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Experimental study of structural damage identification based on WPT and coupling NN

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Abstract: Too many sensors and data information in structural health monitoring system raise the problem of how to realize multi-sensor information fusion. An experiment on a three-story frame structure was conducted to obtain vibration test data in 36 damage cases. A coupling neural network (NN) based on multi-sensor information fusion is proposed to achieve identification of damage occurrence, damage localization and damage quantification, respectively. First, wavelet packet transform (WPT) is used to extract features of vibration test data from structure with different damage extent. Then, data fusion is conducted by assembling feature vectors of different type sensors. Finally, three sets of coupling NN are constructed to implement decision fusion and damage identification. The results of experimental study proved the validity and feasibility of the proposed methodology.

Key words: Damage identification, Experimental study, Wavelet packet transform (WPT), Coupling neural network (NN)
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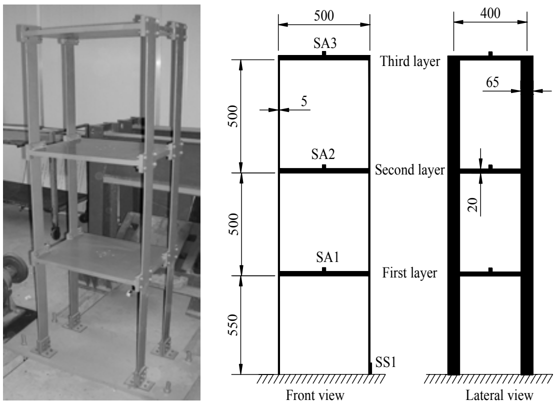
INTRODUCTION

Vibration test data from different sensor are widely applied for damage identification in structural health monitoring (Gao and Spencer, 2002; Teng *et al*., 2004; Wang *et al*., 1998). Commonly, damage identification includes three levels (Doebling *et al*., 1998; Sun and Chang, 2002): damage acknowledgement, damage localization and damage quantification. Most studies on structural damage identification are based on data analysis of single sensor. However, for a given structural damage, test data acquired from different type sensors that fixed at different location contain different information. Each sensor has different sensitivity to the structural damage. How to extract data information from each sensor is a problem. In this work, an experiment on a three-story frame model was conducted by simulating 36 damage conditions to acquire test data, and a methodology of multi-sensor information fusion is proposed to realize damage identification. The proposed methodology has been proved to be valid and feasible.

EXPERIMENTAL APPROACH

To study damage identification based on multi-sensor information fusion, a laboratory model (Fig.1a), was designed and built to simulate the multi-story structure (Guo, 2004). Using four columns and three slabs, a shear type frame structure was fabricated with bolted connections. This scale-model steel structure is depicted in Fig.1b, where SA1, SA2, SA3 are acceleration sensors and SS1 is strain gauge installed on structure. Modal tests were performed on this instrumented laboratory structure to obtain experimental data for damage detection analyses. The baseline undamaged structure and thirty-six damaged structure cases were tested. To study the damaged structure case of every layer, the same three columns, shown in Fig.2, are used to simulate column damage on different layer. Twelve grades of damage were imposed on every damaged column with a hacksaw cut ξ% (damage ratio) through the cross section. The damage of rigidity reductions of 50% on the first layer is shown in Fig.3. All damaged structure cases are listed in Table 1.

An impact force was imposed on the slab of the third layer to excite structural vibration. Thirty-seven sets of dynamic vibration response data were acquired by a dynamic test system (DH5965/5936) for undamaged structure and three damaged structures. Sixty seconds of acceleration response and dynamic strain signal which were sampled at 200 Hz were recorded. Power spectral density (PSD) of every signal was obtained by FT (Fourier Transform). Time domain responses and frequency domain response (PSD) of undamaged structure are shown in Fig.4. The structural natural frequencies were obtained by FT, with the first three natural frequencies being 3.5667, 10.1000, 14.7500 Hz. The natural frequencies would change a little because of structural damage.



(a) (b)

Fig.1 Steel-frame scale model
(a) Photo model in laboratory; (b) Dimension of model structure (Unit: mm)

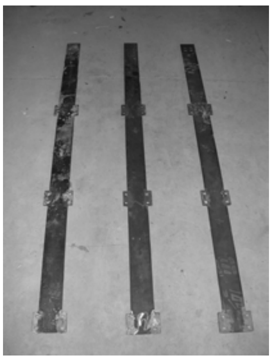


Fig.2 Damaged column

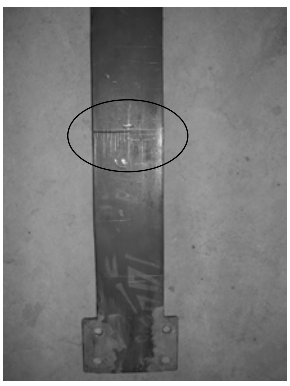


Fig.3 Damage ratio 50%

Table 1 Damage cases of test structure

Damage case	Damage location (Layer)	Damage severity (Damage ratio %)
DA1	First	2.5
DA2	First	5
DA3	First	7.5
DA4	First	10
DA5	First	15
DA6	First	20
DA7	First	25
DA8	First	30
DA9	First	35
DA10	First	40
DA11	First	45
DA12	First	50
DB1	Second	2.5
DB2	Second	5
DB3	Second	7.5
DB4	Second	10
DB5	Second	15
DB6	Second	20
DB7	Second	25
DB8	Second	30
DB9	Second	35
DB10	Second	40
DB11	Second	45
DB12	Second	50
DC1	Third	2.5
DC2	Third	5
DC3	Third	7.5
DC4	Third	10
DC5	Third	15
DC6	Third	20
DC7	Third	25
DC8	Third	30
DC9	Third	35
DC10	Third	40
DC11	Third	45
DC12	Third	50

As an example, the natural frequencies of the first three natural frequencies were 3.5500, 10.0500, 14.7167 Hz for damage case DA12. However, it is difficult to identify structural damage by the change of natural frequency.

DATA ANLYSIS AND DAMAGE FEATURE EXTRACTION

To classify structural condition (whether damage occurred, where damage occurred and extent of damage), the damage index which extract the signal features hidden in the original time domain must be found.

Most vibration-based damage identification methods require modal properties obtained from temporal signals via traditional Fourier Transform (FT), some inherent characteristics of FT might affect the accuracy of damage identification (Yen and Lin, 2000; Sun and Chang, 2002). It is difficult to implement FT-based damage identification techniques as

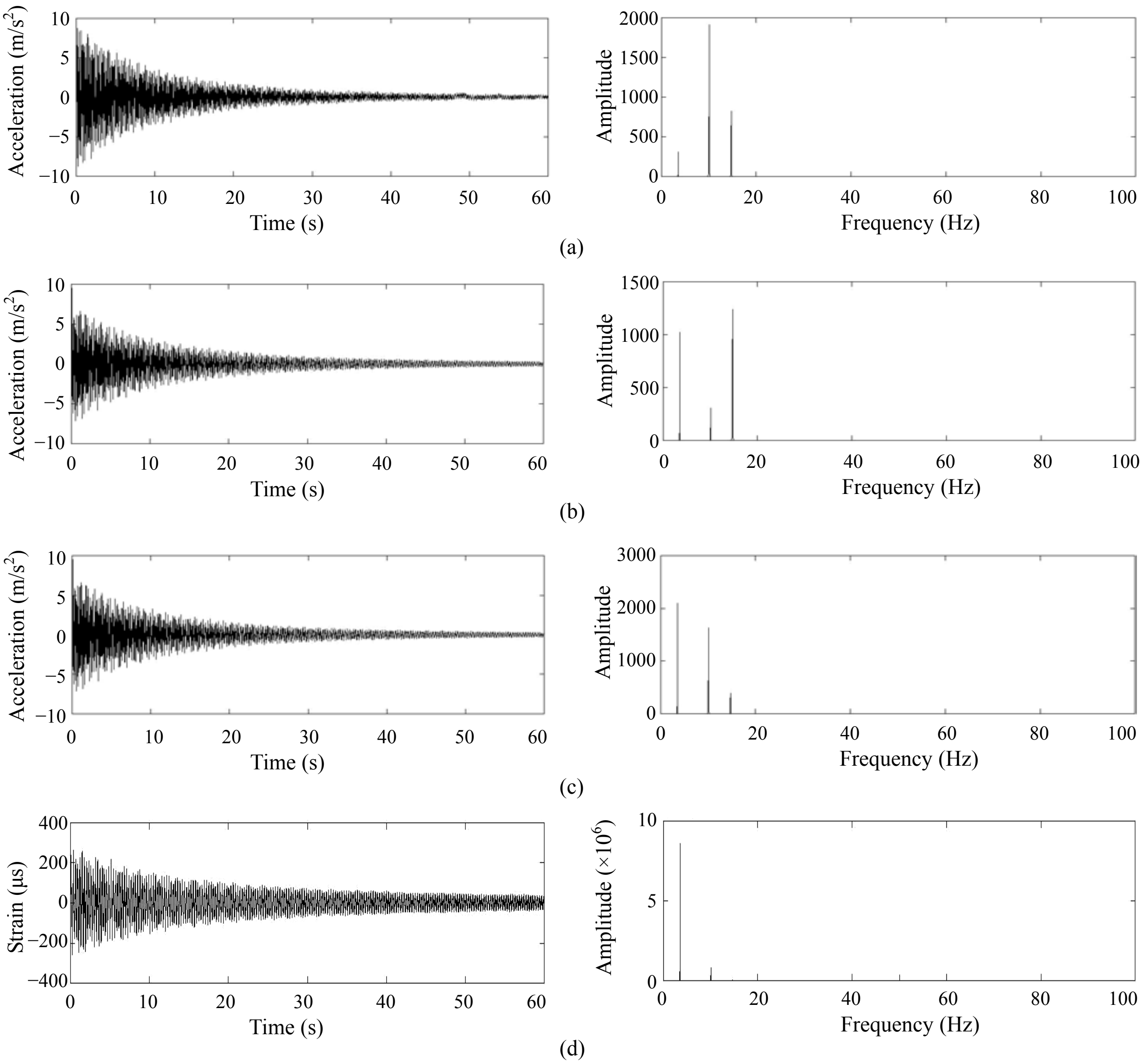


Fig.4 Test signal of undamaged structure. The left is time domain response; the right is power spectral density
(a) Acceleration signal of SA1; (b) Acceleration signal of SA2; (c) Acceleration signal of SA3; (d) Dynamic strain signal of SS1

FT is in fact a data reduction process during which information on structural health might be lost. Wavelet transform (WT) may be viewed as an extension of traditional FT with an adjustable window location and size. Due to its time-frequency multi-resolution property, WT has recently been shown to be a promising tool for damage identification of machines and structures. However, one possible drawback of WT is that the frequency resolution is quite poor in the high frequency region. So it faces difficulties when discriminating signals containing close high-frequency components. Wavelet packet transform (WPT) is one extension of WT that provides complete level-by-level decomposition. In this study, WPT is introduced to extract the damage feature of structural dynamic test signals.

Wavelet packet, a generalization of wavelet bases, is alternative bases formed by taking linear combinations of the usual wavelet functions (Yen and Lin, 1999; Guo and Sun, 2005). The wavelet packet coefficients of a function S can be computed via:

$$C^i_{j,k}(t) = \langle S, \psi^i_{j,k}(t) \rangle \qquad i = 1, 2, ... \tag{1}$$

where $\psi^i_{j,k}(t)$ is wavelet packet function with three indices: integers i, j and k are the modulation, the scale and translation parameters, respectively, and

$$\psi^i_{j,k}(t) = 2^{j/2}\psi^i(2^j t - k) \qquad i = 1, 2, ... \tag{2}$$

The wavelet packet functions can be obtained from the following recursive relationships:

$$\begin{cases} \psi^{2i}(t) = \sqrt{2}\sum_k h(k)\psi^i(2t-k) \\ \psi^{2i+1}(t) = \sqrt{2}\sum_k g(k)\psi^i(2t-k) \end{cases} \tag{3}$$

where $h(k)$ and $g(k)$ are quadrature mirror filter associated with the predefined scaling function and mother wavelet function.

Each $C^i_{j,k}$ coefficient measures a specific frequency band content, controlled by the scale parameter i and j. Then, the node energy of the wavelet packet is defined as

$$e_{j,i} = \sum_k (C^i_{j,k})^2 \tag{4}$$

which measures the signal energy contained in some specific frequency band indexed by parameters j and i. In the following, each (j, i) is called as wavelet packet node. Fig.5 shows a WPT node energy tree of a time domain signal S up to the 3rd level of decomposition. Each node energy value of the tree measures the signal energy contained in some specific frequency band, which gives the energy distribution at different scale and frequency band. Generally, for vibration test data acquired from each damage case, there is different node energy distribution. Therefore, each node energy value of wavelet packet can be defined as an individual feature component and be used as a robust rudimentary exploration of the specific signal features that provide useful information for damage classification purposes.

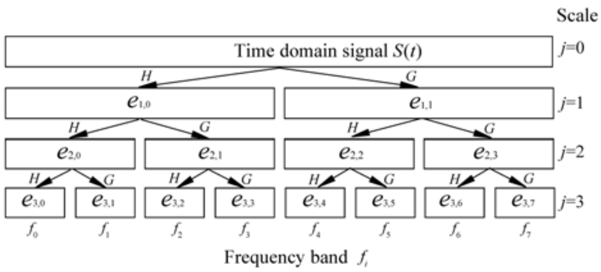


Fig.5 Three levels WPT of a time domain signal

Neural network (NN) was generally adopted as classifier to classify different damage condition after damage feature extraction is conducted (Ni *et al*., 2002; Qu *et al*., 2003). To input classifier of damage identification compatibly, the node energy is normalized as follows:

$$\eta_{j,i} = e_{j,i} \Big/ \sum_{k=0}^{2^j-1} e_{j,k} \tag{5}$$

where $0<\eta_{j,i}<1$. Thus, for a sensor, thirty-two proxy damage feature index $\eta_{j,i}$ are obtained on each case of structural damage when j=5. On the 5th scale of WPT of sensor SS1, the damage feature index of four damage cases are shown in Fig.6.

INFORMATION FUSION AND DAMAGE IDENTIFICATION

To improve precision of structural damage iden-

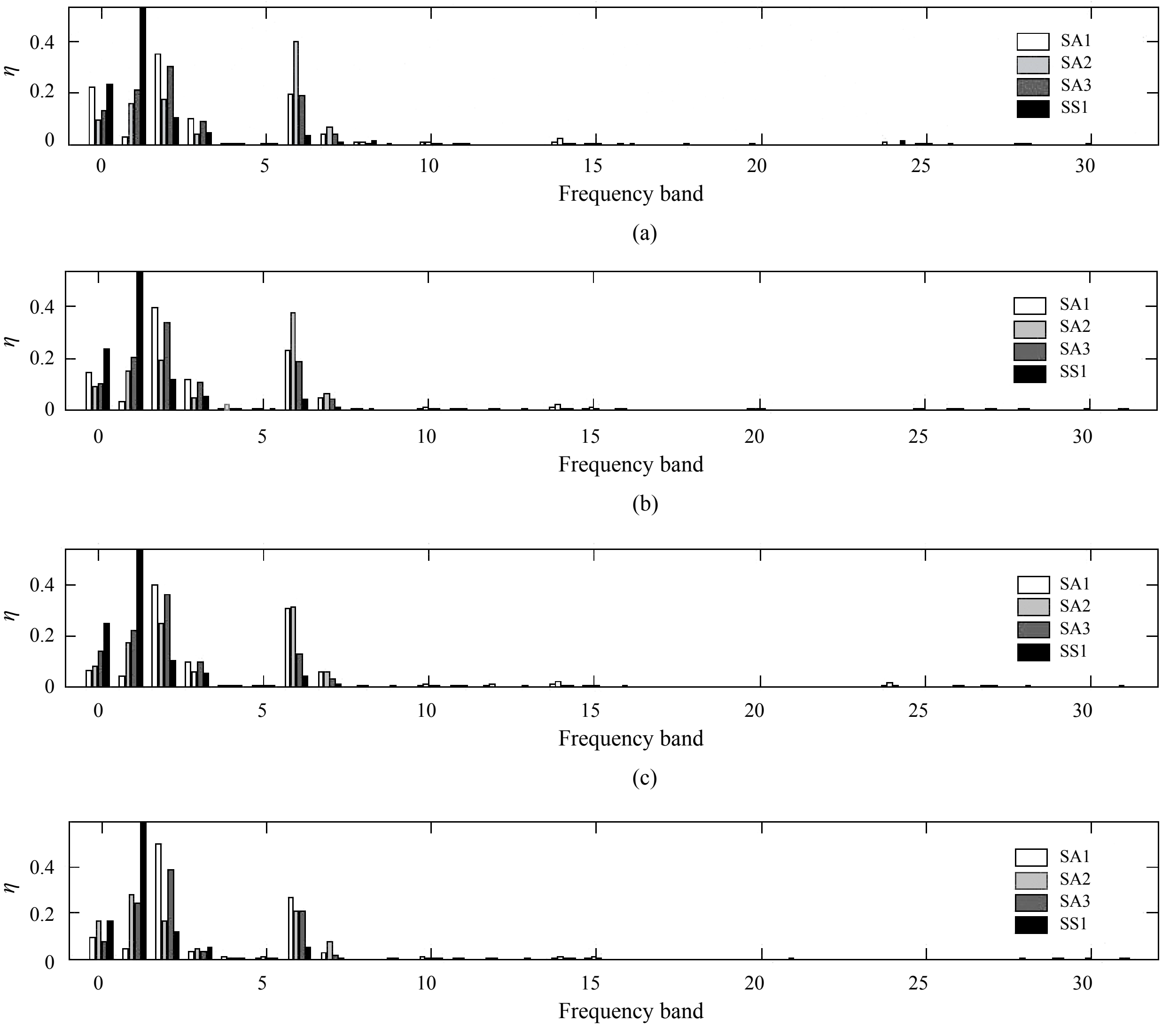


Fig.6 Damage feature index on four structural condition
(a) Undamaged structure; (b) Damage case DA8; (c) Damage case DB8; (d) Damage case DC8

tification, multi-sensor information fusion technique which includes data fusion and decision fusion is introduced to realize damage classification. To delete some feature index lacking sensitivity, number reduction of feature index is conducted and feature vector of four sensors ($\boldsymbol{P}_{Di}^{\mathrm{SA1}}, \boldsymbol{P}_{Di}^{\mathrm{SA2}}, \boldsymbol{P}_{Di}^{\mathrm{SA3}}, \boldsymbol{P}_{Di}^{\mathrm{SS1}}$) are acquired for each damage case *Di*. Each acceleration sensor has best sensitivity to structural damage which occurred at the layer where the acceleration sensor was located. Dynamic strain sensor is sensitive to all damage case. Therefore, new feature vector that contains data feature of different type sensor can be composed respectively as follows:

$$\boldsymbol{P}_{Di}^{\mathrm{I}} = \begin{bmatrix} \boldsymbol{P}_{Di}^{\mathrm{SA1}} \\ \boldsymbol{P}_{Di}^{\mathrm{SS1}} \end{bmatrix}, \boldsymbol{P}_{Di}^{\mathrm{II}} = \begin{bmatrix} \boldsymbol{P}_{Di}^{\mathrm{SA2}} \\ \boldsymbol{P}_{Di}^{\mathrm{SS1}} \end{bmatrix}, \boldsymbol{P}_{Di}^{\mathrm{III}} = \begin{bmatrix} \boldsymbol{P}_{Di}^{\mathrm{SA3}} \\ \boldsymbol{P}_{Di}^{\mathrm{SS1}} \end{bmatrix} \tag{6}$$

The data fusion is thus conducted.

In this study based on decision fusion, three coupling NN are proposed to realize damage acknowledgement, damage localization and damage quantification, respectively. A flow chart to identify damage occurrence is shown in Fig.7 where the coupling NN is composed of three sub-NN and one hub-NN. $\boldsymbol{P}_{Di}^{\mathrm{I}}$, $\boldsymbol{P}_{Di}^{\mathrm{II}}$ and $\boldsymbol{P}_{Di}^{\mathrm{III}}$ are used as inputs to the sub-NN models, and three decisions of structural condition are respectively obtained from the output of the sub-NN models. To eliminate uncertainty of decisions from three sub-NN models, Decision1, Decision2 and Decision3 are inputted to the hub-NN to finish decision fusion, and damage occurrence information is finally obtain from the output of the hub-NN. There is only a node output in each sub-NN and hub-NN model. To enhance computational accuracy, the outputs of the sub-NN and hub-NN model are properly scaled to vary between 0 and 1. The output numerical value indicates the condition of the structure where 0 and 1 correspond to healthy and damaged conditions, respectively.

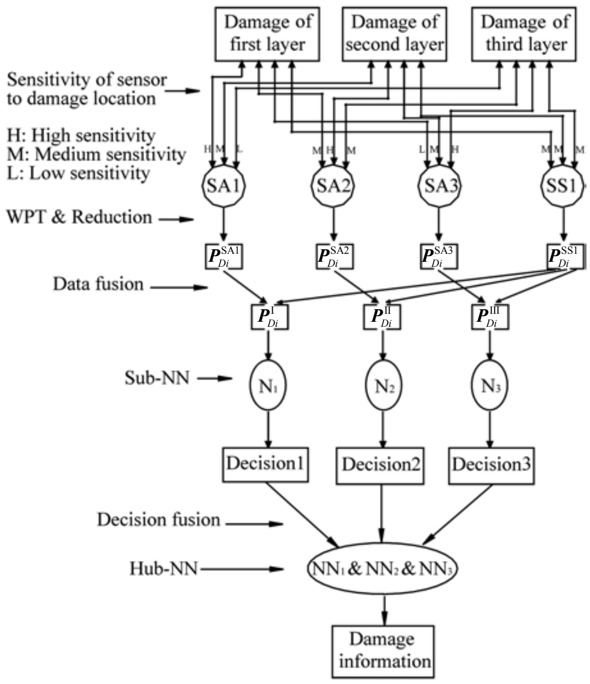


Fig.7 Flow chart to identify damage occurrence

In the same way, identification of damage localization and damage quantification are conducted by the flow shown in Fig.7 respectively. However, it should be noted that there are 3-node output in each sub-NN and hub-NN model. For identification of damage localization, three output values indicate condition of each layer, where 0 and 1 correspond to healthy and damaged conditions, respectively. For damage quantification, the three output values correspond to severity of damage.

As for training of these three groups of coupling NN model, an undamaged structure case and 18 damage cases are used as training cases. The damage cases include DA2, DA4, DA6, DA8, DA10, DA12, DB2, DB4, DB6, DB8, DB10, DB12, DC2, DC4, DC6, DC8, DC10, DC12. The other damage cases are used to validate the NN model after training process is finished. The result of damage identification is shown in Table 2, in which, NN1, NN2 and NN3 are hub-NN of identification of damage occurrence, damage localization and damage quantification respectively. It can be obviously observed that: It is difficult to give indication of damage of rigidity reductions of 2.5%. There is a good precision to identify damage of rigidity reductions of 7.5% or more. There is good precision in damage acknowledgement and damage localization. Though there is small error in damage quantification, it is enough to assess severity of structural damage. In addition, the damage case DB11 cannot be identified because of artificial error in structural test maybe.

CONCLUSION

In structural health monitoring system, many of sensors collect a great deal of dynamic data. The most common methodology of damage identification is based on FT and single sensor analysis. Due to the inherent drawback of FT, the accuracy of damage identification technique based on FT is limited. Assessment of structural condition is affected because of uncertainty of information acquired from single sensor analysis.

In this study, an experiment on a three-story frame model was conducted to study damage identification using WPT and information fusion technique of multi-sensor. WPT is introduced to extract feature of vibration signature in structural damage cases. Algorithm of coupling neural network with data fusion and decide fusion is proposed to realize identification of damage occurrence, damage localization and damage quantification respectively. The study results showed that there is good precision to identify damage occurrence and damage localization and that there is small error to identify damage quantification.

Table 2 Result of damage identification of model structure

Damage case (ξ%)	Output of NN1	Output of NN2			Output of NN3		
		1st layer	2nd layer	3rd layer	1st layer	2nd layer	3rd layer
DA1(2.5)	0.5351	0.7760	0.1190	0.0060	5.9	−2.6	0.4
DA3(7.5)	1.0000	1.0000	0.0000	0.0003	11.2	5.7	1.4
DA5(15)	1.0000	1.0000	0.0001	0.0000	14.4	0.3	−2.9
DA7(25)	1.0000	0.9964	0.0000	0.0000	29.2	−8.5	0.1
DA9(35)	1.0000	1.0000	0.0002	0.0000	36.1	9.3	−2.6
DA11(45)	1.0000	1.0000	0.0000	0.0000	48.7	0.7	−3.0
DB1(2.5)	0.6498	0.0002	0.9395	0.0021	−1.2	0.2	2.6
DB3(7.5)	1.0000	0.0000	0.9999	0.0000	−0.8	8.6	5.1
DB5(15)	1.0000	0.0007	1.0000	0.0000	0.5	19.6	9.3
DB7(25)	1.0000	0.0000	1.0000	0.0012	3.8	24.8	−1.0
DB9(35)	1.0000	0.0000	1.0000	0.0000	−5.4	38.2	12.0
DB11(45)	1.0000	0.0000	0.0000	0.9974	−58.9	1.0	7.1
DC1(2.5)	0.6047	0.1240	0.4338	0.6500	−2.1	7.7	3.6
DC3(7.5)	1.0000	0.0000	0.0000	1.0000	0.1	3.7	9.4
DC5(15)	1.0000	0.0003	0.0040	0.9800	4.9	−3.8	17.5
DC7(25)	1.0000	0.0000	0.0000	1.0000	2.4	0.8	25.3
DC9(35)	1.0000	0.0001	0.0000	1.0000	−7.9	27.0	31.9
DC11(45)	1.0000	0.0000	0.0000	1.0000	13.0	0.3	43.7

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