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Two-stage time-varying linear structural damage detection based on DWT- FastICA and improved multi-particle swarm coevolution optimization

*Shao-Fei JIANG[1)], Wen-Jun Wu[2)], Si-Yao WU[3)] and Chun-Li Zhang[4)]

[1), 2), 3), 4)] *College of Civil Engineering, Fuzhou University, Fuzhou 350108, China*
[1)] cejsf@163.com

ABSTRACT

This paper proposes a two-stage time-varying linear structural damage identification method that is based on DWT-FastICA and improved multi-particle swarm co-evolution optimization (IMPSCO). In the first stage, the measured structural dynamic responses are preprocessed firstly by the discrete wavelet transform (DWT), and then the fast independent component analysis (FastICA) is used to extract the feature components that contain the damage information for the purpose of initially locating damage. In the second stage, the structural responses are divided at the identified damage instant into segments that are used to identify the time-varying physical parameters by the IMPSCO, and the location and extent of damage can accordingly be identified accurately. A numerical example is presented to verify the effectiveness of the proposed method. Meanwhile the effect of noise level and damage extent on the proposed method is also analyzed. The results show that the proposed method can successfully implement the identification of damage instant, location and extent for the linear time-varying structure; furthermore, in accordance with different demands, the proposed method can not only locate and quantify damage within a short time and with a high precision, but also have excellent noise-tolerance, robustness and practicality.

1. INTRODUCTION

Structural damage detection (SDD) is a critical issue of structural health monitoring (SHM). A number of SHM and damage detection approaches have been developed, and the vibration-based SDD method has attracted considerable attention for two decades (Garden and Fanning 2004; Humar et al. 2006; Fan and Qiao 2011).

For time-invariant structures, a large number of vibration-based methods have been proposed and have shown efficiency; however, considerable practical structures in service due to the cumulative damage caused by deterioration tend to be time-varying. In addition, most civil engineering structures exhibit different levels of nonlinearity when

1) Professor，College of Civil Engineering, Fuzhou University, Fuzhou 350108, China(Corresponding author). E-mail:cejsf@fzu.edu.cn
2, 3) Graduate Student, College of Civil Engineering, Fuzhou University, Fuzhou 350108, China.
4) Senior Engineer, Fuzhou University, Fuzhou 350108, China.

subjected to long-term dynamic loads or catastrophic events, such as earthquake and typhoon. Generally, the structures will be in nonlinear state with the appearance of structural damage. Meanwhile, seismic mitigation and isolation structures are usually nonlinear in the field of vibration control. However, the existing damage detection methods are mainly dependent on the linear structural theory. Therefore it is still a challenging problem to develop more efficient and robust detection algorithm for time-varying linear or nonlinear structures.

In recent years, time-domain analysis techniques have been extensively studied and shown to be useful for time-varying structures. Yang et al. (2005, 2008) proposed an adaptive least-square estimation (ALSE) method and an adaptive extended Kalman filter (AEKF) method; however, these methods must initialize the adaptive factor which may produce complex during calculation. Then an improved method integrated with the genetic algorithm (GA) which was employed to optimize the adaptive factor matrix was proposed by Yin and Zhou (2010), nevertheless, for practical applications of the method, only acceleration is measured while velocity and displacement are usually obtained through numerical integrations of acceleration data, which may cause a remarkable data drift especially when damage occurs. Recently, a new system identification method for time-varying structure is proposed by Yang and Nagarajaiah (2012). Firstly, the damage instant and location were identified by wavelet transform (WT) and independent component analysis (ICA). Following which, identification of the time-varying modes was implemented by ICA using the structural responses before and after the identified damage instant. However, the identification result of the damage location is not accurate, and damage extent cannot be directly estimated according to the variation of modal parameters. Therefore an improved multi-particle swarm co-evolution optimization (IMPSCO) is applied in this study and a new two-stage damage detection strategy based on WT, ICA and IMPSCO is proposed for time-varying structure. In the first stage, the measured dynamic responses are processed by WT and ICA in order to initially localize the damage. In the second stage, the IMPSCO algorithm is used to identify the time-varying linear structural parameters so as to precisely localize and quantify the damage.

Particle Swarm Optimization (PSO) proposed by Kennedy and Eberhart (1995) is a popular swarm intelligence method, which mimics the collective motion of insects and birds, known as “swarm behavior”. To date PSO has achieved tremendous progress and has been successfully applied in SDD due to its simplicity, fast convergence speed and outstanding analysis performance. Similar to other evolutionary algorithms, however, standard PSO also has the problem of premature convergence and trapping into some local optima (Chen and Zhao 2009; Chen et al. 2010; Nickabadi et al. 2011). In recent years, the multi-particle swarm co-evolution optimization (MPSCO) by integrating the collaborative theory in ecology with the principle of automatic adjustment has become a popular hotspot (Li 2004; Xu and Liu 2009; Man and Sheng 2010). Nevertheless, it cannot completely solve the problem of local optimum. Therefore the IMPSCO algorithm integrates the evolutionary theory with MPSCO so as to reduce the possibility of falling into the local optimum in further and has been validated to be effective in the community of structural damage detection (Jiang et al. 2014).

The organization of the paper is as follows: Section 2 provides the basic theory of WT, ICA and IMPSCO. Section 3 describes the damage detection strategy based on

DWT-FastICA and IMPSCO. Numerical simulations are carried out in Section 4, and Section 5 gives the concluding remarks finally.

2. BASIC THEORY

2.1 Wavelet singularity analysis

Discrete wavelet transform (DWT) (Mallat 1999) is a useful tool for time-frequency analysis, which achieves multi-resolution analysis of a signal $X(t)$ by decomposing it into high-frequency (detail) and low-frequency (approximation) component at each level. If a signal $X(t)$ is decomposed into L levels, then it can be reconstructed by:

$$X(t) = \sum_{l=1}^{L} X_d^l(t) + X_a^L(t) = \sum_{l=1}^{L} \sum_{k=-\infty}^{\infty} d_{k,l}\psi_{k,l}(t) + \sum_{k=-\infty}^{\infty} c_{k,L}\phi_{k,L}(t) \tag{1}$$

where $X_d^l(t)$ is the detailed component at the l-th scale level; and $X_a^L(t)$ is the approximated component at the L-th scale level; k and l are the translation and scale parameters, respectively; $d_{k,l}$ and $\psi_{k,l}(t)$ are the detail coefficient and wavelet function at the l-th scale level, respectively; $c_{k,L}$ and $\phi_{k,L}(t)$ are the approximation coefficient and scaling function at the L-th scale level, respectively.

Wavelet singularity analysis (WSA) based on DWT is a method used for detecting the singularity (or discontinuity points) of a signal. Firstly, the signal is processed by DWT with reasonable choice of wavelet basis and decomposition level, then the discontinuity points can be distinguished from the detailed components through the spikes corresponding to the abrupt changes in the original signal. When damage occurs in the structure, the local discontinuity points caused by abrupt stiffness variation may be hidden in the corresponding time-series responses. Therefore, the WSA method can be used for detecting structural damages by observing the spikes in the time history of the details extracted from the original dynamic responses. However, the performance of WSA is greatly affected by the measurement noise, and additionally, the damage feature may be buried in the wavelet-domain signals when the structure is subjected to complex external excitation (e.g., seismic excitation).

Recently, a new singularity analysis method called WT-ICA which integrates DWT with fast independent component analysis (FastICA) is proposed and applied to structural damage detection by Yang and Nagarajaiah (2012).

2.2 Fast Independent component analysis

Independent component analysis (ICA) (Comon and Pierre 1994) is a computational technique for feature extraction in signal processing, which can separate a multivariate observed signal to statistically independent sources. It can be specially described as:

$$\boldsymbol{X}(t) = \boldsymbol{AS}(t) \tag{2}$$

where $\boldsymbol{X}(t)=[X_1(t),X_2(t),\cdots,X_m(t)]^{\mathrm{T}}$ represents an m-dimensional observed signal matrix; $\boldsymbol{S}(t)=[S_1(t),S_2(t),\cdots,S_m(t)]^{\mathrm{T}}$ represents an n-dimensional independent source matrix; $\boldsymbol{A}$ represents an $m \times n$ ($m \geq n$) mixing matrix.

The principle of ICA can be summarized as an optimization process to search for proper estimation of the inverse of $\boldsymbol{A}$ (i.e., de-mixing matrix $\boldsymbol{W}$) such that the source signal matrix $\boldsymbol{S}$ can be recovered by:

$$\boldsymbol{S}(t)\approx \boldsymbol{W}\boldsymbol{X}(t) \tag{3}$$

Therefore there are two key issues in the ICA: (1) the proper objective function in order to decide whether the obtained source signals are statistically independent; (2) the effective algorithm to implement the optimization of the objective function. The FastICA proposed by Hyvärinen and Oja (2000) is one of the most efficient and popular algorithm for ICA. It is based on a fixed-point iteration scheme maximizing non-Gaussianity as the objective function.

2.3 Improved multi-particle swarm co-evolution optimization algorithm

The IMPSCO algorithm is applied to identify time-varying structural parameters for the purpose of locating and quantifying damage in this study. In basic MPSCO, multi-subpopulations are divided into two layers. All particles from the upper-layer follow the optimum of the entire population so as to obtain a faster convergence speed, while all particles from the lower-layer follow the optimum of the subpopulation to which it belongs, so as to ensure the population diversity. In the IMPSCO algorithm, an improved strategy to replace the worst particles in the lower-layer with the gravity position of the selected excellent particles in current entire population is employed and integrated with basic MPSCO in order to reduce the possibility of falling into the local optimum in further. All in all, the IMPSCO algorithm is described as follows:

Step1: Population Initialization. Generate m subpopulations randomly, and each of them contains n particles. Then divide them into the upper-layer having only one subpopulation and the lower-layer having m-1 subpopulations. After that, set the iteration index k to zero.

Step2: Fitness Calculation. Calculate the fitness of each particle and save the personal best as p_i (i=1,2,...,n). Simultaneously, record the best individual of each subpopulation and the entire population as p_{g_j} (j=1,2,...,m) and p_{g}, respectively.

Step3: Particles Updating. Update the particles in the upper layer and the lower layer according to Eq. (4) and Eq. (5), respectively, and the worst particles in the entire population are recorded.

$$\begin{aligned} v_i^{k+1} &= wv_i^k + c_1r_1(p_i - z_i^k) + c_2r_2(p_{\mathrm{g}} - z_i^k) \\ z_i^{k+1} &= z_i^k + v_i^{k+1} \end{aligned} \tag{4}$$

$$\begin{aligned} v_i^{k+1} &= wv_i^k + c_1r_1(p_i - z_i^k) + c_2r_2(p_{\mathrm{g}_j} - z_i^k) \\ z_i^{k+1} &= z_i^k + v_i^{k+1} \end{aligned} \tag{5}$$

where z_i and v_i are the position and velocity of the particle, respectively; r_1 and r_2 are the random numbers between zero and one; c_1 and c_2 are the learning factors; w is the inertia weight.

Step4: Optimum Updating. Calculate the fitness of each updated particle and compare it with the values before. If better, then update p_i, p_{g_j} and p_g, respectively. Let k=k+1.

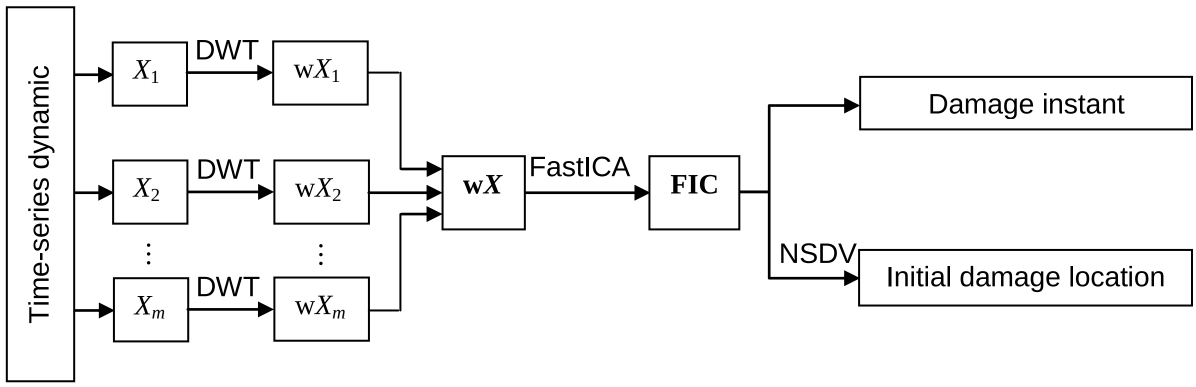
Step5: Worst Particle Replacement. Repeat steps 3-4. When the particle is recorded as the worst for the predetermined times I_w, replace it with G_g:

$$G_g = \sum_{i=1}^{s} z_i \Big/ s \tag{6}$$

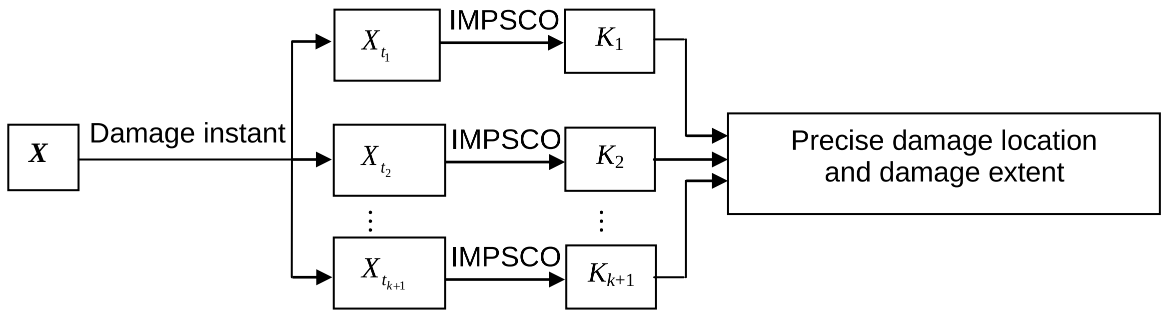
where s and z_i represent the number of the selected excellent particles and their position, respectively.

Step 6: Go to step 3, and repeat until the maximum iteration times k_{max} is reached.

3. DAMAGE DETECTION STRATEGY



(a) The first stage: damage initially location



(b) The second stage: damage precisely location and quantification

Fig. 1 The two-stage time-varying structural damage detection strategy

On the basis of the above-mentioned, this section proposes a new two-stage damage detection strategy by integrating DWT-FastICA and the IMPSCO algorithm. The schematic diagram of the damage detection strategy is depicted in Fig. 1.

In the first stage, the measured structural dynamic responses are preprocessed firstly by DWT, and then the FastICA is employed to extract the feature components that contain the damage information so as to initially locate the structural damage. In the second stage, the structural responses are divided at the identified damage instant into segments which are used to identify the time-varying structural parameters by the IMPSCO algorithm, so that the damage location and extent can be identified accurately.

3.1 Wavelet detailed components separation

The first task is to preprocess the time-series dynamic responses by DWT in order to separate the wavelet detailed components. Firstly, select the proper wavelet basis and decomposition level involving in DWT and then perform DWT on the structural dynamic responses X_i (i = 1,2, ..., m) measured from each sensor location such that the wavelet detailed components $\mathrm{w}X_i$ on a certain scale which contain most damage information can be separated respectively, and m is the total number of sensors. Secondly, build the wavelet detailed signal matrix $\mathbf{w}\boldsymbol{X}=[\mathrm{w}X_1, \mathrm{w}X_2, \ldots, \mathrm{w}X_m]^{\mathrm{T}}$.

3.2 Feature independent component extraction

To extract the damage information hidden in the noisy wavelet-domain signals, the detailed signal matrix $\boldsymbol{wX}$ is processed by using the FastICA, thereby n independent components IC_j (j = 1,2, ..., n) can be obtained. Subsequently, the feature independent component (FIC) which contains the spike property can be extracted, and the position of the spike in the time history indicates the damage occurrence instant.

3.3 Damage initially location with NSDV

After conducting the FastICA, the wavelet detailed signal matrix $\boldsymbol{wX}$ can be reconstructed by:

$$\boldsymbol{wX} = \boldsymbol{A} \times \mathbf{IC} = \sum_{i=1}^{n} \boldsymbol{a}_j \cdot \mathrm{IC}_j \tag{7}$$

where $a_j = [a_{1j}, \ldots, a_{ij}, \ldots, a_{mj}]^{\mathrm{T}}$ is the mixing vector which is proposed as the source distribution vector (SDV). Herein, the element a_{ij} that is defined as the source distribution factor (SDF) represents the proportion of IC_j distributed in wX_i.

When IC_j is the feature independent component (FIC_k, k=1,2, ...,h) extracted by the Fast ICA and a_{ij} is the largest among its SDV, this indicates that corresponding location where the response measured in the i-th sensor location X_i contains the most FIC is possibly damaged location.

The SDV can be normalized in further by Eq. (8). Therefore the structural damage can be initially localized by the maximum among the NSDV of the FIC.

$$\mathbf{NSDV} = [\mathrm{NSDF}_1, \mathrm{NSDF}_2, \cdots, \mathrm{NSDF}_i, \mathrm{NSDF}_m]^{\mathrm{T}}$$
$$\mathrm{NSDF}_i = \frac{|a_{ij}|}{\sum_{i=1}^{m} |a_{ij}|} \, (i = 1, 2, \cdots, m) \tag{8}$$

3.4 Time-varying parameter identification with IMPSCO and results output

(1) Divide the original time-series responses into k+1 segments as $X_{t_1}, X_{t_2}, \cdots, X_{t_{k+1}}$ according to the damage instant identified through FIC_k, k=1,2, ...,h.

(2) Encode parameters involving in the IMPSCO, such as stiffness and damping coefficients, and then determine their corresponding search spaces.

(3) The most important task is to determine the fitness function for the IMPSCO. In this study, the mean square error (MSE) of the predicted time history $X(t\,|\,\mathrm{p})$ as compared to the reference measured time history $X(t)$ is used as the fitness function. Only if the predicted time history is close to the measured ones, can it be determined that the estimated structural properties agree well with the actual damage scenarios. When cast in discrete form, it can be expressed as:

$$\max\ f(\boldsymbol{\theta}) = \frac{1}{\sum_{i}^{N} \sum_{k}^{L} (X_i(t_k) - X_i(t_k\,|\,\mathrm{p}))^2} \tag{9}$$

where $\boldsymbol{\theta}$ is the structural parameters vector to be optimized ; N is the number of measuring points; L is the length of time history.

(4) To implement optimization, some parameters should be set and initialized in advance, including the total number of subpopulations m, subpopulation size n, learning factors c_1 and c_2, limited times for the worst record I_{w}, maximum iteration times $k_{\max}$, the number of the selected excellent particles s and the inertia weight w. Subsequently, perform IMPSCO on the k+1 segment $X_{t_1}, X_{t_2}, \cdots, X_{t_{k+1}}$, respectively, so that the damage location and extent can be identified precisely according to the stiffness variation of each time period.

4. NUMERICAL STUDIES

In this section, a three-story linear shear frame is modeled in order to validate the effectiveness of the proposed strategy.

4.1 Model description

The numerical model can be simplified as a three degree-of-freedom (DOF) linear structure subjected to El Centro earthquake excitation at the base, as shown in Fig. 2.

The structural parameters are set as follows: the mass is m_i=125.53kg, the story stiffness is k_i =24.2 kN/m, the damping coefficient is c_i =0.07 kN.s/m, i=1,2, and 3.

Table 1 Damage scenarios

Damage Scenario	Damage Instant, location and extent
Case 1	t=10s, k_1=24.2 →12.1 kN/m
Case 2	t=10s, k_1=24.2 →12.1 kN/m t=20s, k_3=24.2 →12.1 kN/m

As shown in Table 1, two damage scenarios are simulated and discussed here. Therefore by setting the sampling frequency of 50Hz and the loading time t=30s, the structural acceleration responses can be calculated using the Newmark-Beta algorithm, as shown in Fig. 3.

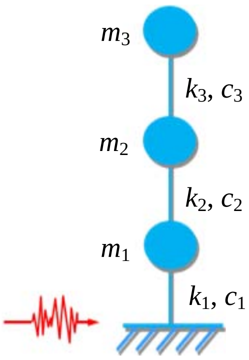


Fig. 2 The 3-DOF linear structure

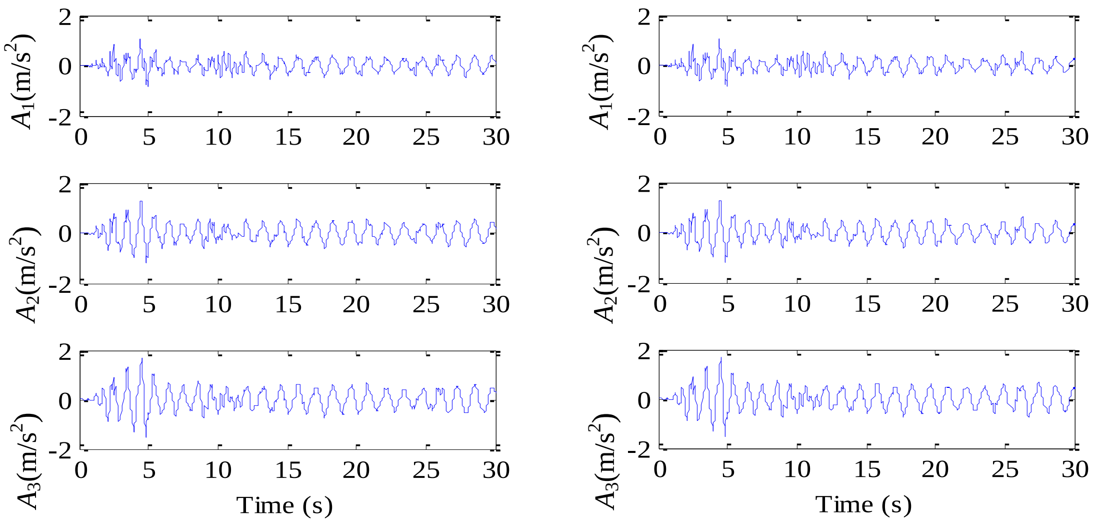


Fig. 3 Original acceleration responses

4.2 Damage detection model

Following the steps presented in Section 3, the damage detection model can be established in the case of noise-free.

4.2.1 Wavelet detailed components separation Firstly, the measured acceleration response A_i (i=1,2, ..., 3) is decomposed in single level with wavelet basis function *db4* respectively. The corresponding detailed components $\mathrm{w}X_i$ (i=1,2, ..., 3) are then selected and built as the wavelet detailed signal matrix $\mathbf{w}\boldsymbol{X}$=[$\mathrm{w}X_1$, $\mathrm{w}X_2$, $\mathrm{w}X_3$]$^{\mathrm{T}}$.

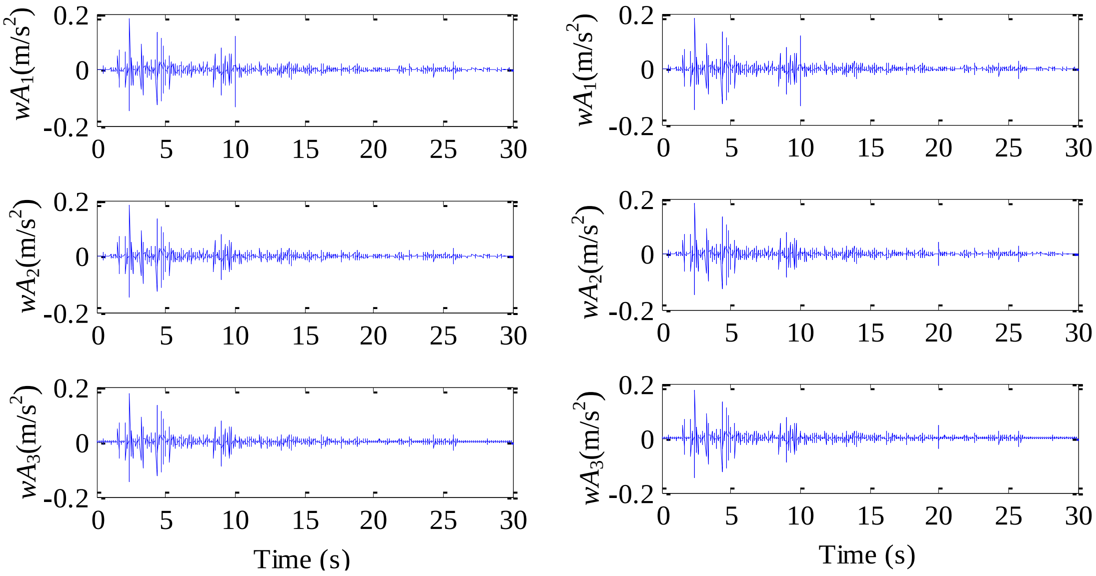
4.2.2 Feature independent component extraction and damage initially location with NSDV The FastICA is performed on $\mathbf{wX}$ so as to obtain the independent components and FICs. According to the position of spike in the FIC, the damage instant can be identified, and the corresponding NSDV of the FIC can be calculated via Eq.(8), thereby the damage location can be initially estimated.

4.2.3 Time-varying parameter identification with IMPSCO and results output Divide the original acceleration responses A_i (i=1,2, ...,3) into several segments according to the obtained FICs, and then perform IMPSCO in each segment to identify the time-varying structural parameters. In this example, the structural mass is assumed known in advance, therefore the parameter vector to be optimized is $\boldsymbol{\theta}=[k_1,k_2,k_3,c_1,c_2,c_3]$. The search range of $\boldsymbol{\theta}$ is within the interval of [0.5$\boldsymbol{b}$, 2$\boldsymbol{b}$], and $\boldsymbol{b}$ is the theoretical value of $\boldsymbol{\theta}$. Additionally, the IMPSCO parameters are set as follows: m=3, n=10, c_1=c_2=2, I_{w}=5, $k_{\max}$=60, s=6, and w is linearly decreased from 0.9 to 0.4 before the 45th iteration and afterwards it maintains at 0.4 to enhance the local search capability. Meanwhile, because the IMPSCO algorithm is a probabilistic optimization algorithm, the identification process is performed for ten times and the average values are regarded as the final results in order to eliminate the influence of randomness. Finally, the damage can be localized and quantified accurately depending on the stiffness variation of each time period.

4.3 Identification results and discussion

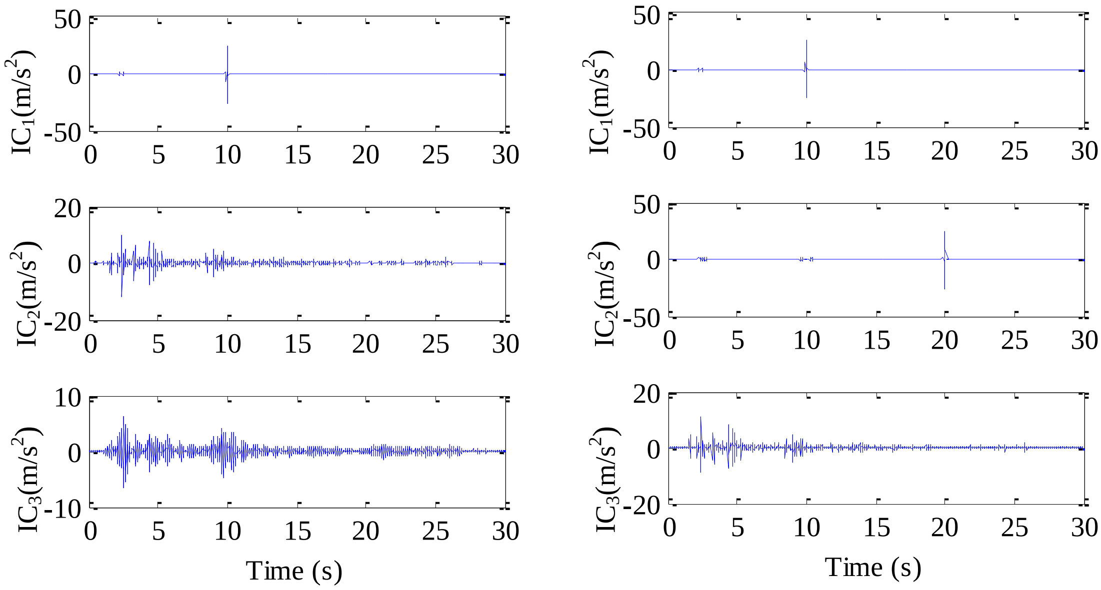
4.3.1 Damage identification results The first identification stage is conducted firstly. The results of wavelet detailed component separation and feature independent component extraction are shown in Fig. 4 and Fig. 5, respectively.

It is seen that, no significant damage information can be directly identified from the wavelet detailed components when the structure is subjected to the earthquake excitation. However, after the FastICA processing, the FIC containing the spike is extracted. For case 1, IC_1 is the FIC and it indicates that the structure is probably damaged at t=10s since the spike occurs at t = 10s. Similarly for case 2, both IC_1 and IC_2 are the FICs and can be used to estimate the occurring time of damage. It is found from Fig. 5, as a consequence, that the structure is probably damaged at t=10s and t=20s respectively.



(a) Case 1 (b) Case 2

Fig. 4 Wavelet detailed components



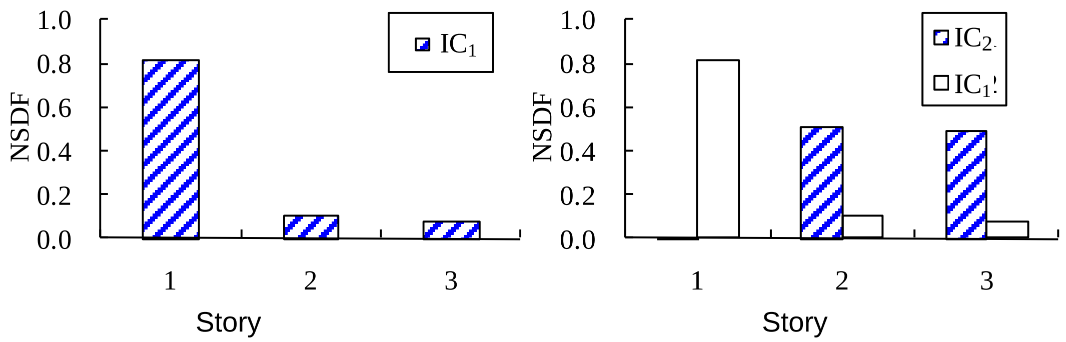
(a) Case 1 (b) Case 2

Fig. 5 Feature independent components

The damage can then be initially localized by the NSDV of each FIC, as shown in Fig. 6.

It can be seen that the maximum of NSDF corresponding to IC_1 occurs at the first story for both case 1 and case 2, which indicates that the first story is probably damaged when t=10s. In addition, for case 2, the maximum of NSDF corresponding to IC_2 occurs at the second story which is approximately equal to the value of the third story. This implies that either the second story or the third story is probably damaged when t=20s.

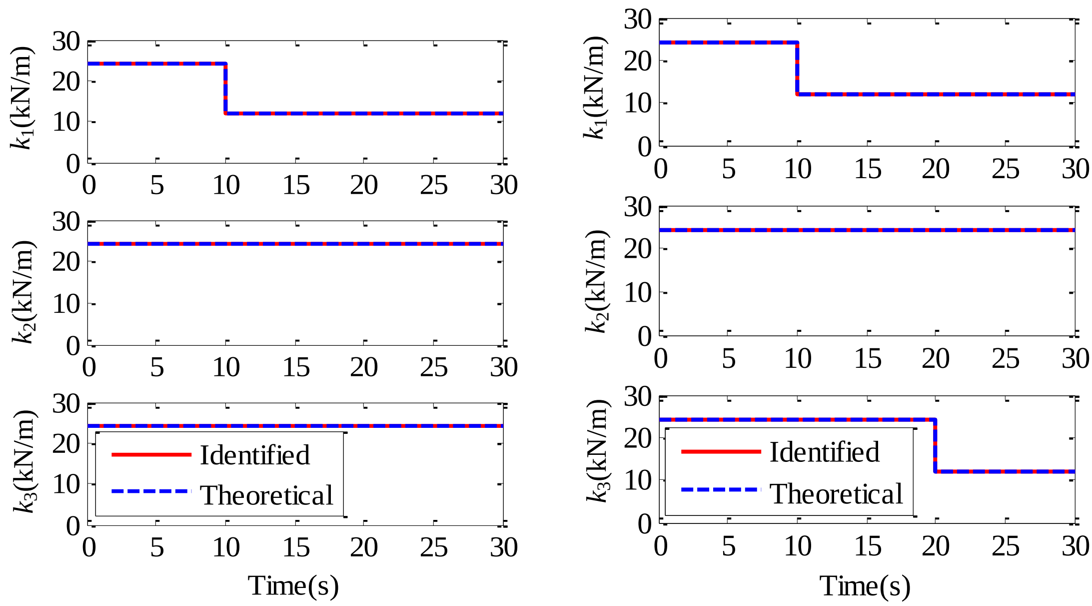
The above results show that the damage instant can be identified correctly according to the first identification stage. Moreover, the damage can be localized quickly and correctly for the single-damage case (Case 1) while the damage initially location can be implemented for the multi-damage case (Case 2).



(a) Case 1 (b) Case 2

Fig. 6 NSDV of the FIC

Subsequently, the second identification stage is conducted. For case 1, the identification process is divided into two segments, namely, 0~10s and 10~30s; for case 2, the identification process is divided into three segments, namely, 0~10s, 10~20s and 20~30s. Therefore, the story stiffness can be identified as shown in Fig. 7.



(a) Case 1 (b) Case 2

Fig. 7 Story stiffness identification results

It can be seen that the identification results of the story stiffness agree well with the theoretical values for both the two cases, which indicates that the precise damage localization and accurate assessment of damage extent can be realized using the second identification stage in further.

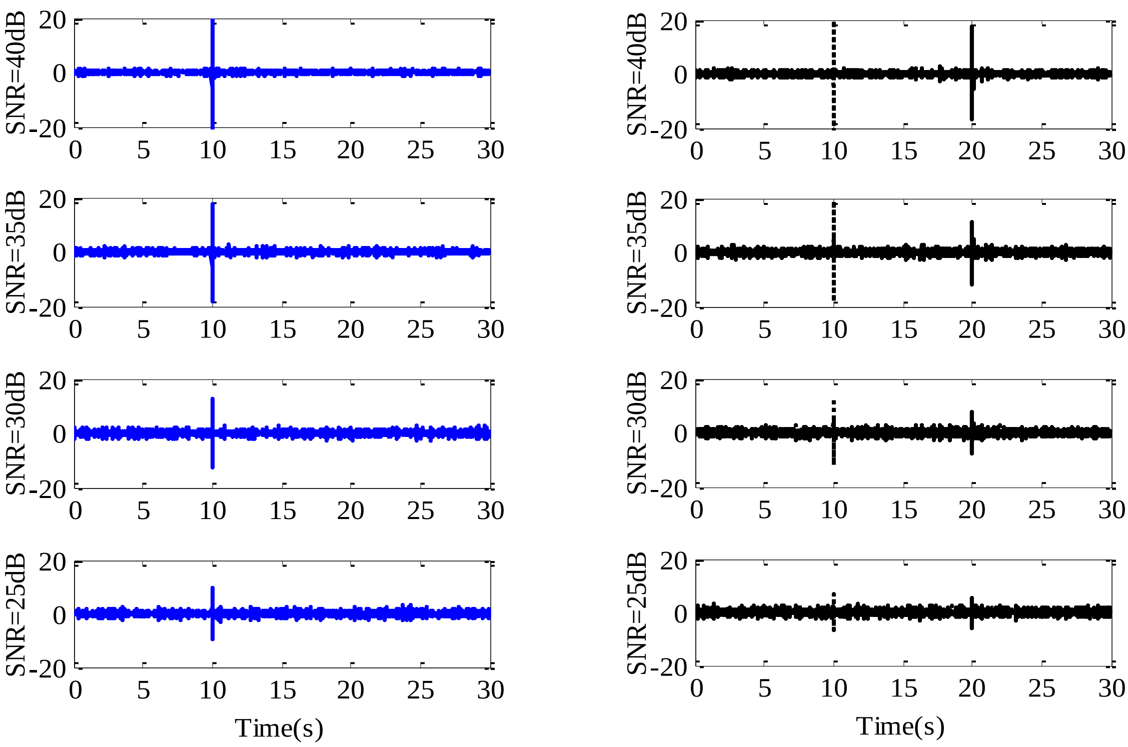
All in all, the above study indicates that the proposed structural damage detection strategy is effective and reliable for the time-varying linear structure with either the single-damage or the multi-damage patterns when measurement noise is not considered.

4.3.2 Comparison and discussion In order to validate the applicability and effectiveness of the proposed strategy considering different noise level and damage extent, the following section is investigated with emphasis.

(1) Noise level To approach the operating environment, Gaussian white noise with different levels is added to all the responses and the earthquake excitation as Eq. (10):

$$y_i = y_i^a \times (1 + \varepsilon R) \tag{10}$$

where y_i and y_i^a represent the contaminated and theoretical signals, respectively; R is a normally distributed random variable with zero mean and a derivation of 1; ε is an index representing the noise level.



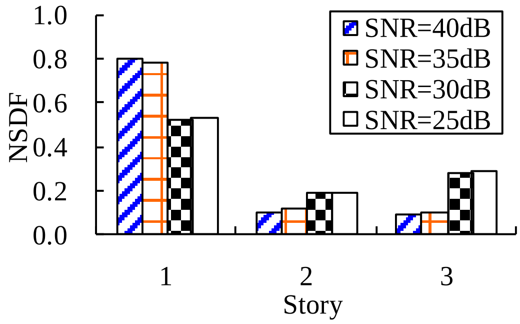
(a) Case 1 (b) Case 2

Fig. 8 FIC under different noise levels

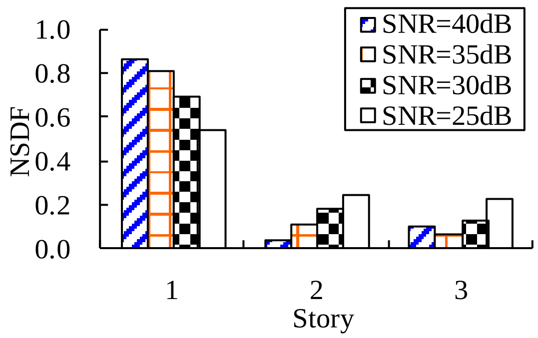
Therefore the signal-to-noise ratio (SNR) is defined as:

$$\mathrm{SNR} = 20\log_{10}\left(1/\varepsilon\right) = 20\log_{10}\left(A_{\mathrm{signal}}/A_{\mathrm{noise}}\right) \tag{11}$$

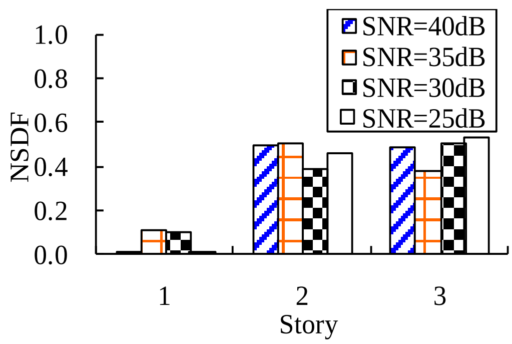
where A_{signal} and A_{noise} represent the amplitude of the signal and noise, respectively.



(a) Case 1



(b) Case 2 (IC_1)



(c) Case 2 (IC_2)

Fig. 9 NSDV of the FIC under different noise level

In order to analyze the anti-noise performance of the proposed strategy, the SNR levels of 40dB, 35dB, 30dB and 25dB are used herein. Following the steps presented in section 4.1.2, the extracted FICs for case 1 and case 2 are shown in Fig. 8. In addition, the dotted line in Fig. 8 (b) represents IC_1 while the solid line represents IC_2, and Fig. 9 shows the NSDV of the FICs accordingly.

It is seen from Fig. 8 and Fig. 9 that the spike caused by damage can still be clearly identified in the FIC even when SNR = 25dB. Furthermore, the damage occurs at t = 10s for both the two cases can be precisely localized according to the corresponding NSDV, while the damage occurred at t = 20s for case 2 can be initially localized.

The time-varying parameter identification results using the IMPSCO algorithm when SNR = 25dB are shown in Table 2.

Table 2 Parameter identification results (SNR=25dB)

Damage scenario	Time(s)	Identified results	Stiffness (kN/m)			Damping (kN·s/m)		
			k_1	k_2	k_3	c_1	c_2	c_3
Case 1	0~10	Identified value	24.34	24.00	24.13	0.07	0.07	0.07
		Error (%)	0.58	0.83	0.29	0.00	0.00	0.00
	10~30	Identified value	12.11	24.34	24.15	0.07	0.08	0.06
		Error (%)	0.08	0.58	0.21	0.00	14.29	14.29
Case 2	0~10	Identified value	24.09	24.40	24.30	0.07	0.07	0.07
		Error (%)	0.44	0.83	0.41	0.00	0.00	0.00
	10~20	Identified value	12.08	24.22	24.17	0.07	0.08	0.07
		Error (%)	0.17	0.08	0.12	0.00	14.29	0.00
	20~30	Identified value	12.12	24.15	12.08	0.06	0.08	0.08
		Error (%)	0.17	0.21	0.17	14.29	14.29	14.29

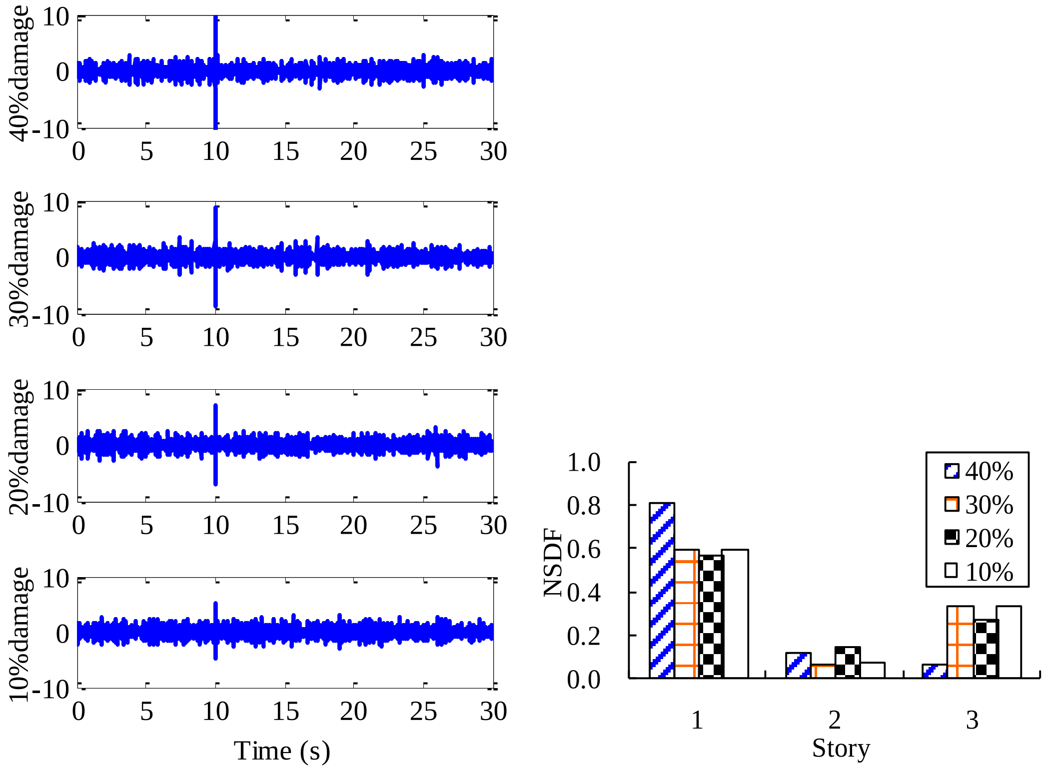
It is seen from Table 2 that although the maximum relative error of the damping coefficient is 14.29%, the maximum relative error of the stiffness coefficient is only 0.83% for all damage scenarios. Since the damping of the structure is reasonably small and only a short time history is required, this damping is unlikely to have a significant effect on the identification results of floor stiffness. This implies that structural damage can be detected effectively and accurately with noise-contaminated measured data using the proposed strategy.

(2) Damage extent To analyze the identification performance of the proposed strategy when the structure is damaged with different extent, we assume that the first story stiffness (k_1) is reduced by 40%, 30%, 20% and 10%, respectively. Following the steps presented in section 4.1.2, the damage identification results of the first stage are shown in Fig. 10, and Table 3 lists the time-varying parameter identification results of the second stage when 10% damage is considered.

Table 3 Parameter identification results (10% damage)

Time(s)	Identified results	Stiffness (kN/m)			Damping (kN·s/m)		
		k_1	k_2	k_3	c_1	c_2	c_3
0~10	Identified value	24.25	24.13	24.21	0.07	0.08	0.07
	Error (%)	0.21	0.29	0.04	0.00	14.29	0.00
10~30	Identified value	21.60	24.25	24.29	0.06	0.06	0.08
	Error (%)	0.83	0.21	0.37	14.29	14.29	14.29

It is seen from Fig. 10 that the spike caused by damage can still be clearly identified in the FIC even when the damage extent is only 10%. Furthermore, the damage can be initially localized according to the corresponding NSDV in the first identification stage. And it can be seen from Table 3 that although the maximum relative error of the damping coefficient is also 14.29%, the maximum relative error of the stiffness coefficient is only 0.83% based on the second stage identification. This implies that the proposed strategy is effective and applicable to small damage as well.



(a) Feature independent component (b) NSDV of the FIC

Fig. 10 First stage identification results

5. CONCLUSIONS

This paper proposes a two-stage damage detection strategy by combining the DWT-FastICA technology and the IMPSCO algorithm for linear time-varying structures. From the damage detection results, some conclusions can be drawn as follows:

(1) According to different demands, the proposed method can not only locate the structural damage initially and quickly, but also locate and quantify the damage accurately. It is noted that the proposed strategy is implemented only by using any kinds of structural time-series responses and the excitation force.

(2) The proposed strategy is applicable and effective for detecting damages of time-varying linear structure using the noisy measured data.

In summary, the proposed damage detection strategy is effective and robust for the numerical simulation of a three-story linear frame, and it still needs more experiments and structures to validate its efficiency in the future.

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