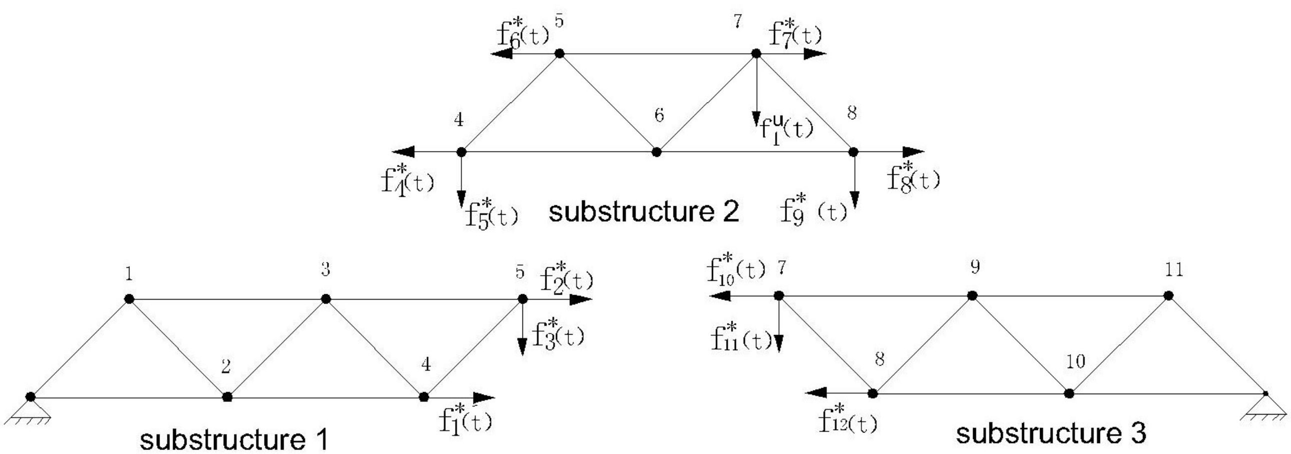

Fig.2 Substructures of the truss

Formulations of the interaction forces are shown in Eq.(6), where $\boldsymbol{M}_{rs} = 0$ as the global mass matrix is diagonal, matrix $\boldsymbol{K}_{rs}$ can be derived the stiffness of the elements at the substructural interfaces based on the assembling of the global stiffness matrix as shown aforementioned, and $\boldsymbol{C}_{rs} = \beta K_{rs}$.

Structural local damage is simulated by the degrading of the bar stiffness parameters of the truss. Two damage patterns are considered. In damage pattern 1(DP1), damage is assumed to occur in the 2nd bar which causes k_2 to reduce from 894.76N/m to 626.33N/m. In damage pattern 2(DP2), structural local damage is assumed to occur in both the 2nd and 22nd bars which causes k_2 and k_{22} both to reduce from 894.76N/m to 626.33N/m. Based on the proposed distributed damage detection approach, the identified stiffness parameters of the truss in undamaged pattern and the damage pattern1 are shown in Table 1. And the truss in undamaged pattern and the damage pattern 2 are shown in Table 2. From the comparison of the identified results with their analytical values, it is shown that the proposed method can identify structural element stiffness parameters with good accuracy and structural damage can be detected and located from the degrading of element stiffness parameters.

Table 1 Identification results for damage pattern 1

Sub No.	Bar No.	Bar Stiffness k_i (N/m)					
		Undamaged(Exact)	Undamaged(Identified)	Error (%)	DP1(Exact)	DP1 (Identified)	Error (%)
Sub 1	1	1265.4	1251.9	-1.07	1265.4	1251.1	-1.13
	2	894.8	897.5	0.31	**626.3**	**607.4**	-3.02
	3	1265.4	1263.9	-0.11	1265.4	1252.7	-1.00
	4	894.8	903.8	1.01	894.8	910.1	1.71
	5	1265.4	1237.6	-2.19	1265.4	1245.4	-1.58
	6	894.8	891.0	-0.42	894.8	906.2	1.28
	7	1265.4	1280.3	1.18	1265.4	1281.6	1.28
	8	894.8	900.7	0.66	894.8	892.2	-0.29
	9	1265.4	1266.8	0.11	1265.4	1259.7	-0.45
Sub 2	9	1265.4	1256.6	-0.69	1265.4	1252.7	-1.00
	10	894.8	898.7	0.44	894.8	905.2	1.17
	11	1265.4	1252.8	-0.99	1265.4	12412.0	-1.85
	12	894.8	852.4	-4.73	894.8	898.4	0.41
	13	1265.4	1278.2	1.02	1265.4	1283.1	1.40
	14	894.8	878.9	-1.77	894.8	882.8	-1.34
	15	1265.4	1268.6	0.26	1265.4	1276.1	0.85
Sub 3	15	1265.4	1278.1	1.00	1265.4	1276.5	0.88
	16	894.8	884.0	-1.20	894.8	875.3	-2.17
	17	1265.4	1262.5	-0.23	1265.4	1268.4	0.24
	18	894.8	884.9	-1.11	894.8	897.5	0.31
	19	1265.4	1275.0	0.76	1265.4	1270.1	0.37
	20	894.8	895.1	0.04	894.8	890.1	-0.52
	21	1265.4	1275.8	0.82	1265.4	1263.0	-0.19
	22	894.8	898.0	0.37	894.8	903.0	0.92
	23	1265.4	1260.8	-0.36	1265.4	1263.5	-0.15

Table 2 Identification results for damage pattern 2

Sub No.	Bar No.	Bar stiffness k_i (N/m)					
		Undamaged(Exact)	Undamaged(Identified)	Error (%)	DP2(Exact)	DP2(Identified)	Error (%)
Sub 1	1	1265.4	1251.9	-1.07	1265.4	1264.6	-0.06
	2	894.8	897.5	0.31	**626.3**	**644.9**	2.97
	3	1265.4	1263.9	-0.11	1265.4	1268.7	0.26
	4	894.8	903.8	1.01	894.8	905.0	1.15
	5	1265.4	1237.6	-2.19	1265.4	1259.9	-0.43
	6	894.8	891.0	-0.42	894.8	882.4	-1.38
	7	1265.4	1280.3	1.18	1265.4	1267.4	0.16
	8	894.8	900.7	0.66	894.8	895.7	0.10

	9	1265.4	1266.8	0.11	1265.4	1274.0	0.68
Sub 2	9	1265.4	1256.6	-0.69	1265.4	1272.2	0.54
	10	894.8	898.7	0.44	894.8	905.7	1.22
	11	1265.4	1252.8	-0.99	1265.4	1253.7	-0.92
	12	894.8	852.4	-4.73	894.8	909.9	1.69
	13	1265.4	1278.2	1.02	1265.4	1270.1	0.37
	14	894.8	878.9	-1.77	894.8	877.6	-1.92
	15	1265.4	1268.6	0.26	1265.4	1266.1	0.06
Sub 3	15	1265.4	1278.1	1.00	1265.4	1273.1	0.61
	16	894.8	884.0	-1.20	894.8	893.1	-0.19
	17	1265.4	1262.5	-0.23	1265.4	1269.0	0.29
	18	894.8	884.9	-1.11	894.8	886.9	-0.88
	19	1265.4	1275.0	0.76	1265.4	1266.1	0.06
	20	894.8	895.1	0.04	894.8	899.4	0.52
	21	1265.4	1275.8	0.82	1265.4	1277.8	0.98
	22	894.8	898.0	0.37	**626.3**	**635.7**	1.49
	23	1265.4	1260.8	-0.36	1265.4	1267.3	0.15

4. A NEW SMART WIRELESS SENSOR NETWORK FOR EXECUTING DISTRIBUTED DAMAGE DETECTION

With the developments of wireless communication, wireless sensing systems have been proposed to eradicate the extensive lengths of wires in the tethered systems. Some innovative wireless sensing systems have been proposed in recent years as a promising solution for efficient and low-cost structural monitoring[10-11]. While wireless sensing network provides an economical data acquisition technology for monitoring large size structures, a greatest attribute of the wireless sensor network is its distributed computational resources collocated with the sensor nodes[11-12]. Such resources can be leveraged to allow the sensor to perform its own data interrogation tasks. This capability is particularly attractive within the context of SHM for large size structures. Specifically, wireless sensors proposed for SHM will be responsible for screening their own measurement data to identify the possible existence of damage. Already, many data processing algorithms have been embedded in wireless sensors for autonomous execution[13-15].

In this paper, a new type of wireless sensing network is proposed to incorporate the aforementioned distributed damage detection approach for the autonomous damage detection of large size structures [16]. To meet the demands of large network nodes, low complexity, long distance data transmission and low power in wireless senor network for the application of the proposed distributed damage detection approach, a cluster-tree network topology is proposed for the new wireless sensor network as shown in Fig. 3.

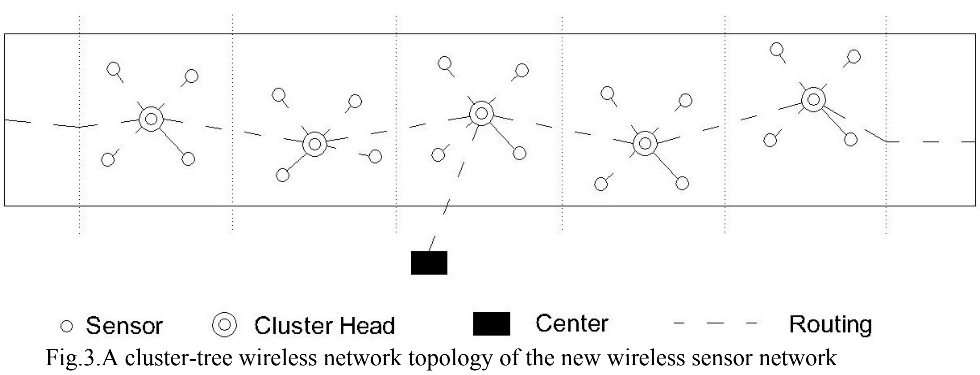

Fig.3.A cluster-tree wireless network topology of the new wireless sensor network

The distributed sensing nodes in a substructure are grouped into a cluster. A cluster head is assigned to each cluster to coordinate the sensing node in its cluster and to collect data from them during monitoring. Communication between the distributed sensing nodes with their corresponding cluster head forms the lower tier and the network of cluster heads forms the upper tier. A cluster head not only serves as a router of the network messages but also possesses computational capabilities with the data collected from the sensing nodes in the cluster. This network topology provides parallel computation between the substructures, which is a useful feature to incorporate with the proposed distributed damage detection approach for large size structures.

Figure 4 and Figure 5 show the hardware design of a wireless sensing node and a cluster head, respectively. It is noted that the difference lies in their computational cores [16-17]. The computational core of the wireless unit is responsible for executing embedded software instructions for engineering analyses. For a normal wireless sensing node, the 8-bit Atmel ATmega128L AVR microcontroller is selected as the principle component of the computational core. A more powerful, high-performance but low-power digital signal processor (DSP) TMS320C5509 with a RAM 256K*16bit, ROM 64K*16bit, and a maximum operating frequency up to 200-MHz clock rate is selected as the computational core of the cluster head for executing the embedded software of the proposed distributed damage detection.

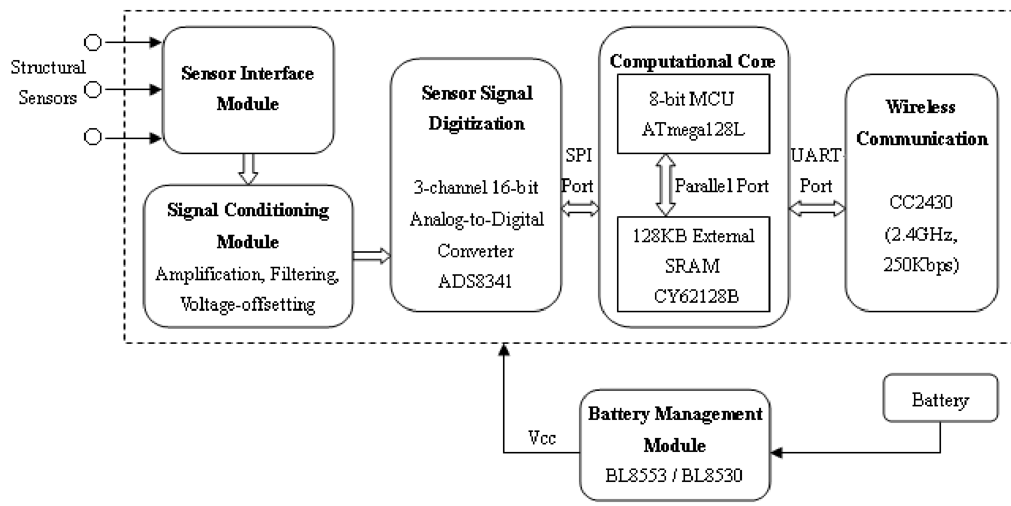

Fig.4 .Hardware structure of a wireless sensing node in the wireless sensor network

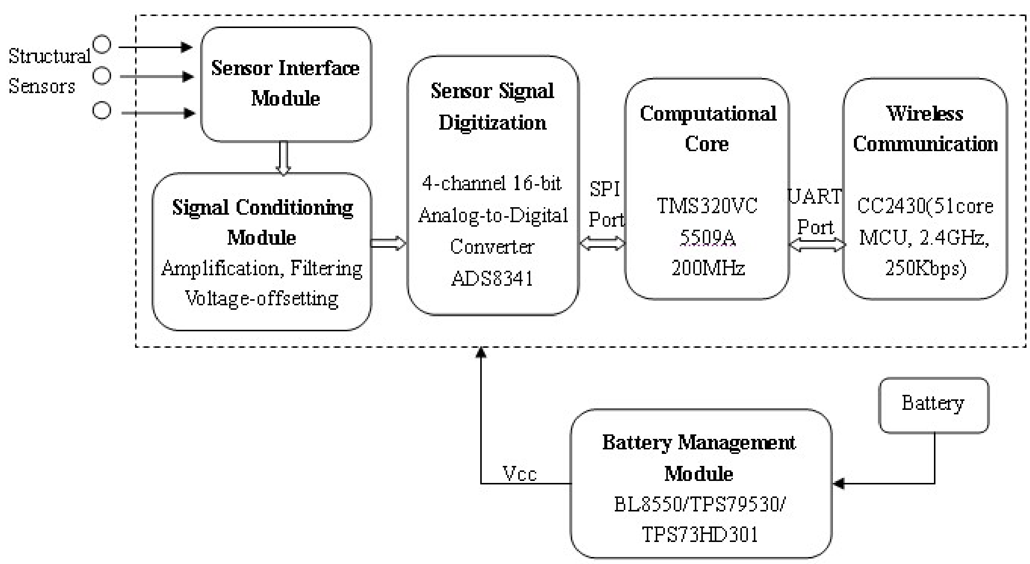

Fig.5 .Hardware structure of a cluster head in the wireless sensor network

The algorithm of proposed distributed damage detection approach is embedded in the cluster heads of the wireless sensor network. The computational core with embedded software grants the wireless sensor network the 'smart' characteristics, which can be applied for autonomous structural damage detection of large size structures. The developed smart wireless sensor network with embedded distributed detection approach is applied to the numerical example of detecting structural local damage in the large size plan truss. As shown in Figure 6, the wireless sensor network consists of three clusters for the three sub-trusses. DSP in each cluster head is embedded with the algorithm of the proposed distributed detection approach. Communication between the adjacent cluster head transfers the estimated values of interaction forces at substructure interfaces based on their formation in Eq. (15).

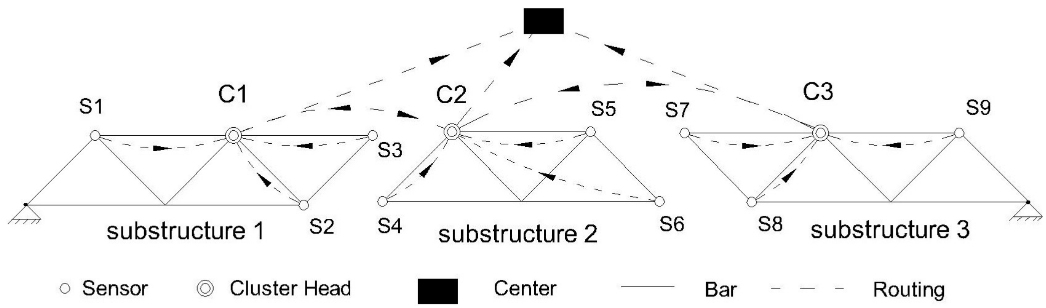

Fig.6 wireless sensor network for substructure approach

5. CONCLUSIONS

In this paper, a technique is proposed for autonomous detecting structural damage in large size structures with smart wireless sensor network. Based on substructure approach, a distributed structural damage detection algorithm is proposed for large size structures under limited input and output measurements. Interaction effect between adjacent substructures is accounted by considering the interaction forces at substructural interfaces as the 'additional unknown inputs' to the substructures. Damage detection of each substructure can be identified concurrently with parallel computing when measurements at the substructure interfaces are not available. Under the condition that the number of response measurement is more than that of the unknown external excitation, structural parameters at element level and the unknown external excitation can be estimated sequentially based on the extended Kalman estimation and recursive least-square estimation. A numerical example demonstrates that the technique is capable of detecting local damage in a large size plane truss bridge with satisfactory accuracy.

The proposed distributed structural damage detection strategy is suitable for automated damage detection implemented by smart wireless sensor network based on its distributed computing capacity. A wireless sensor network is developed by the authors for this purpose. The algorithm of the proposed distributed structural damage detection approach can be embedded into the smart wireless sensor network based on its cluster-tree topology architecture and the distributed computation capacity of each cluster head. Application of the technique for the developed smart wireless sensor network with embedded distributed detection algorithm to the numerical example of detecting structural local damage in the large size plan truss is illustrated. Relevant experimental work is undertaken by the authors.

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