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DIAGNOSTIC ASSESSMENT SYSTEM FOR STRUCTURAL SEISMIC SAFETY - DAMAGE IDENTIFICATION BASED ON NEURAL NETWORKS AND TORSION -

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SUMMARY

Japan is subjected to frequent seismic activity due to its location within three major earthquake zones: the Pacific Ocean zone, Japan Sea zone, and inland zone. Structures in Japan are "older" than their actual age due to the poor quality of concrete used during Japan's high-growth period (1960's). Infrastructure constructed in the early 1900's in the U.S. has also similarly aged. In recent years, many structures tend to be maintained or their performance managed due to environmental problems, such as waste of resources (e.g., tile, glass, wood) and increase in non-recycled products (e.g., columns, wallpaper, floor covering). Interest in applying a monitoring system to such structures has been strong in order to maintain and manage performance of a building to assure its safety and functionality. Although methods to detect damage sites and to determine the extent of the damage have been actively researched, no study has indicated the final application of their methods.

Here, we developed a damage assessment system that can assess structural integrity. In this system, first, a sensor that measures a specific parameter, such as acceleration, is placed in the structure. Then, damage to the structure is identified based on the value of the measured parameter in order to detect the sites and extent of the damage both globally and locally. Finally, the performance of the structure is evaluated to determine whether to repair or reinforce the structure.

In this system, the damage-detection strategy is classified as two stages. In the first stage, the damage is detected globally by using a neural networks method to identify the stories where damage occurred and the extent of the damage. In the second stage, the damage is identified locally by determining the changes in monitored structure's eccentricity between centers of rigidity and weight due to the damage in order to narrow down the possible damage sites. To validate these two stages, we applied this damage-detection strategy to a scaled 5-story aluminum structure.

In conclusion, the location and extent of damage can be identified first globally by applying the neural network method, and then locally by detecting the changes in eccentricity. Results show that the

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diagnostic assessment system was successfully validated by applying this two-stage damage detection strategy.

INTRODUCTION

A "smart" structure, which includes a monitoring function, control function, and repair function, can adapt to environmental changes such as structural degradation and earthquakes. Many of these functions can currently be utilized in the construction of building structures such as isolated structures or controlled structures. Additional functions, such as self-restoration of concrete beams by using SMA wire, are now being studied.

Japan is subjected to frequent seismic activity due to its location within three major earthquake zones; the Pacific Ocean zone, which produces large earthquakes, the Japan Sea zone, which produces medium-sized earthquakes, and the inland zone, which produces shallow, medium-sized earthquakes. Structures are also "older" than their actual age due to the poor quality of concrete used during Japan's high-growth period (1960's). Also, social infrastructure constructed in the early 1900's in the U.S. has also aged. Therefore, interest has been strong for applying monitoring functions to structures so that the structure can be maintained or managed to assure its safety and functionality. Such monitoring can be useful in other fields, such as insurance or real estate, for risk management and due diligence and for evaluating seismic risk. To include diagnosis as a monitoring function, a diagnostic system that monitors the structural integrity must be established. In addition to such a system, if a self-repair function could be included, structures will then have one of the numerous functions of artificial life.

In recent years, many methods to detect structural damage have been developed. These methods are based on changes in modal parameters and use different algorithms, such as system identification or neural networks. Commonly used modal parameters include natural frequencies, modal damping, mode shapes, and flexibility. Although studies on these methods involve damage identification by assessing changes in modal parameters, no studies have reported a diagnostic method and the damage identification step from global to local areas. For a detection method, we propose a structural assessment system for damage and degradation.

In this study, we developed a system to assess structural integrity. This system includes a diagnostic system for structural damage and degradation, subsequent diagnosis, and finally repair or reinforcement. The damage-detection strategy in our system is first to detect the damage sites globally by using neural networks method, and then to narrow down the damage location locally by determining the changes in eccentricity between centers of rigidity and weight. To validate this system, we used the diagnostic system to detect the damage sites and extent in a 5-story structure in which the beams were fixed at both ends.

STRUCTURAL ASSESSMENT SYSTEM

System flowchart [1], [2]

Techniques to assure quality in structures have lagged far behind techniques to detect defects and to assure quality in machinery. Research on the detection of structural damage has been so sparse, that the overall direction of damage identification is difficult to summarize. A comprehensive system whose function ranges from damage identification to diagnosis, repair, and reinforcement is required for quality assurance of a structure. Therefore, we developed a monitoring system that includes structural integrity assessment. The flow diagram of such a system is shown in Fig. 1. Before such a system is implemented, however, the vibration source (e.g., grand motion or micro-tremor), the type of indicator used for the diagnosis (e.g., trace crack or residual strain), and the signal transduction method (e.g., real time OS or wireless LAN) must be decided. Then, diagnosis proceeds as follows.

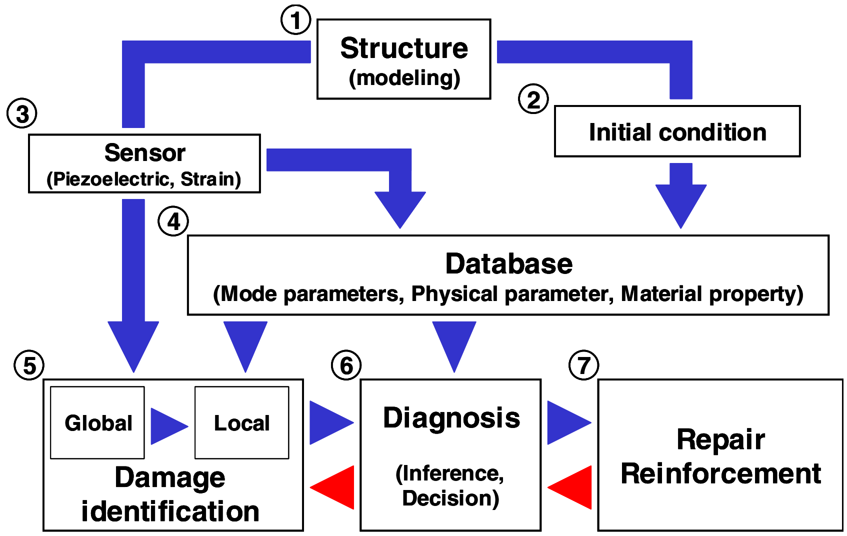


Fig. 1 Flowchart for structural assessment system.

1. Obtain information about the monitored structure; specifically, type of structure (e.g., reinforced-concrete frame structure or steel frame structure), and decide the analytical model.

2. Obtain the initial conditions about the structure and store them in a database. These conditions are required for damage identification and diagnosis, and include time domain, frequency domain, and type of material of the structure.

3. Decide the type of sensor (e.g., piezoelectric of strain) and parameters used to identify the damage (e.g., natural frequencies of natural mode shapes). The parameters measured from these sensors will be stored in a database.

4. Complete the database for initial conditions to identify and diagnose damage.

5. Start damage identification. Before identifying the damage and degradation, however, the level of identification must be decided. For instant, if a global level is desired, then the existence of damage and which layer of the structure was damaged will be identified. If a local level is desired, then that damaged part of the frame of the structure will be identified. The two stages in the damage detection strategy will be explained in next section.

6. Confirm the extent of damage (e.g., any decrease in the bearing force). Assume that the bearing force is the force needed by the structure to resist an external force. Based on the diagnosis (shown in step 6 in Fig. 1), decide if the structure needs to be repaired or reinforced.

7. Repair or reinforce the structure accordingly.

Iterate steps 5 to 7 of the diagnostic system for structural damage and degradation to maintain the structure safely.

Figure 2 shows the relationship between age and safety level of such a monitored structure. Any structure will deteriorate in performance as time passes. Until now, inspection of the condition of a structure must be done manually and continuously, and thus defects or damage inside a structure can not be determined and inspections are limited due to labor cost. Our proposed system enables constant inspection to assure the performance of the monitored structure. From a safety-level perspective, when the performance of a structure gradually declines to a caution level or dangerous level due to age or damage (Fig. 2), the system informs us of the need for repair or reinforcement while continuing to inspect the structure.

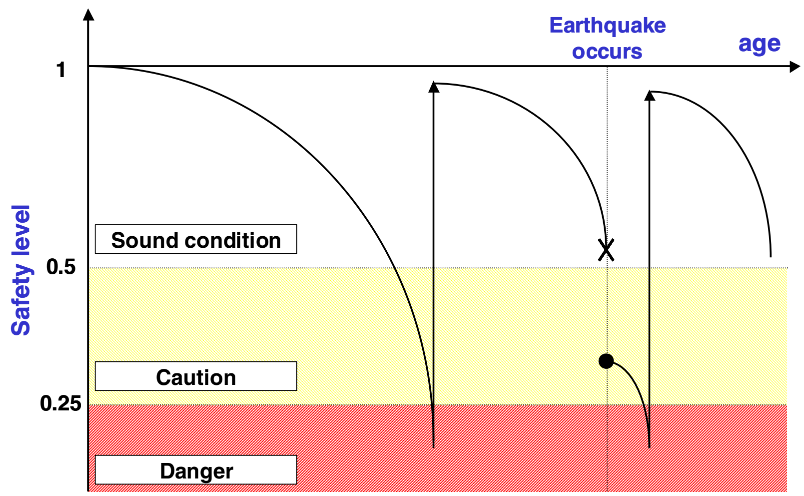


Fig. 2 Safety level for a monitored structure.

Two-stage damage detection

In our damage assessment system, the diagnostic system for structural damage and degradation first uses a neural networks method and then uses eccentricity-monitoring method. Figure 3 shows a flowchart for damage identification by using these two methods. First, at the global level, a neural networks method is used to identify the possibility of damage and also to detect the location and extent of damage. Then, if damage is detected at the layer level, eccentricity-monitoring method is used to locate and evaluate the damage in detail locally by determining change in monitored structure's eccentricity between centers of rigidity and weigh.

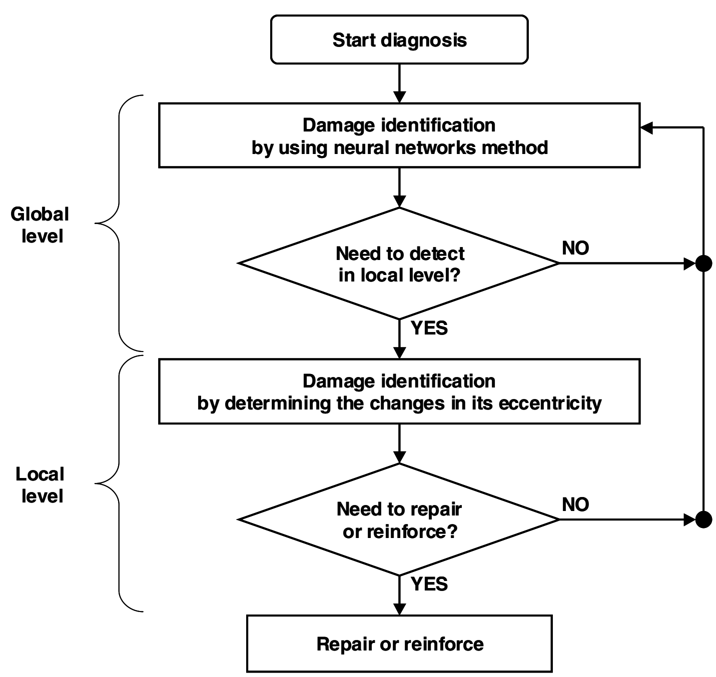


Fig. 3 Flowchart for two-stage damage detection.

DAMAGE IDENTIFICATION STRATEGY

Global damage identification based on neural networks

Figure 4 shows a schematic of the global damage identification based on neural networks. The overall procedure is divided into two stages, that is, training and identification.

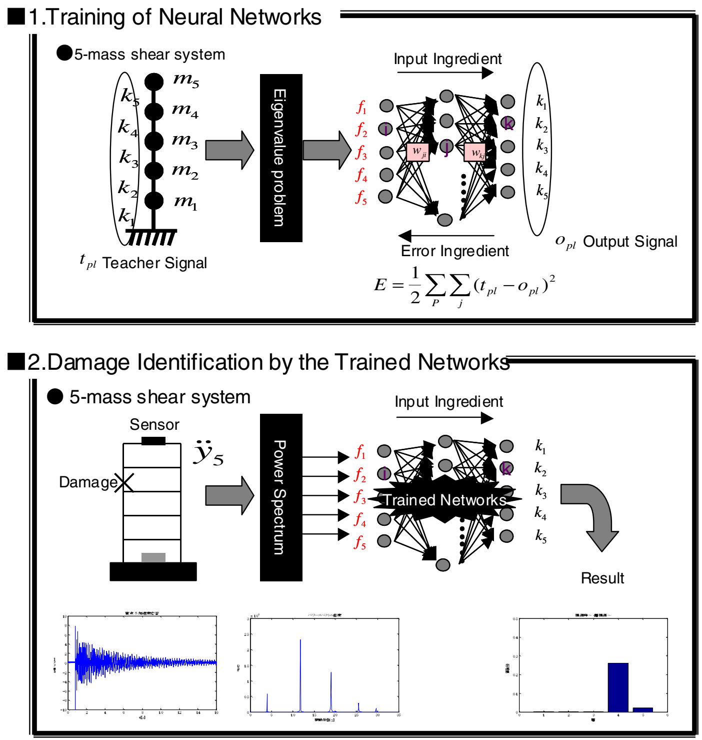


Fig. 4 Schematic for global damage identification.

In the training stage (upper schematic in Fig. 4), the neural network depends on a feed-forward network. The basic element of a neural network consists of nodes, layers, and activation functions. A network is also characterized by its structure. Commonly used structures are multi-layer perceptrons. The neural network used in the global damage identification strategy has 5 input nodes and 5 output nodes. The decrease rate of the k^{th} natural frequency (k = 1~5) is selected as the input, and the reduction rate of the stiffness of each element (or story) is selected as the output. In our strategy, we assume that the decrease rate of the stiffness indicates structural damage.

The training of neural networks strategy is first to prepare training patterns by solving the generalized eigen-value solution. Then, the neural networks is completed by using these training patterns. The neural network has one hidden layer that has 7 nodes (Fig. 5).

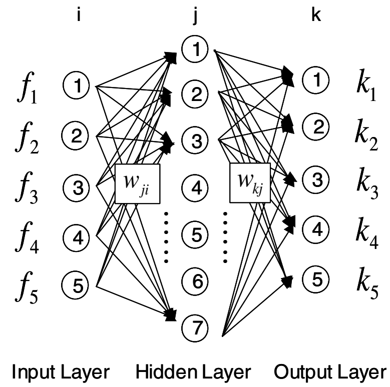


Fig. 5 Feed-forward neural networks.

The output of the multi-layer feed-forward network is given as

$$y_k = f\left(\sum_{j=1}^{7} w_{kj} \cdot f\left(\sum_{i=1}^{5} w_{ji} \cdot x_i + b_j\right) + b_k\right) \tag{1}$$

where w_{ji} and w_{kj} are the interconnection weights, b represents the bias (or threshold) terms, and $f(\ )$ is the activation function. Typical selections for the function $f(\ )$ are the logistic function, hyperbolic tangent, sigmoid function, or radical basis function. In our strategy, the sigmoid function defined as follows is selected as the activation function at each node due to the node non-linearity:

$$f(x) = \frac{1}{1+e^{-\beta x}} (\beta = 1) \tag{2}$$

The output of a sigmoid function is 0 to 1. Therefore, to increase the accuracy in the training, input and output should be standardized from 0 to 1. The linear standardization method used in our strategy is defined as

$$X = \frac{(1-2\varepsilon) \cdot x + \varepsilon \cdot x_{\max} - (1-\varepsilon) \cdot x_{\min}}{x_{\max} - x_{\min}} \tag{3}$$

where $\varepsilon\ (0 < \varepsilon \quad 1)$ is the parameter for restricting the output range of a sigmoid function to increase the accuracy in the training.

In the detection strategy (lower schematic in Fig. 4), the power spectrum is derived using relative acceleration obtained from sensors at the top and bottom of the structure. Then the decrease rate of the k^{th} natural frequency is derived and standardized using eq.(3). This data is then input to the trained neural networks. Finally, the reduction rate of stiffness of each element (or story) is output as the damage rate at the story level.

Local damage identification based on the changes in eccentricity

This local damage identification method is defined when the sites and extent of damage are already detected by using global damage identification. The aim of this method is to localize the damaged area of the damaged story when changes in eccentricity occurred by the reduction in stiffness. In this method, we assume that the damage is occurred only as the reduction in stiffness of element and that the reduction in mass doesn't affect the changes in eccentricity.

The formulation of a 3 degrees-of-freedom model that is based on torsion along the x- and y-axes can be expressed as

$$m \cdot \ddot{x} + K_x \cdot x + K_x \cdot e_{y(sound)} \cdot \theta = f(t) \tag{4}$$

$$m \cdot \ddot{y} + K_y \cdot y + K_y \cdot e_{x(sound)} \cdot \theta = f(t) \tag{5}$$

where $\ddot{x}$, $\ddot{y}$, is the acceleration and x, y is the displacement along each axis, m is the mass, K_x, K_y is the stiffness along each axis, θ is the rotation angle of the structure, e_x, e_y is the eccentricity along each axis, and $f(t)$ indicates the output force.

If the site and extent of damage are detected by using the neural networks, then eqs. (4) and (5) can be expressed as

$$m \cdot \ddot{x} + (K_x - \Delta K_x) \cdot x + (K_x - \Delta K_x) \cdot e_{y(damage)} \cdot \theta = f(t) \tag{6}$$

$$m \cdot \ddot{y} + (K_y - \Delta K_y) \cdot y + (K_y - \Delta K_y) \cdot e_{x(damage)} \cdot \theta = f(t) \tag{7}$$

where ΔK_x and ΔK_y indicate the stiffness reduction along each axis caused by the damage.

Although the stiffness reduction along each axis is already detected by global identification, rotation θ is an unidentified parameter. To determine the changes in eccentricity caused by stiffness reduction, θ needs to be identified from information obtained from the sensors. To identify θ, we use the first mode subjected to θ. Each parameter shown in eqs.(6) and (7) such as acceleration and displacement will be processed by using a bandpass filter with first mode subjected to rotation. Then, each parameter will be substituted into eqs.(8) and (9) to detect changes in eccentricity along each axis:

$$e_x = \frac{f(t) - m \cdot \ddot{y} - (K_y - \Delta K_y) \cdot x}{(K_y - \Delta K_y) \cdot \theta} \tag{8}$$

$$e_y = \frac{f(t) - m \cdot \ddot{x} - (K_x - \Delta K_x) \cdot y}{(K_x - \Delta K_x) \cdot \theta} \tag{9}$$

In this study, we used this strategy to narrow down the damaged area of the damaged story from the changes in eccentricity between sound condition (no-damage) and damage condition.

EXPERIMENTAL STUDIES

5-story experimental structure

Photo 1 shows the experimental structure, which is used in order to validate our diagnostic assessment system. The scaled structure was constructed with aluminum-bolted columns, beams, and slabs.

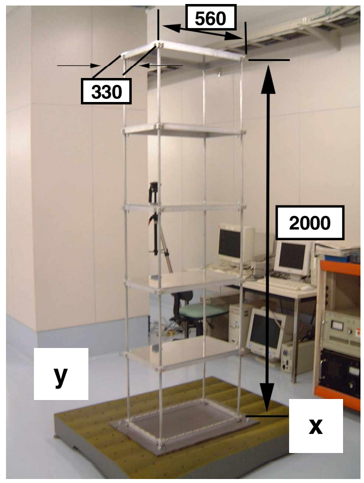


Photo 1 5-story experimental structure.

Each column was 400-mm high, and each beam was 560-mm long and 330-mm wide. The 5-story structure was bolted to a surface plate to isolate it from any external disturbance. The 5-story structure was modeled as a 5-mass shear system as shown in Fig. 6, where each element represents a single story.

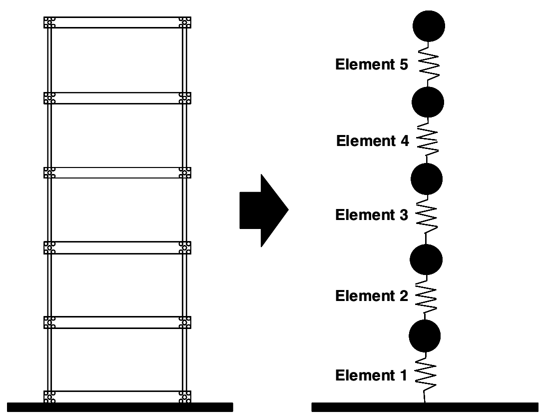


Fig. 6 Multi-mass shear system.

Table 1 lists the physical parameters for each story (or element). Each axis of stiffness was calculated by using the first-mode shape.

Table 1 Physical parameters for 5-mass shear system.

	1^{st} story	2^{nd} story	3^{rd} story	4^{th} story	5^{th} story
Mass [kg]	5.51	5.51	5.51	5.51	5.29
x-Stiffness [N/m]	39442	35409	36237	34990	35974
y-Stiffness [N/m]	29659	31505	30744	28195	30039

Experimental method for global damage identification

An impulse hammer was placed on top of the 5-story structure to measure the acceleration of the top and bottom stories under sound condition. The sensor location for global damage identification based on neural networks is shown in Fig. 7.

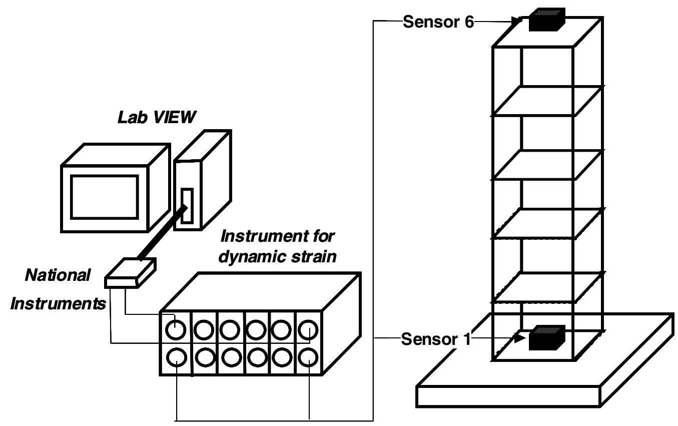


Fig. 7 Sensor location for global damage identification.

As shown in Fig.7, Lab VIEW is the system which could extract the observed value from each sensor converted by National Instrument. The center of each story was subjected to strain acceleration (frequency range of 60 Hz and maximum acceleration of 19.6 m/s^2). The natural frequencies under this damage condition were obtained using the same procedure used in the sound condition.

Experimental method for local damage identification

An impulse hammer was placed on top of the 5-story structure to measure the acceleration and displacement of damaged stories. Figure 8 shows the sensor location for local damage identification based on the changes in eccentricity and shows the sensor location in case of damage to the first story (indicated by the × in the figure).

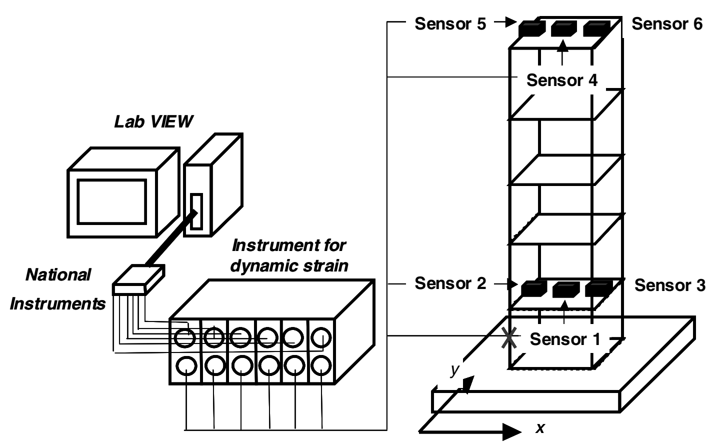
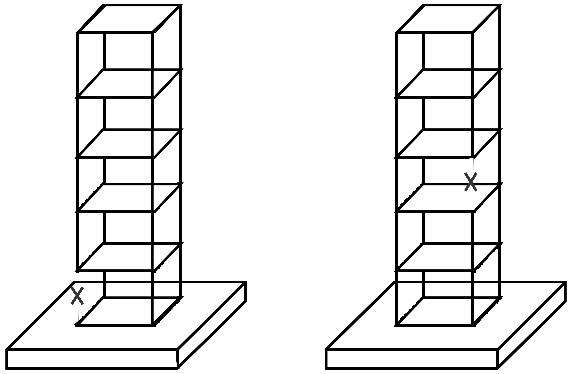


Fig. 8 Sensor location for local damage identification.

To identify the first mode subjected to rotation θ, sensors 4, 5, and 6 are located at sound condition; sensor 4 monitors the acceleration along both the x- and y-axes, and sensors 5 and 6 monitor the acceleration along the y-axis to identify θ. At damage conditions (Fig. 8), a sensor is located at the damaged story; sensor 1 monitors the acceleration of both the x- and y-axes, and sensors 2 and 3 monitor the acceleration of the y-axis to identify θ.

Figure 9 shows the two damage scenarios studied here. Damage conditions in the structure (indicated by the × in the figure) were assumed to remove a column that represents 25% reduction in the stiffness of each axis.



(a) Scenario 1 (b) Scenario 2

Fig. 9 Damage scenarios for 5-story structure.

Experimental results

Tables 2 and 3 list the measured natural frequency of each axis for sound condition and the two damage scenarios.

Table 2 Measured natural frequencies of no-damage and damage scenarios for x-axis.

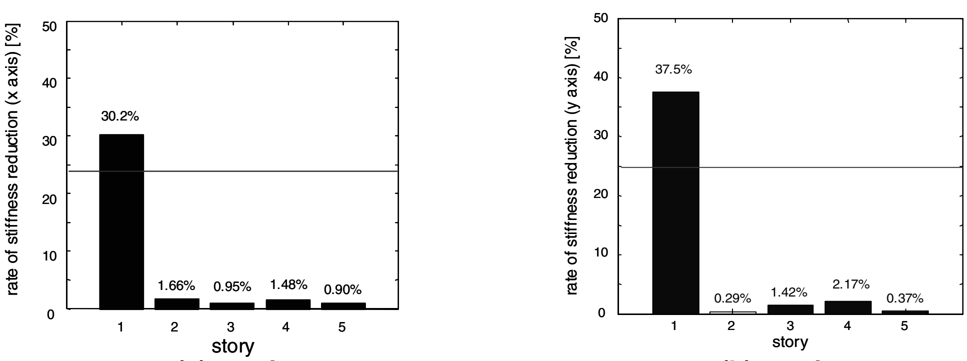
	1st mode	2nd mode	3rd mode	4th mode	5th mode
No damage [Hz]	3.56	10.56	17.13	22.50	26.25
Scenario 1	3.25	10.00	16.63	22.06	26.13
Scenario 2	3.38	10.19	16.13	22.63	25.19

Table 3 Measured natural frequencies of no-damage and damage scenarios for y-axis.

	1st mode	2nd mode	3rd mode	4th mode	5th mode
No damage [Hz]	3.08	9.00	14.56	19.25	22.00
Scenario 1	2.56	8.25	14.31	19.06	21.88
Scenario 2	2.93	8.34	13.19	19.18	20.36

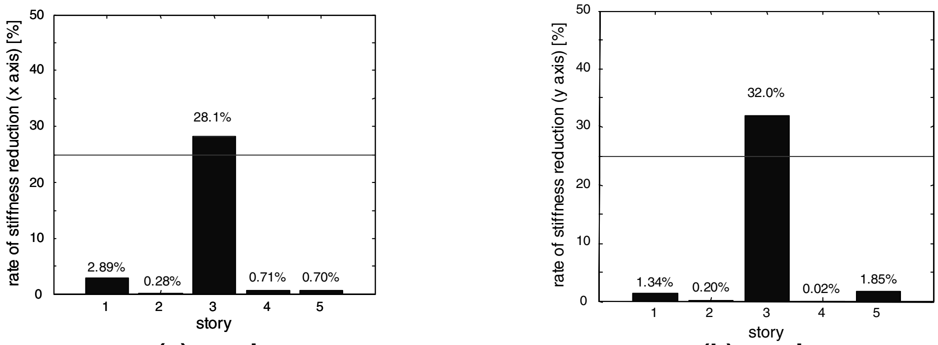
Experimental results for global damage identification

To train the neural networks, 16 patterns of damage conditions were estimated by solving the generalized eigen-value solution. These 16 patterns were used to determine the sound condition and one-story-damage condition in which the reduction rate of stiffness of each element was 10%, 20%, and 30%. The network was trained using the general error back-propagation algorithm. In order that an error fully converges, the training was repeated 1500 times. Figures 10 and 11 indicate the reduction rate of stiffness for each axis by utilizing trained neural networks for both damage scenarios (Fig. 8).



(a) x-axis (b) y-axis

Fig.10 Rate of stiffness reduction for Damage scenario 1.



(a) x-axis **(b) y-axis**

Fig.11 Rate of stiffness reduction for Damage Scenario 2.

The neural networks method accurately detected both the location and extent of damage along the x-axis in each damage scenario (Figs. 10 and 11). The detected rate of stiffness reduction along the y-axis for damage scenario 1, however, slightly differed from the true rate (25%) despite the high accuracy in detecting the damage location. This error is due to the joint between the column and beam. Therefore, the theoretical stiffness reduction along the y-axis could be greater than 25%. The results in Figs. 10 and 11 indicate that this method can effectively identify the possibility of damage and the extent of that damage by using only the changes in natural frequencies.

Experimental results for local damage identification

Table 4 lists measured 1st natural frequency subjected to rotation for no-damage condition and the two damage scenarios.

Table 4 Measured 1st natural frequency subjected with rotation for 5-story structure.

	No-damage condition	Damage scenario 1	Damage scenario 2
1st natural frequency [Hz]	4.81	4.56	4.62

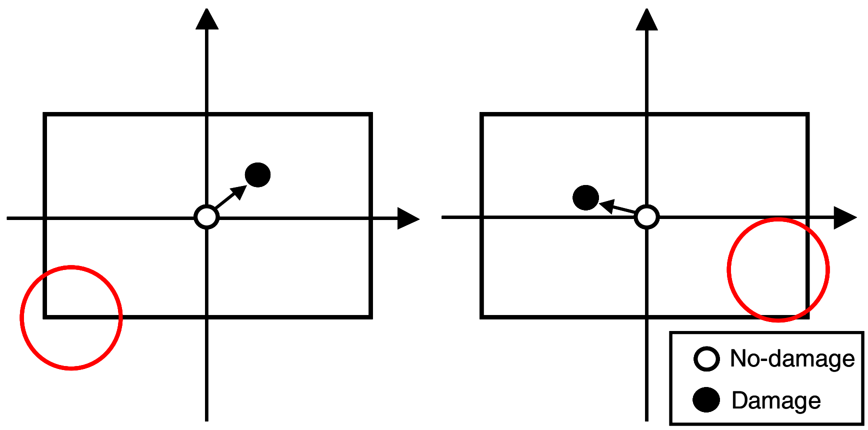
This measured reduction in the 1st natural frequency subjected with rotation was due to the damage caused by the reduction in stiffness.

The changes in eccentricity along each axis were identified based on the acceleration and displacement of the damaged story determined by the neural networks and rotation θ. To detect the eccentricity, we substituted experimental parameter (e.g., acceleration and displacement for each axis, and rotation) into eqs. (8) and (9). Table 5 lists the measured eccentricity and theoretical eccentricity for both damage scenarios.

Table 5 Measured eccentricity from damage identification and theoretical eccentricity for 5-story structure.

	No-damage condition		Damage scenario 1		Damage scenario 2	
	Theoretical	Measured	Theoretical	Measured	Theoretical	Measured
e_x	0.000	1.40×10^{-3}	0.070	0.041	-0.073	-0.056
e_y	0.000	1.99×10^{-4}	0.044	0.040	0.040	0.013

Figure 12 indicates the identification of the damaged area based on changes in eccentricity.



(a) Damage scenario 1 (b) Damage scenario 2

Fig. 12 Identification of damaged area in each damage scenario.

These results indicate that by considering the changes in eccentricity along each axis, the damaged area of the damaged story could be narrowed down.

CONCLUSION

A monitoring system that includes a diagnostic system to assess structural integrity was developed. This diagnostic system uses a two-stage damage identification strategy in which damage is identified globally based on neural networks and locally based on changes in eccentricity along each axis. The two-stage damage detection strategy first identifies the possibility of damage and detects the sites of the damage by using neural networks and then narrow downs the location of the damage in detail by considering changes in eccentricity. Neural networks showed good accuracy in identifying the possibility and extent of damage, and by detecting change in eccentricity, the damage sites could be clearly narrowed down.

The diagnostic system will be available in practice when certain issues can be resolved, such as process of damage identification, development of a high-performance sensor, and effective transmission of information from the sensor. As a result, the diagnostic assessment system that consists of the two-stage damage identification strategy, which we proposed could then be further validated.

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REFERENCES

1. Tsuchimoto K, Wada N, Kitagawa Y. "Study on diagnostic system of structural damage and degradation. - Damage identification by using mode parameter and wave propagation -" SPIE's 10th Annual International Symposium on Smart Structures and Materials, San Diego, United States of America, Mar. 2003.
2. Wada N, Tsuchimoto K, Kitagawa Y. "Structural integrity assessment system. Global damage identification." The First International Conference on Structural Health Monitoring and Intelligent Infrastructure, Tokyo, Japan, Nov. 2003.