Smart Structures and Systems, *Vol. 12, No. 3-4 (2013) 399-414*
DOI:http://dx.doi.org/10.12989/sss.2013.12.3_4.399

Wireless sensor network for decentralized damage detection of building structures

Jong-Woong Park[1], Sung-Han Sim[*2] and Hyung-Jo Jung[**1]

[1]*Department of Civil and Environmental Engineering, KAIST, Daejeon, Korea*
[2]*School of Urban and Environmental Engineering, UNIST, Ulsan, Korea*

(Received Novemeber 1, 2012, Revised June 21, 2013, Accepted July 12, 2013)

Abstract. The smart sensor technology has opened new horizons for assessing and monitoring structural health of civil infrastructure. Smart sensor's unique features such as onboard computation, wireless communication, and cost effectiveness can enable a dense network of sensors that is essential for accurate assessment of structural health in large-scale civil structures. While most research efforts to date have been focused on realizing wireless smart sensor networks (WSSN) on bridge structures, relatively less attention is paid to applying this technology to buildings. This paper presents a decentralized damage detection using the WSSN for building structures. An existing flexibility-based damage detection method is extended to be used in the decentralized computing environment offered by the WSSN and implemented on MEMSIC's Imote2 smart sensor platform. Numerical simulation and laboratory experiment are conducted to validate the WSSN for decentralized damage detection of building structures.

Keywords: damage detection; decentralized data processing; wireless smart sensor network; smart sensor

1. Introduction

Structural health monitoring (SHM) is an important technology for civil engineers to evaluate the structural integrity and performance that may degrade due to unexpected loadings and harsh environmental conditions during their lifetime. In particular, constructions of taller and slenderer structures such as long-span bridges and high-rise building have been increasing, while such structures can be vulnerable to external loadings and cause disasters unless properly maintained. As such, the role of SHM becomes more important in modern societies to ensure public safety.

One of the notable advances in the field of SHM is the smart sensor technology which provides numerous useful SHM applications by realizing low-cost smart sensors with on-board computation, wireless communication, sensing capability, and independent power sources. These unique features of the smart sensor have shown great potential to overcome intrinsic difficulties found in traditional monitoring systems using wired sensors. However, the WSSN also have limitations such as communication failures and power consumption (Ling *et al*. 2009). Especially in large

∗Corresponding author, Assistant Professor, E-mail: ssim@unist.ac.kr
∗∗Corresponding author, Associate Professor, E-mail: hjung@kaist.ac.kr

http://www.techno-press.org/?journal=sss&subpage=8 ISSN: 1738-1584 (Print), 1738-1991 (Online)

WSSNs deployed in full-scale civil structures, extensive wireless communications are required for all sensors to transmit measured data to the central location, which increases the chance of unreliable communications (e.g., packet loss) as well as drastically drains sensor batteries, reducing the operational lifetime of the WSSN. To improve the communication reliability and extend the network lifetime, in-network data processing approaches are introduced. Smart sensor's onboard computation is utilized to process raw sensor data to extract essential information. By collecting this condensed information only, the amount of wireless transmission can be significantly reduced.

The decentralized processing embedded in the WSSN has empowered damage detection particularly for bridge structures. Lynch *et al*. (2004) developed a smart sensor system, one of the earliest works for the embedded processing to be employed in detection structural damage. A time-series damage detection algorithm was implemented to find structural changes from a simple lumped-mass test structure. For more realistic damage analysis of large civil structures, Gao *et al*. (2005) proposed a decentralized computing strategy for damage localization that intends the use of smart sensors in full-scale civil infrastructure. Implemented in the WSSN employing MEMSIC's Imote2 smart sensor platform, Nagayama and Spencer (2007) experimentally verified the decentralized computing in the laboratory-scale testing. Subsequently, Jang *et al*. (2012) applied the decentralized approach using the WSSN to the damage detection of a full-scale truss bridge.

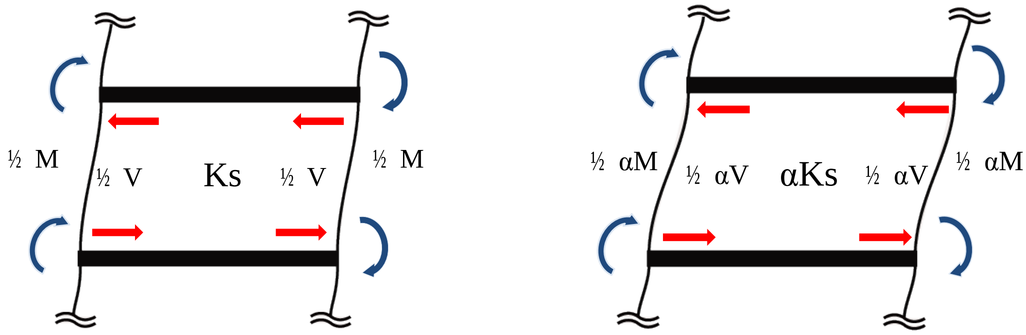
Furthermore, Park *et al*. (2008) developed a wireless sensor system for damage detection of a PSC girder model using smart sensor's local processing. As such, most research efforts to date in the use of the smart sensors for damage detection have been focused on bridge structures; relatively less attention is paid to applying to building structures.

Several researches have been conducted on the building structures using WSSNs. Kurata *et al.* (2005) investigated feasibility of risk monitoring using a network of WSSNs. The WSSNs for monitoring of a building structure was validated through shaking table tests employing a two-story steel structure. However, centralized data processing which can be limited in the building structure due to wireless communication range was considered in the study. Ling *et al.* (2009) presented a decentralized data processing algorithm for a building structure based on the embedded AR-ARX method. Each sensor node independently calculates a statistical damage-sensitive coefficient using the measured acceleration response. However, the efficiency of the algorithm was only validated through numerical simulation study.

This study proposes a WSSN-based decentralized processing scheme for damage detection of building structures. As the damage-sensitive nature of the flexibility-based damage detection approaches, Damage Induced Inter-story Deflection (DI-ID) proposed by Koo *et al*. (2011) is adopted in this study and extended to be used in a decentralized computing environment in the WSSN. To validate the proposed approach, numerical simulation is performed using a 21-story shear building model. The decentralized damage detection method is implemented on the WSSN of Imote2 smart sensors and used in the laboratory experiments with a 5-story shear building structure.

2. Backgrounds

This section provides relevant backgrounds that this study is based on: (1) a flexibility-based damage detection method, (2) wireless smart sensor, and (3) decentralized processing in the WSSN.



(a) Intact case (b) Damaged case

Fig. 1 Free body diagram of member-level shear building model

2.1. Damage Induced Inter-story Deflection (DI-ID) method

For completeness, the DI-ID method (Koo *et al*. 2011) is briefly described herein. Consider a shear building model described by stiffness matrix K_0, subjected to a force F with the resulting deflection U_0

$$K_0 U_0 = F \tag{1}$$

If a damage defined by stiffness reduction ΔK is inflicted to this structure, the deflection-force relationship can be written as

$$\left(K_0 - \Delta K\right)\left(U_0 + \Delta U\right) = F \tag{2}$$

where ΔU is the damage-induced deflection by the stiffness reduction under the same force F. Subtracting Eqs. (1) from (2)

$$\Delta U = G_D\left(\Delta K U_0\right) = G_D \Delta F \tag{3}$$

where $G_D = (K_0 - \Delta K)^{-1}$ is the flexibility of the damaged structure and $\Delta F = \Delta K U_0$ is the force change due to the stiffness reduction.

Damage locations can be found by applying a set of forces that produce positive shear forces in the structure. Under the positive shear force, the DI-ID is positive in the damaged floors and zero in the non-damaged floors. Fig. 1 shows the free body diagrams of member-level shear building model with floor stiffness values K_s and αK_s of the intact and damaged cases, respectively. The member-level damage severity α ($0<\alpha<1$) can be estimated by the damage-induced inter-story deflection as follows

$$\Delta U^{IS} = \frac{1}{(1-\alpha)Ks} \times \alpha V = \frac{\alpha}{(1-\alpha)} \times U_0^{\ IS} \tag{4}$$

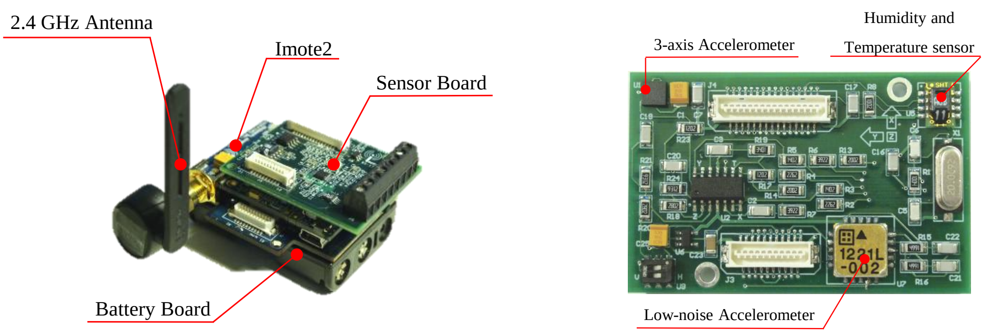
where U^{IS} is the inter-story deflection of the intact floor, K_S and $(1-\alpha)K_s$ are the member-level stiffness of the intact and the damaged floors, respectively; αV is the shear force lost by damage. From (8), the damage index α at the damaged floor can be expressed as

$$\alpha = \frac{\Delta U^{IS}}{U_D^{IS}} \tag{5}$$

where $U_D^{IS} = U_0^{IS} + \Delta U^{IS}$ is the inter-story deflection of the damaged floor.

2.2. Wireless Smart Sensor (WSS)

To realize the damage detection algorithm on the WSSN, MEMSIC's Imote2 sensor platform (see Fig. 2) is selected due to its sufficient memory space and computing capability for data storage and processing required in the in-network damage detection. Imote2 has Intel's low power X-scale processor with variable clock speeds of 13 – 416 MHz and memory spaces of 256kB SRAM, 32MB FLASH, and 32MB SDRAM. Imote2 uses 2.4 GHz wireless communication which supports a 250 Kbps data rate. Imote2 is considered to be suitable for the embedded processing of the large amount of data for damage detection.



(a) Imote2 (b) SHM-H sensor board (SD1221 Manual)

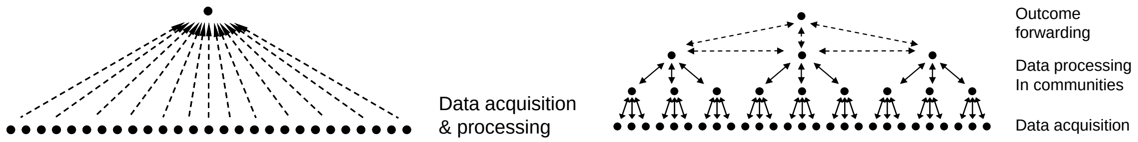
Fig. 2 Imote2 smart sensor platform and SHM-H acceleration sensor board

Imote2 can be interfaced with sensor boards that can measure data such as acceleration, strain, temperature, humidity, and light, depending on the attached sensor boards. As the damage detection method in this study requires acceleration signals, the SHM-H sensor board developed in the University of Illinois at Urbana-Champaign is selected. The SHM-H sensor board employs 3-axis analog accelerometer LIS344ALH (see Table 1) for x and y-axis and low-noise single-axis accelerometer SD1221L-002 for z-axis. The low-noise accelerometer provides excellent resolution for low-level ambient vibration than the 3-axis accelerometer adoptable for general purpose measurement. The low-noise accelerometer, Silicon Designs SD1221L-002, has 5 $\mu g/\sqrt{Hz}$

noise floor and 2 V/g sensitivity. The analog signal from the accelerometer are digitized by the embedded Quickfilter QF4A512, which has a 4-channel, 16-bit analog to digital converter (ADC) and programmable signal conditioner with user-selectable sampling rates and programmable digital filters. The performance of SHM-H is considered to be sufficient for damage detection.

Table 1 Specification of accelerometers

Parameter	LIS344ALH	SD1221L-002
Axes	3	1
Measurement range	±2 g	±2g
Noise density	50 μg/√Hz	5 μg/√Hz
Resolution	0.66 V/g	2 V/g
Power supply	2.4 V to 3.6 V	5V
Temperature range	-40 to 85 ℃	-55 to 125 ℃
Supply current	0.85 mA	8 mA



(a) Independent processing (b) Coordinated processing

Fig. 3 Decentralized processing schemes

2.3. Decentralized computing in WSSN

The WSSN in the early period of smart sensor research has used the centralized data collection and processing, which is typically used in the traditional wired sensor system. In the centralized WSSN, each sensor node measures and transfers data sequentially to the central base-station. Collecting all raw sensor data at the central location not only causes data inundation problems but also requires excessive power associated with wireless data transmission. Thus, the centralized WSSN is considered to be inappropriate for the large-scale sensor networks.

Alternatively, WSSN research has been evolved to decentralized approaches that utilize smart sensor's on-board computation to reduce the size of data to be transmitted. Two types of decentralized computing strategies are most commonly adopted: (1) independent processing and (2) coordinated processing as shown in Fig. 3. In the independent processing, all sensor nodes independently process measured data to extract essential information. Thus, data processing methods that do not require data sharing between sensor nodes are appropriate for the independent processing, such as the fast Fourier transform (FFT) (Lynch *et al*. 2003), autoregressive time-series modeling (Lynch *et al*. 2004), and signal-based cable tension estimation (Cho *et al*. 2010). The decentralized coordinated processing uses a hierarchical network that consists of subdivided local communities. Sensor data is processed and shared within each local community. Based on the decentralized coordinated processing, several systems have been proposed for damage detection

(Nagayama and Spencer 2007, Hackmann *et al*. 2012, Ho *et al*. 2012), modal analysis (Zimmerman *et al*. 2008, Sim *et al*. 2010), model updating (Zimmerman and Lynch 2009).

3. Decentralized damage detection in building structures

Collecting measured responses to a central location from all wireless sensors distributed over a high-rise building is inadequate due to the possible communication failures and excessive power consumption; in-network processing in a decentralized network is an excellent alternative in the damage detection. The decentralized coordinated processing shown in Fig. 3(b) is considered to be appropriate for the decentralized damage detection. This study investigates and extends the use of the flexibility-based DI-ID method developed by Koo *et al*. (2011) in the decentralized data processing environment.

Consider a shear building model with a wireless network of sensors that is divided into N local sensor communities (see Fig. 4). The global flexibility matrix using m lower modes G_m can be expressed in terms of the mass-normalized global mode shape matrix Φ_m

$$G_m = \Phi_m \Lambda^{-1} \Phi_m{}^T \tag{6}$$

where Λ_m is the n th natural frequency, n =1, 2, . . . ,m; Φ_m = {φ1, φ2, . . . ,φ_m}; and φ_n is the n th mode shape with a mass-normalization.

Let Φ_i and Φ_{ic} the local mode shapes for the i-th community and the rest of the communities, respectively and Λ is the diagonal matrix with ω_i^2 on its diagonal, to expand G_g.

$$G_g = \begin{bmatrix} \Phi_i \\ \Phi_{ic} \end{bmatrix} \Lambda^{-1} \begin{bmatrix} \Phi_i{}^T & \Phi_{ic}{}^T \end{bmatrix} = \begin{bmatrix} \Phi_i \Lambda^{-1} \Phi_i{}^T & \Phi_i \Lambda^{-1} \Phi_{ic}{}^T \\ \Phi_{ic} \Lambda^{-1} \Phi_i{}^T & \Phi_{ic} \Lambda^{-1} \Phi_{ic}{}^T \end{bmatrix} \tag{7}$$

Applying load L_i to the i-th community

$$\begin{bmatrix} u_i \\ u_{ic} \end{bmatrix} = G_g \begin{bmatrix} L_i \\ 0 \end{bmatrix} = \begin{bmatrix} \Phi_i \Lambda^{-1} \Phi_i{}^T L_i \\ \Phi_{ic} \Lambda^{-1} \Phi_i{}^T L_i \end{bmatrix} \tag{8}$$

where u_i and u_{ic} are the deflection for the i-th community and the rest, respectively. Thus, the flexibility matrix for the i-th community G_i, is:

$$G_i = \Phi_i \Lambda^{-1} \Phi_i{}^T \tag{9}$$

Note that the local mode shape does not normalize the local mass whereas the global mode shape is mass normalized

$$\begin{aligned} \Phi_i{}^T M_i \Phi_i &\neq I \\ \Phi_g{}^T M \Phi_g &= I \end{aligned} \tag{10}$$

Thus, when estimated from measured data in each sensor community, local mode shapes should be normalized with respect to the mass-normalized global mode shapes to estimate the local flexibility matrix using Eq. (9).

The damage detection process based on the decentralized coordinated computing is summarized in Fig. 5. In the initialization stage, the reference data (i.e., mode shapes and flexibility matrix for the undamaged state) is obtained by collecting all sensor data at the central base station. This reference information is stored in the sensor network and used in the operation stage. In each local sensor community, local mode shapes are calculated and used to estimate the local flexibility matrix; the damage detection is performed, producing the local damage index that is sent to the base station and combined with indices from other communities. The final damage assessment can be made using the combined damage indices from all local communities. This damage detection process is numerically verified in the next section.

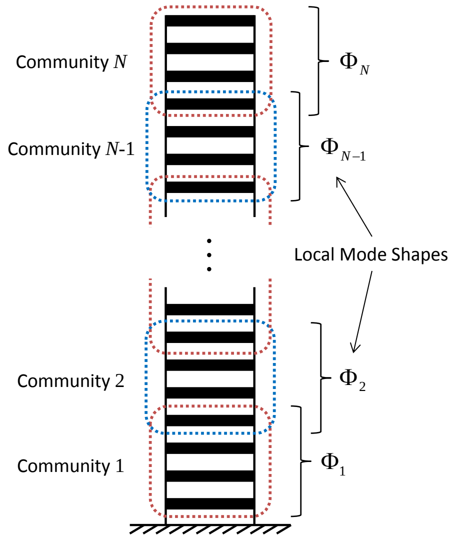


Fig. 4 Local sensor communities for decentralized computing

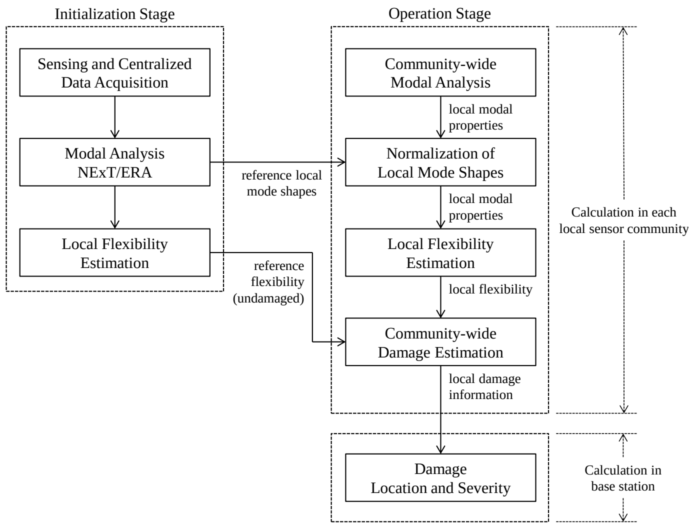


Fig. 5 Schematic flow of the decentralized damage detection

4. Numerical validation

To demonstrate the feasibility of the decentralized damage detection described in the previous section, numerical simulations are carried out using a 21-story shear building model. Mass and stiffness of each floor are assumed to be 2.7×10^5 kg, 1.4×10^8 N/m and the modal damping of 1% is introduced. To simulate the decentralized damage detection, the structure is divided into 5 local communities, in which local flexibilities are evaluated.

A total of three damage cases are considered as shown in Table 2. Changes in the modal parameters due to the damages are shown in Table 3, in which the natural frequencies are found to be reduced by 1~2%.

Table 2 Damage Scenario

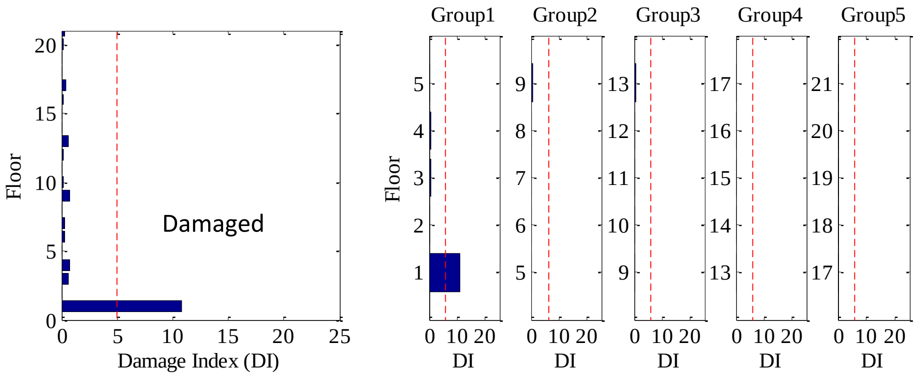
Case	Damage Location	Extent of Damage (Reduction of stiffness)
1	1	10%
2	1, 12	20%
3	1, 8, 17	10%, 20%, 10%

Table 3 Change in natural frequencies

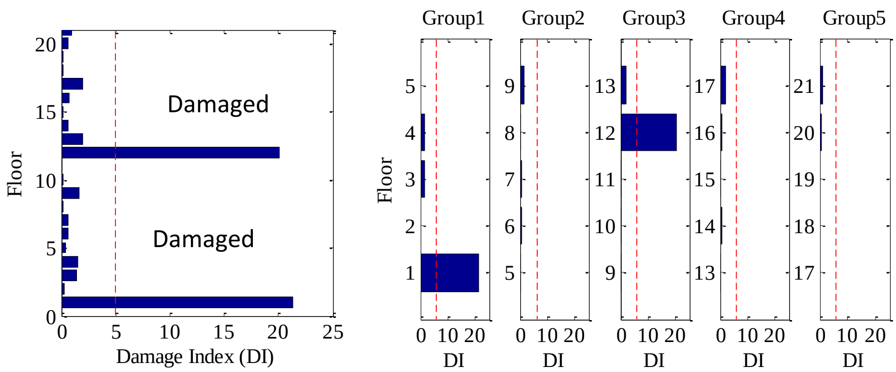
Damage Case	1st mode		2nd mode		3rd mode	
	f_1 (Hz)	$\Delta f_1/f_1$ (%)	f_2 (Hz)	$\Delta f_2/f_2$ (%)	f_3 (Hz)	$\Delta f_3/f_3$(%)
Intact	0.265	0	0.793	0	1.317	0
Damage 1	0.263	-0.49	0.789	-0.50	1.310	-0.532
Damage 2	0.260	-1.62	0.778	-1.89	1.300	-1.291
Damage 3	0.261	-1.40	0.786	-0.88	1.291	-1.974

In each community, local flexibility matrices are obtained using the numerical model. In practice only first few natural modes are identified and used in estimating the flexibility; 6 lower modes of the shear building are used herein.

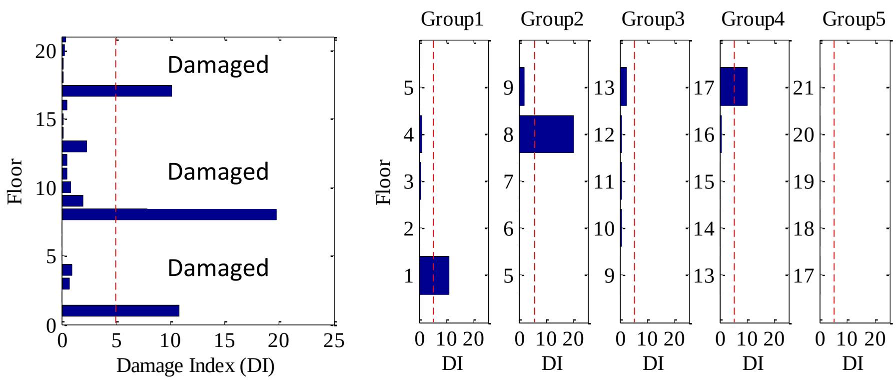
The decentralized damage detection is conducted using the flexibility matrices, approximate estimated using the 6 lower modes. The damage severity values for the three damage cases are calculated and shown in Fig. 6: the damage severity for each group is shown on the right side and the combined severity for the entire structure is on the left side. The combined damage severity obtained using the approximate flexibility is summarized and compared to the exact stiffness reduction in Table 4. All damage cases are successfully identified with the accurate damage severity estimation using the decentralized damage detection approach. Note that non-zero damage severity values can occur at undamaged floors due to the inaccuracy in the flexibility matrix; thus, the threshold of 5%, marked as the red lines in Fig. 6, is considered to prevent false positive detections (i.e., undamaged but found to be damaged).



(a) Damage case 1



(b) Damage case 2



(c) Damage case 3

Fig. 6 Damage severity by decentralized modal flexibility

Table 4 Estimated damage severity using the approximate flexibility

Damage Case	1	2		3		
Damaged Floors	1	1	12	1	8	17
Imposed stiffness reduction (%)	10	20	20	10	20	10
Damage severity α estimated using 6 modes (%)	10.76	21.32	20.09	10.80	19.77	10.10

5. Implementation on WSSN

5.1. Software development environment

The decentralized damage detection is implemented on the Imote2-based sensor network based on Illinois SHM Project (ISHMP) Services Toolsuite. To run applications on wireless smart sensors, complex programming is generally required for essential components of sensing, wireless communication, networking, and algorithm implementations. The ISHMP Service Toolsuite provides open-source middleware services implementing the components. These software components provided in the form of software services can be used as building blocks to develop a new sensor application, significantly reducing time and effort in programming. More detailed information regarding the ISHMP Services Toolsuite can be found in Rice *et al.* (2009).

The application, *Decentralized Damage Locating and Quantification (DDLQ)*, is developed to estimate the damage severity based on the decentralized coordinate processing. The implementation of *DDLQ* combines the damage detection algorithm with the services in the ISHMP Services Toolsuite, including:

- *Time Synchronization* to synchronize local clocks in each sensor node
- *Unified Sensing* for measuring acceleration
- *SensingUnit* to perform network-wide sensing utilizing *Time Synchronization* and *Unified Sensing* services
- *ReliableComm* for reliable wireless communication
- *RemoteCommand* for gateway and leaf nodes to interact with each other in a way that command messages are conveyed to receiver nodes that perform designated tasks such as sensing and computing.
- *DecentralizedDataAggregation* to estimate correlation functions in the hierarchical sensor network
- *ERA* to identify modal properties from sensor data using the Eigensystem Realization Algorithm (ERA) (Juangand Pappa 1985)

Note that the italicized denotes service names in the ISHMP Services Toolsuite. Although these services provides essential functionalities such as sensing, communication, and fundamental computations, careful considerations need to be paid to appropriately organize these services in the fault-tolerant network control flow.

5.2. Control flow of DDLQ

The cluster tree network topology shown in Fig. 7 is adopted in *DDLQ*. This network topology consists of three components: (1) gateway node connected to the base station, (2) cluster-head, and (3) leaf node.

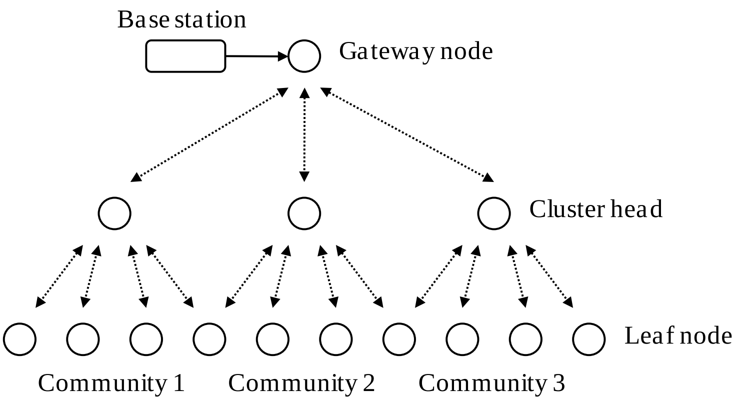


Fig. 7 Network topology for *DDLQ*

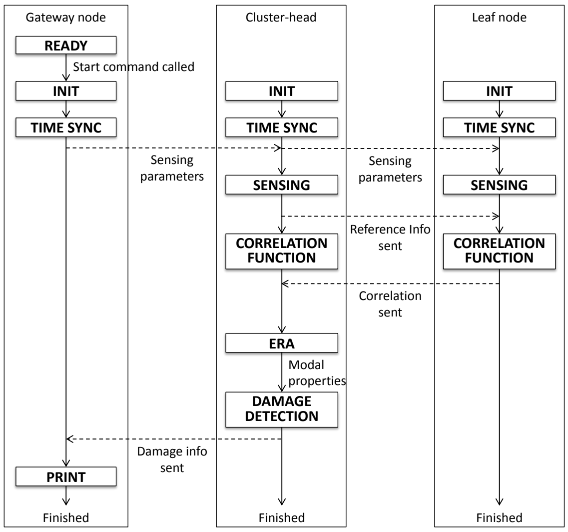


Fig. 8 Flowchart of *DDLQ*

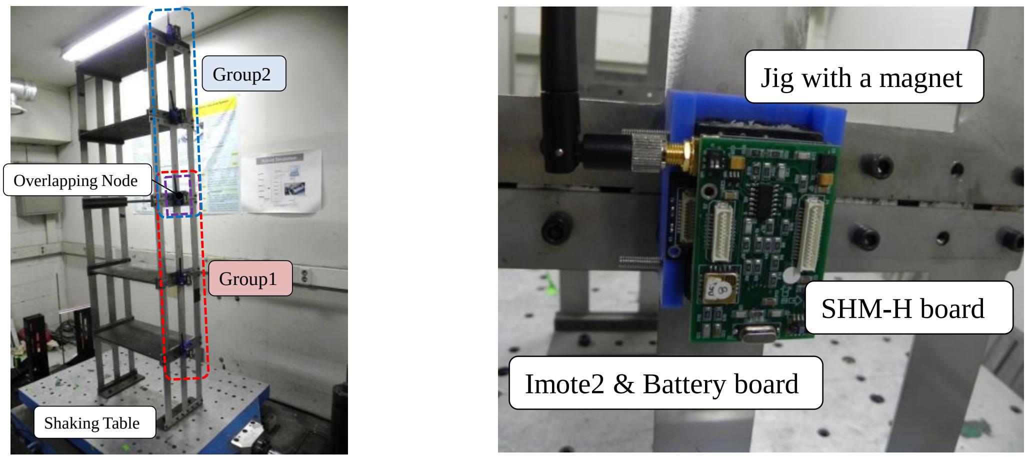
The gateway node controls the WSSN, sending command messages to the network and collecting important information. Each local sensor community has one cluster-head and multiple leaf nodes that commonly perform synchronized sensing. The cluster-head manages data transmission and processing in its local community and delivers processing results to the gateway node.

The flowchart in Fig. 8 describes the operation of the WSSN for decentralized damage detection. When the start command is called by the user, the gateway node initiates the network-wide time synchronization that synchronizes sensors' local clocks and measures clock drift rates for each sensor node that are used to synchronize sensor data. More detailed information for the time synchronization and synchronized sensing is found in Nagayama and Spencer (2007). The cluster-head in each local community broadcasts reference data to the leaf nodes: all sensor nodes including the cluster-head and leaf nodes calculate correlation functions that are collected in the cluster-head. Subsequently, ERA is employed with the correlation functions in the cluster-head to estimate local modal properties. Finally, damage information is calculated and transferred to the base station, where local damage information is combined to produce global one.

The feasibility testing for the decentralized damage detection approach and its software implementation on the WSSN is described in the following section.

6. Experimental validation

To experimentally validate the decentralized damage detection using the WSSN, 5-story shear building model is prepared as shown in Fig. 9(a). As the stiffness of the floor is much greater than that of the columns, this building is assumed to be governed by the shear behavior. The 5-story model has equal floor mass and stiffness, of which structural properties are summarized in Table 5. A single-axis shaking table is prepared under the test structure to provide excitations for the dynamic testing. From preliminary experiments, the excitation level and bandwidth are determined to be 10 mg and 20 Hz, respectively.



(a) 5-story shear building model (b) WSS on the structure

Fig. 9 Experimental setup

Five Imote2 sensor nodes with SHM-H boards are deployed on the structure with magnets that can hold up to 10 kg. For decentralization, the 5-story model is divided into two groups, each of which has three sensor nodes, allowing one of them to overlap. For each test, the sensor nodes measure acceleration data for 10 minutes with the sampling rate of 25 Hz and the cutoff frequency of 10 Hz.

To simulate the structural damage, the width of the columns on the damaged floor is reduced. Note that the moment of inertia is proportional to the column width. Two damage cases with the intact case are considered in the experiment (see Table 6).

Table 5 Structural parameters of the 5-story shear building model

Parameters	Value
Mass	16.09 kg
Damping	3.27 Ns/m
Mass density	7850 kg/m^3
Poisson's ratio	0.28
Elasticity modulus	200 GPa
Bending stiffness	20 Nm^2
Length of each floor	34.3 cm

Table 6 Experiment cases

Experiment Cases		Description
Intact Case		No damage Determines reference information
Damage Cases	Case 1 (Single-damage)	10% stiffness reduction in the 1st floor
	Case 2 (Single-damage)	10% stiffness reduction in the 4th floor
	Case 3 (Multi-damage)	10% stiffness reduction in the 1st and 4th floors

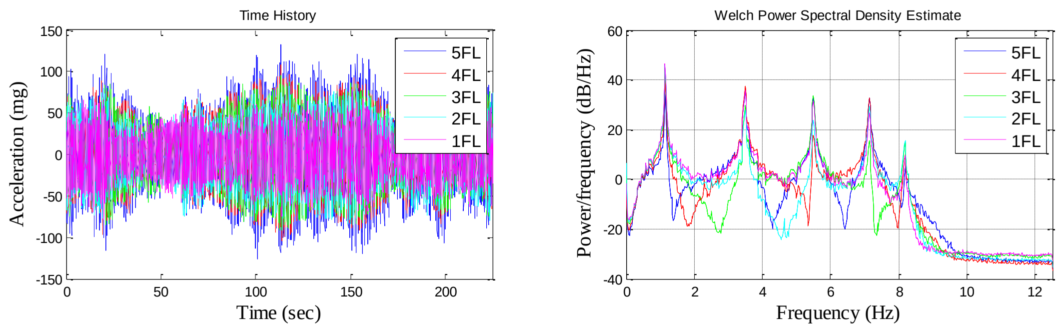
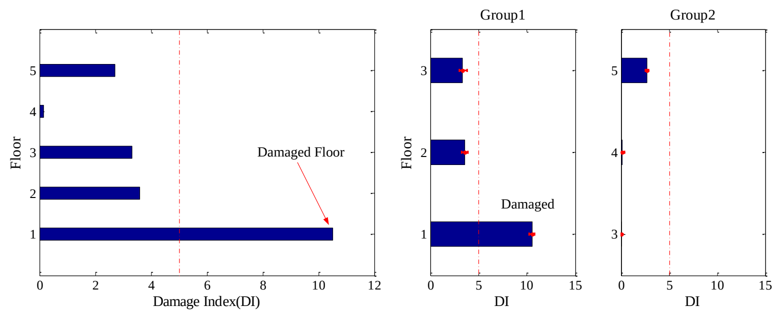
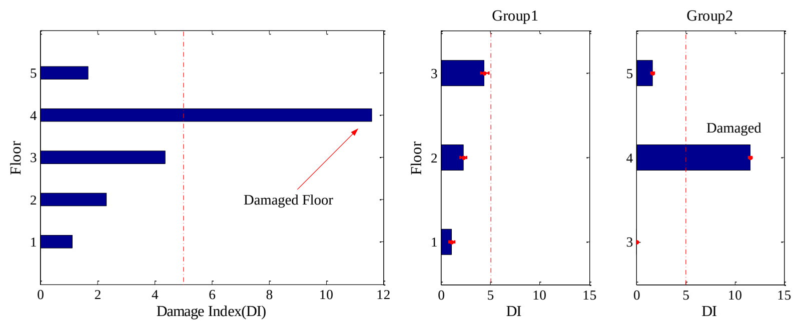


Fig. 10 Time history data (left) and their PSD (right)

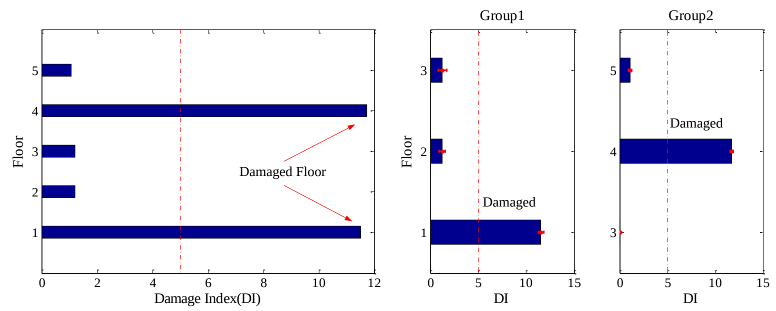
In the initialization stage, acceleration responses are collected at the base station to determine modal properties and flexibility matrix from the undamaged structure. The dynamic testing for the intact case is repeated seven times to accurately obtain reference data. Sample acceleration data are plotted both in time and frequency domains as shown in Fig. 10. The vibration levels are about 50~100 mg and five clear peaks are present in the power spectrum. The modal parameters of each group are extracted by ERA and the mode shapes are mass-normalized using the mass matrix and used for constructing the flexibility matrix. These reference data is stored in the sensor network for the further damage detection analysis.



(a) Damage case 1



(b) Damage case 2



(c) Damage case 3

Fig. 11 Damage severity estimation by *DDLQ*

For the damage cases, a total of 15 experiments (i.e., 5 for each case) are conducted with the prescribed damage. Fig. 11 shows the damage severity indices for each damage case and sensor group. The bar plots represent the mean values of the damage severity indices while the error bars on the plot indicate the maximum and minimum values of the five experiments for each case.

The same threshold value of 5% as in the numerical simulation is employed. The mean values for the actual damage locations are: (1) case 1 - α =10.52%, (2) case 2 - α =11.60%, and (3) case 3 - α =11.53% and 11.74%, which are all above the threshold value. Although the damage severity indices are overestimated 0.5~1.8% more than the inflicted damage of 10%, all damage locations are successfully found with the damage severity indices reasonably close to the actual stiffness reduction. Furthermore, the threshold value of 5% allows no false positive detections.

7. Conclusions

The decentralized damage detection approach tailored to the WSSN for building structures was presented. The flexibility-based damage detection method developed by Koo *et al*. (2011) was investigated for the use in the decentralized computing environment for the efficient and reliable operation of the WSSN. The efficacy of the decentralized damage detection was numerically verified with the 21-story building model. Subsequently, the approach was implemented on the WSSN using MEMSIC’s Imote2 smart sensor platform. The software development was based on the Services Toolsuite provided by the Illinois SHM Project, from which important software components such as sensing, communication, time synchronization and basic numerical libraries, significantly reducing the time and effort spent in the development. The experiment using the 5-story building model was conducted to verify the decentralized damage detection and its software implementation on the network of smart sensors. The damage severity values estimated by the WSSN were reasonably close to the inflicted damages for all damaged members. In addition, the damage severities for undamaged members were less than the prescribed threshold, having no false positive detections. From the numerical simulation and the laboratory experiment, the validity of the decentralized damage detection using the WSSN has been successfully demonstrated.

Acknowledgements

The authors gratefully acknowledge the support of this research by the Global Research Network program from the National Research Foundation of Korea.

References

Cho, S., Lynch, J.P., Lee, J.J. and Yun, C.B. (2010), “Development of an automated wireless tension force estimation system for cable-stayed bridges”, *J. Intel. Mat. Syst. Str*., **21**, 361-376.

Design, S. SD1221 Manual. Available online: http://www.silicondesigns.com/pdfs/1221.pdf

Gao, Y., Spencer Jr., B.F. and Ruiz-Sandoval, M. (2005), “Distributed computing strategy for structural health monitoring”, *Struct. Health Monit.*, **43**(1), 488-507.

Hackmann, G., Sun, F., Castaneda, N., Lu, C. and Dyke, S. (2012), “A holistic approach to decentralized structural damage localization using wireless sensor networks”, *Comput Commun*., **36**(1), 29-41.

Ho, D.D., Lee, P.Y., Nguyen, K.D., Hong, D.S., Lee, S.Y., Kim, J.T. and Shinozuka, M. (2012),

"Solar-powered multi-scale sensor node on lmote 2 platform for hybrid SHM in cable-stayed bridge", *Smart Struct. Syst.*, **9**(2), 145-164.
Juang, J.N. and Pappa, R.S. (1985), "An eigensystem realization algorithm for modal parameter identification and model reduction", *J. Guid. Contr. Dynam.*, **8**(5), 620-627.
Jang, S., Sim, S.H., Jo, H. and Spencer, Jr., B.F. (2012), "Full-scale experimental validation of decentralized damage identification using wireless smart sensors," *Smart Mater. Struct.*, **21**(11), 115019.
Jo, H., Sim, S.H., Nagayama, T. and Spencer Jr, B. (2011), "Development and application of high sensitivity wireless smart sensors for decentralized stochastic modal identification", *J. Eng. Mech. - ASCE*, **138**(6), 683-694.
Koo, K., Sung, S. and Jung, H. (2011), "Damage quantification of shear buildings using deflections obtained by modal flexibility", *Smart Mater. Struct*, **20**, 045010.
Kurata, N., Spencer, B.F. and Ruiz-Sandoval, M. (2005), "Risk monitoring of buildings with wireless sensor networks", *Struct. Health Monit.*, **12**(3-4), 315-327.
Ling, Q., Tian, Z., Yin, Y. and Li, Y. (2009), "Localized structural health monitoring using energy-efficient wireless sensor networks", *IEEE Sens. J.*, **9**(11), 1596-1604.
Lynch, J.P., Sundararajan, A., Law, K.H., Kiremidjian, A.S., Carryer, E., Sohn, H. and Farrar, C.R. (2003), "Field validation of a wireless structural health monitoring system on the Alamosa Canyon Bridge", *Proc. of the SPIE*, **5057**, 267-278
Lynch J.P., Sundararajan A., Law K.H., Kiremidjian A.S. and Carryer E. (2004), "Embedding damage detection algorithms in a wireless sensing unit for operational power efficiency", *Smart Mater. Struct.*, **13**(4) 800-810
Nagayama, T. and Spencer Jr., B.F. (2007), *Structural health monitoring using smart sensors*, Newmark Structural Engineering Laboratory (NSEL) Report Series, No. 1, University of Illinois at Urbana-Champaign, Urbana, Illinois.
Park, J.H., Hong, D.S., Kim, J.T., Koo, K.Y., Yun, C.B. and Park, G. (2008), "Wireless sensing and embedded monitoring algorithm for damage diagnosis in PSC girders", *Adv. Sci. Technol.*, **56**, 420-425.
Rice, J.A. and Spencer, Jr., B.F. (2009), *Flexible smart sensor framework for autonomous full-scale structural health monitoring*, Newmark Structural Engineering Laboratory (NSEL) Report Series, No. 18, University of Illinois at Urbana-Champaign, Urbana, Illinois.
Sim, S., Spencer Jr. B., Zhang, M., Xie, H. (2010), "Automated decentralized modal analysis using smart sensors", *Struct. Health Monit.*, **17**(8), 872-894.
STMicroelectronics LIS344ALH manual. Available online: http://www.st.com/internet/analog/product/207281.jsp
Zimmerman, A.T., Shiraishi, M., Swartz, R.A. and Lynch, J.P. (2008), "Automated modal parameter estimation by parallel processing within wireless monitoring systems", *J. Infrastruct. Syst.*, **14**(1), 102-113.
Zimmerman, A.T. and Lynch, J.P. (2009), "A parallel simulated annealing architecture for model updating in wireless sensor networks", *IEEE Sens. J.*, **9**(11), 1503-1510.