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# Synergetics based damage detection of frame structures using piezoceramic patches

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**Abstract.** This paper investigates the Synergetics based Damage Detection Method (SDDM) for frame structures by using surface-bonded PZT (Lead Zirconate Titanate) patches. After analyzing the mechanism of pattern recognition from Synergetics, the operating framework with cooperation-competition-update process of SDDM was proposed. First, the dynamic identification equation of structural conditions was established and the adjoint vector (AV) set of original vector (OV) set was obtained by Generalized Inverse Matrix (GIM).Then, the order parameter equation and its evolution process were deduced through the strict mathematics ratiocination. Moreover, in order to complete online structural condition update feature, the iterative update algorithm was presented. Subsequently, the pathway in which SDDM was realized through the modified Synergetic Neural Network (SNN) was introduced and its assessment indices were confirmed. Finally, the experimental platform with a two-story frame structure was set up. The performances of the proposed methodology were tested for damage identifications by loosening various screw nuts group scenarios. The experiments were conducted in different damage degrees, the disturbance environment and the noisy environment, respectively. The results show the feasibility of SDDM using piezoceramic sensors and actuators, and demonstrate a strong ability of anti-disturbance and anti-noise in frame structure applications. This proposed approach can be extended to the similar structures for damage identification.

**Keywords:** structural condition identification; Synergetics; lead zirconate titanate (PZT); frame structure; damage detection

## 1. Introduction

Frame structures have been extensively used in various engineering applications, including civil infrastructures and large orbital space stations, among others. Structural Health Monitoring (SHM) systems have seen increased attention due to their potential in providing real time structural diagnosis to issue early warning to prevent catastrophic failures (Keith *et al*. 2008). Structural damage identification theories and methods are the key elements of SHM.

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Comprehensive reviews of major identification methodologies, including natural frequency-based methods, mode shape-based methods, curvature/strain mode shape-based methods and statistical algorithm-based methods, can be found in the literature (Fan and Qiao 2011, Carden and Fanning 2004). In recent years, smart structures have gained importance because of advantages in having integrated smart material technology into structures. As one of the most promising active SHM techniques for engineering structures, the Lead Zirconate Titanate (PZT) -based approach has been widely recognized, with the strong points of the availability in broadband response frequency, low price and the ability of being employed as actuators and sensors simultaneously (Shi and Zhang 2008). After Sun *et al.* (1995) proposed to apply the PZT patches to structural health monitoring, PZTs were spread to different smart structures in succession. For example, as the first few researchers aiming at the application of the PZT-based monitoring method for RC structures in civil engineering, Gu *et al.* (2006) and Song *et al.* (2007, 2008) developed PZT-based smart aggregates as multi-functional sensors and used an active sensing approach. Recent studies show that one potential application using piezoelectric transducers is the monitoring of structural integrity for frame structures. For example, Shanker *et al.* (2008) described an experimental study to extract the dynamic characteristics of a frame structure based on Fast Fourier Transforms using PZT. Sethi and Song (2005, 2006) performed a time domain based subspace system identification to identify the first three modes of the structural frame by using PZT patches. Yan *et al.* (2007) proposed a coupled approach combining EMI technique and a reverberation matrix to quantitatively correlate damages in framed structures with high-frequency signature. Wang *et al.* (2008) presented the basic idea of a piezoelectric admittance technique for a steel frame structure by the use of the high-frequency piezoelectric admittance signals.

Due to multiple uncertainties including incomplete observed data, modeling error, noise and disturbance in the applications of engineering structures, the measured data from PZT sensors and the structural model can be more prone to contamination by uncertainties. Such uncertainties can pose challenges to effectively utilizing frame structural responses. If the structural uncertainty problems were neglected, it will lead to observable differences between theoretical methods and applications. Artificial Neural Networks (ANNs) have drawn considerable attention in the field of engineering, and have been employed to damage identification of frame structures. For example, Xu *et al* (2011) presented a structural identification and damage detection approach for a frame structure model using vibration displacement measurement with parametric evaluation neural network (PENN) and displacement-based neural network emulator (DNNE). Chakraverty *et al.* (2010) used the powerful technique of artificial neural network models to simulate and estimate structural response of two-story shear building by training the model for a particular earthquake. Long (2012) developed a way of predicting cyclic rupture in steel moment frames by employing artificial neural networks. Furthermore, Shim and Suh (2003) presented to use a synthetic artificial intelligence technique, i.e., Adaptive Network-based Fuzzy Inference System (ANFIS) and Continuous Evolutionary Algorithms (CEAs) to identify the location and depth of a crack in a planar frame structure. However, the optimization of the neural network model, the requirement of excessive number of the training targets, and the uncertainties of convergence can restrict ANN's further developments and real-time online applications.

Synergetics is an effective theory which deals with uncertainties of complex systems with a relatively small number of training samples, low calculating burden, and rapid convergence (Haken 1991a). Synergetics has since attracted much attention in the field of engineering. For example, Nikiforov and Markhadaev (2009) discussed the synergetic properties of mechatronic manipulation systems based on Synergetics. Voronin (2006) proposed a synergetic method of data complexation from Synergetics that makes it possible to obtain a maximal amount of available information using a limited number of channels. Jiang *et al.* (2007) studied the cooperative manners among multi-agents using Synergetics. Xiao *et al.* (2012) studied multiple-input multiple-output Gaussian channels based on Synergetics. Belyakov (2009) examined a system approach to obtain high-quality transparent ceramic from the standpoint of Synergetics. Hong *et al.* (2010, 2008) developed a multi-sensor cooperative measurement mechanism and its decision method based on Synergetics according to the nonlinear dynamic characteristics and uncertainty of multi-sensor integrated system. Moreover, after Haken, who is the founder of Synergetics, put forward the new concept that Synergetics can be applied to pattern recognition and set up the SNN at the end of the 1980s, the application in image recognition becomes an emerging new field. As an example, Haken (1991b) had taken the lead in 2D industrial parts identification, the script character recognition, face recognition and 3D image correction. Wang *et al.* (1993) discussed the application of the synergetic pattern recognition method to a robotic vision system for work piece identification and manipulation in automated flexible manufacturing environment. Zhao *et al.* (2003) exploited a new interpretation of the control parameter used in SNN and used it as the basis of a similarity function for shape-based retrieval. Kosarev and Piotrowski (1997) created the developmental technology for a speech understanding system based on Synergetics. Hong *et al* (2013) proposed a dynamic cooperative identification method for pipe based on Synergetics. Wang *et al.* (2007) applied cooperative mode in the traffic condition identification. Akhromeeva and Malinetskii (2008) have indicated developments in Synergetics, which have since opened up new scope for metrology and measurement engineering. From the above literature reviews, it is seen that Synergetics has not been applied in the health monitoring of frame structures. Haken (2004) had pointed out Synergetics was still a very young discipline and that a lot of amazing achievements and research fields would be found.

In this paper, the authors present exploratory research of active damage detection of frame structures based on Synergetics using piezoceramic patches to deal with uncertainty and improve online identification performance. PZT patches were surface-bonded on the frame structure at appropriate locations and function as actuator and sensor. The identification design of flexible structures relies on dynamic vibration within low frequency range. Firstly, the framework of detection method based on Synergetics was established, including the cooperative process, the competitive process and the update process. Then the corresponding theoretical development of three sequential processes was deduced logically. Finally, the pathway in which SDDM was realized through the modified SNN was proposed and its assessment indexes of identification performance were confirmed. To verify the effectiveness of the proposed SDDM for frame structures with PZTs, the frame structure model was performed in Smart Materials and Structures Laboratory (SMSL) at University of Houston (UH). Identified structural conditions for the frame structure model were composed of the healthy state and various damage scenarios by loosening the different screw nuts groups. A series of experiments were implemented in different damage degrees, noisy environments and disturbance environments.

## 2. Damage detection method based on Synergetics

### 2.1 The operating framework of damage detection method

As a comprehensive discipline, Synergetics has established a set of mathematical models and research theories to describe the common law from disorder to order transformation for various systems. Since Synergetics captures the common features of different systems, it can be extended to new subjects with similar phenomenon from a known disciplinary. Nowadays, it is known that Synergetics has been used successfully for pattern recognition (Haken 1991a). The main process of pattern recognition is as follows: For a state of a complex system, there exists a corresponding original pattern, which can be represented by features. Under the premise of the existence of the various original patterns, when one to-be identified pattern appears, the competition can start among all order parameters (*order parameter* is a physical feature, which can describe the dynamic performance of corresponding pattern). The order parameter with the strongest initial value will win. Then the to-be identified pattern can be identified as same as the original pattern which corresponds to the winning order parameter even if some features of the to-be identified pattern had been missed. The identification process is as shown in Fig. 1. In accordance with the process of pattern recognition, the SDDM for frame structures was proposed, as shown in Fig. 2. On the basis of dynamic equations of structural conditions, the dynamic operation of the SDDM consists of three main parts, including (1) the cooperative process, (2) the competitive process and (3) the update process. The cooperative process can obtain the Original Vectors (OV) set and the corresponding Adjoint Vectors (AV) set. During the experimental process, the OV will be used as the baseline to compare with the new vectors set created during the actual test. The competitive process presents the iteration evolution of order parameters to obtain the identification results. The update process can add new structural conditions online to form the new OV set and its AV set. The theoretical derivation of implementation process of the SDDM will be introduced in the next section.

## *2.2 Theoretical development*

### *2.2.1 Dynamic identification equation of structural conditions*

Assuming the structural conditions of a frame are presented by vector $p$, which has $m$ kinds of original structural conditions, the frame structure conditions can be expressed as

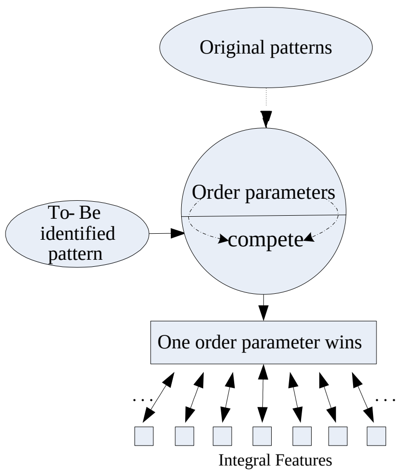



Fig. 1 Main process of pattern recognition based on Synergetics

$$p = \{v_1, v_2, \cdots, v_k, \cdots, v_m\} \tag{1}$$

Each kind of original structural conditions $v_k$ possesses $n$ characteristic values as

$$v_k = (v_{k1}, v_{k2}, \cdots, v_{kj}, \cdots, v_{km}) \quad , \quad 1 \le k \le m \tag{2}$$

The $v_k$ must meet the requirements of normalization and zero mean as

$$\sum_{l=1}^{n} v_{kl} = 0, \|v_k\|_2 = \left[\sum_{l=1}^{n} v_{kl}^2\right]^{1/2} = 1 \tag{3}$$

where $\|v_k\|_2$ represents the Euclidean Norm (EM) of $v_k$.

Then the OV set $V$ can be described as

$$V = \begin{bmatrix} v_{11}, v_{12}, \cdots, v_{1j}, \cdots, v_{1n} \\ v_{21}, v_{22}, \cdots, v_{2j}, \cdots, v_{2n} \\ \cdots \\ v_{k1}, v_{k2}, \cdots, v_{kj}, \cdots, v_{kn} \\ \cdots \\ v_{m1}, v_{m2}, \cdots, v_{mj}, \cdots, v_{mn} \end{bmatrix} \tag{4}$$

where the number *n* is determined by certain identifying requirements, including excitation signal cycle and sampling frequency. An additional requirement to be fulfilled is $m \ge n$. According to Synergetics, a to-be identified structural condition *q* obeys (Haken 1991a)

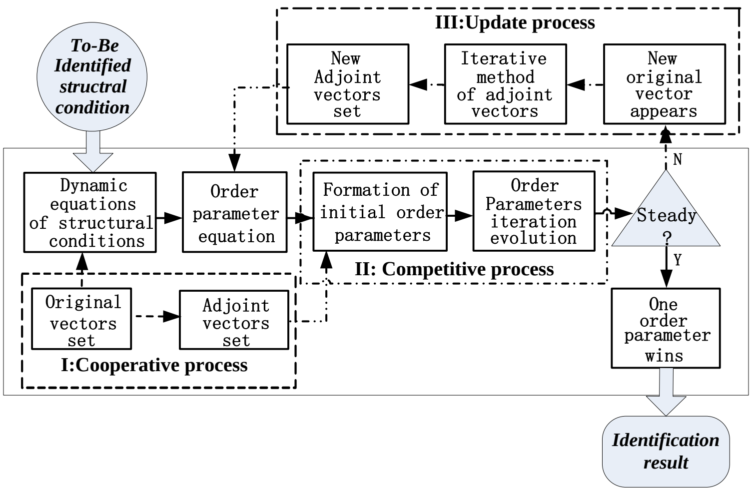



Fig. 2 One of the PLVM of the undamaged structure

$$\dot{q}(x,t) = N\left[q(x,t), \nabla, \alpha, x\right] + F(t) \tag{5}$$

where *N* indicates a functions. $\nabla = (\frac{\partial}{\partial x})$ is the differential operator of stress wave propagation space, $\alpha$ is the parameter for identifying requirement and $F(t)$ represents uncertain fluctuation. As time goes on, $q(0)$, which is the initial characteristic values of *q*, can pass the intermediate state $q(t)$ and reaches the vector $v_k = \left(v_{k1}, v_{k2}, \cdots, v_{kj}, \cdots, v_{kn}\right)$, which represents the $k^{th}$ row of OV set. The dynamic process can be simply described as $q(0) \to q(t) \to v_k$. So the dynamic identification equation of to-be structural condition can be described as (Haken 1991a)

$$\dot{q} = \sum_k \lambda_k v_k (v_k^+, q) \quad D\sum_{k \neq k'} (v_{k'}^+, q)^2 (v_k^+, q) v_k \quad S(q^+, q) q + F(t) \tag{6}$$

where $v_k^+$ is the AV of $v_k$. $\lambda_k$ indicates the identification parameter, which is positive, and can describe the recognition process. Additionally, *D* and *S* are constant coefficients. *D* depends on $k$ and $k'$, where $D \to D_{kk'}$ .The first term $v_k \cdot v_k^+$ is regarded as the learning matrix. *q* increases exponentially when $\lambda_k$ is positive. The third term is the factor restricting growth. The second term is used to identify information regarding the structural conditions.

The initial vector $q_{(0)}$ also needs to meet the requirements of normalization and zero mean. $v_k^+$ and $v_k$ have the relationship

$$\left(v_k^+, v_{k'}\right) = v_k^+ v_{k'} = \delta_{kk'} \tag{7}$$

Therefore $v_k^+$, which can be also described as $V^+$, can be obtained by the Generalized Inverse Matrix (GIM) as follows:

It is known the $V$ is $m \times n$ matrix from Eq. (4) and $m \geq n$. Assuming $R(V\bar{V}) = r$, the *m*-order reversible matrices *P* and *Q* are placed to respond the Eq. (8)

$$P(V\bar{V})Q = \begin{bmatrix} E_r & 0 \\ 0 & 0 \end{bmatrix} \tag{8}$$

where $\bar{V}$ is the TransposedMatrix (TM) of *V* and *r* is the rank of $V\bar{V}$ matrix. The Elementary Transformation (ET) is executed for the partitioned matrix as

$$\begin{bmatrix} V\bar{V} & E_m \\ \bar{V} & 0 \end{bmatrix} \xrightarrow{P \times r_1} \begin{bmatrix} P(V\bar{V}) & P \\ \bar{V} & 0 \end{bmatrix} \xrightarrow{Q \times c_1} \begin{bmatrix} P(V\bar{V})Q & P \\ \bar{V}Q & 0 \end{bmatrix} = \begin{bmatrix} \begin{bmatrix} E_r & 0 \\ 0 & 0 \end{bmatrix} & P \\ \bar{V}Q & 0 \end{bmatrix} \tag{9}$$

Where $r_1$ indicates the first row and $c_1$ is the first column of one matrix. Then the Adjoint Matrix (AM) $V^+$ of $V$ is

$$V^+ = \bar{V} Q \begin{bmatrix} E_r & 0 \\ 0 & 0 \end{bmatrix} P \tag{10}$$

$V^+$ is a matrix, which is formed by $v_k^+,\ k = 1,2,\cdots,m$.

### *2.2.2 Order parameter equation and its evolution process*

The to-be identified structural condition vector $q$ can be decomposed into $v_k$ and random vectors $w$ (Haken 1991a)

$$q = \sum_{k=1}^{m} \xi_k v_k + w,\ k = 1,\cdots,m \tag{11}$$

where $\xi_k$ is the $k^{th}$ order parameter and $(v_k^+ w) = 0$. As well, its AV is also defined as

$$q^+ = \sum_{k=1}^{m} \xi_k v_k^+ + w^+,\ k = 1,\cdots,m \tag{12}$$

where $(w^+ v_k) = 0$. Distinctly

$$(v_k^+, q) = (q^+, v_k) \tag{13}$$

By means of orthogonality, the $\xi_k$ can be achieved by substituting Eq. (11) into Eq. (13), giving rise to

$$\xi_k = (v_k^+, q) \tag{14}$$

Then, based on the governing principle, the equation of order parameter can be obtained after eliminating the stable mode.According to Eq. (6), its corresponding equation of order parameter is the following

$$\dot{\xi}_k = \lambda_k \xi_k - S\xi_k^3 - (D + S)\sum_{k'=k} \xi_{k'}^2 \xi_k \tag{15}$$

In this equation, when the system achieves a stable state, $\dot{\xi}_k = 0, 1 \le k \le m$. The Eq. (15) can then be discretized into

$$\xi_k(n+1) - \xi_k(n) = \gamma(\lambda_k - E + D\xi_k^2)\xi_k(n) \tag{16}$$

Where $E = (D + S)\sum_{k=1}^{m} \xi_k^2$. $\gamma$ is the iteration step length and controls the stability of the recognition process. $\lambda_k$ indicates the identification parameter and determines the terminal steady value of the order parameter. From Eq. (16), every order parameter implements with an iterative operation, which belongs to the competitive process of the SDDM. That is to say that every order parameter value varies at different times. Until one order parameter wins, the terminal steady values of all the order parameters appear. When $\lambda_k$ is a constant, the terminal steady value of the winning order parameter is 1 and others are all 0. For most cases, $\gamma = 1/E$ and $\lambda_k = 1$.

#### *2.2.3 Structural condition online update*

Supposing a new structural condition $v_{n+1}$ appears, the previous AV set of structural conditions will not meet the requirement that the orthogonality of $(v_k^+, v_{k'}) = \delta_{kk'}$. Therefore, a new AV set of structural conditions needs to be constructed, which is presented as

$$z_k^+,\ k = 1, \cdots, n+1 \tag{17}$$

$z_k$ must meet the orthogonal requirement as

$$(z_k^+, v_{k'}) = \delta_{kk'},\ k, k' = 1, \cdots, n+1 \tag{18}$$

According to the iterative update principle (Haken 1991a), the new AV set of structure conditions can be obtained as

$$z_j^+ = v_j^+ - Q_{j,n+1} W \Big(\sum_{k=1}^{n} Q_{n+1,k} v_k^+ - \bar{v}_{n+1}\Big),\ j = 1, \cdots, n \tag{19}$$

$$z_{n+1}^+ = -\sum_{k=1}^{n} Q_{n+1,k} z_k^+ - \bar{v}_{n+1},\ j = n+1 \tag{20}$$

where $W = \Big(\sum_{k=1}^{n} Q_{n+1,k} Q_{k,n+1} - 1\Big)^{-1}$, $Q_{n+1,k} = (\bar{v}_{n+1}\ v_k)$, and $Q_{k,n+1} = (v_k^+ v_{n+1})$.

Assuming the transposed vector $\bar{v}_{n+1}$ of new structural condition vector $v_{n+1}$ is orthogonal to every original structural condition $v_k$, then, $Q_{n+1,k} = (\bar{v}_{n+1}\ v_k) = 0,\ k = 1, \cdots, n$. According to Eqs. (19) and (20),the new AVset can be gained as

$$z_j^+ = v_j^+,\ j = 1, \cdots, n \tag{21}$$

$$z_{n+1}^+ = \bar{v}_{n+1} \tag{22}$$

In general, the results after cooperative and competitive processes include two different cases: one vector (one baseline structural condition) of OV set wins and no vector of OV set wins. The detailed SDDM process is shown as follows: *m* kinds of original structural conditions are known for the given frame structure, which determines the number *m* of order parameters in Eq. (16).

Based on the vectors of original structural conditions (OV set), the AV set can be obtained in the cooperative process. When a to-be identified structural condition appears, *m* initial values of original order parameters can be gained by means of Eq. (14). Then the iteration evolution of *m* order parameters implements in the competitive process. Finally, the original structural condition corresponding to the to-be identified structural condition can be acquired. If no original structural condition wins, the to-be identified structural condition may be a new structural condition, which distinguishes from all the existing original structural conditions. At this moment, the new original structural conditions vector forms, which consists of the new structural condition and previous original structural conditions, and the new AV set can be obtained by Eqs. (19) and (20) or Eqs. (21) and (22) in the update process. Then a new order parameter corresponding to the new structural condition is obtained through the Eq. (16). When another to-be identified structural condition arises, the above process is repeated.

### *2.3 Realization based on modified SNN and performance evaluation*

#### *2.3.1 Realization based on modified SNN*

In accordance with the theoretical development in Section 2.2, the SDDM can be realized through the modified SNN, as shown in Fig. 2. The modified SNN consists of three layers of neurons. The first layer can receive the input of $q(0)$. $q(0)$ represents the input characteristic values of to-be identified structural condition corresponding to the existing structural condition for the network, while $q^u(0)$ indicates the input characteristic values of to-be identified structural condition corresponding to the online updated structural condition. The subscript *j* of $q_j(0)$ or $q_j^u(0)$ represents *j* input characteristic value of $q(0)$ or $q^u(0)$ and the superscript *u* of $q^u$ shows $q^u$ is the online updated structural condition, which can be distinguished from the existing original structural condition. Results with synergistic effects in the first layer are mapped to the second layer, which consists of the order parameter $\xi_k$ and $\xi_k^u$. Between the first layer and the second layer, $v_{kj}^+$ is the AV between the $j^{th}$ neuron in the first layer and the $k^{th}$ order parameter in the second layer, which can be acquired from Eq. (10). Once the to-be identified structural condition vector is determined, the initial values $\xi_k(0)$ of all order parameters in the second layer can be obtained from

$$\xi_k(0) = \sum_{j=1}^{n} v_{kj}^+ q_j(0) \tag{23}$$

The above formula is in accordance with Eq. (14). As a result, all order parameters compete with one another. After the modified SNN converges to a stable state, a certain order parameter $\xi_k$ will win the competition. Afterwards, the definite relations from the middle layer to the output layer is

$$q_l(t) = \sum_{k=1}^{m} \xi_k(t) v_{lk},\ l = 1,2,\cdots,N \tag{24}$$

The third layer represents the output $q_1(t)$ or $q_1^u(t)$ originating from the winning order parameter $\xi_k$ or $\xi_k^u$. $q_1(t)$ is the output characteristic values of the original structural condition $\nu_1$. $q_1^u(t)$ represents the output characteristic values of the original online updated structural condition. $\nu_{1k}$ is the weight vector between the $k^{th}$ order parameter in the second layer and the $j^{th}$ output neuron in the third layer, which can be obtained from Eq. (4).

Consequently, on the basis of the modified SNN model as shown in Fig. 3, when a new structural condition appears, the SDDM can update rapidly the online structural condition, as suggested by Eqs. (19) and (20) or Eqs. (21) and (22).

### *2.3.2 Index system of performance evaluation*

In order to check the evolution state and the processing performance of SDDM, the evaluation indexes system must first be established. The initial data of order parameter is represented as $\xi(0)$ by Eq. (23). The iterative error of order parameter from Eq. (16) was expressed by $\psi$ as

$$\psi = \left|1 - \xi_k(n+1)\right| \tag{25}$$

When $\psi$ is less than a given very small constant, the value of the $\xi_k$ is close to 1, which indicates that the $k^{th}$ order parameter $\xi_k$ wins and the values of other order parameters are equal to 0. At this moment, the iteration time of the winning order parameter can be represented by the steady step number $L$ from Eq. (16). $\Gamma$ denotes the identification result, which is either true (T) or false (F).

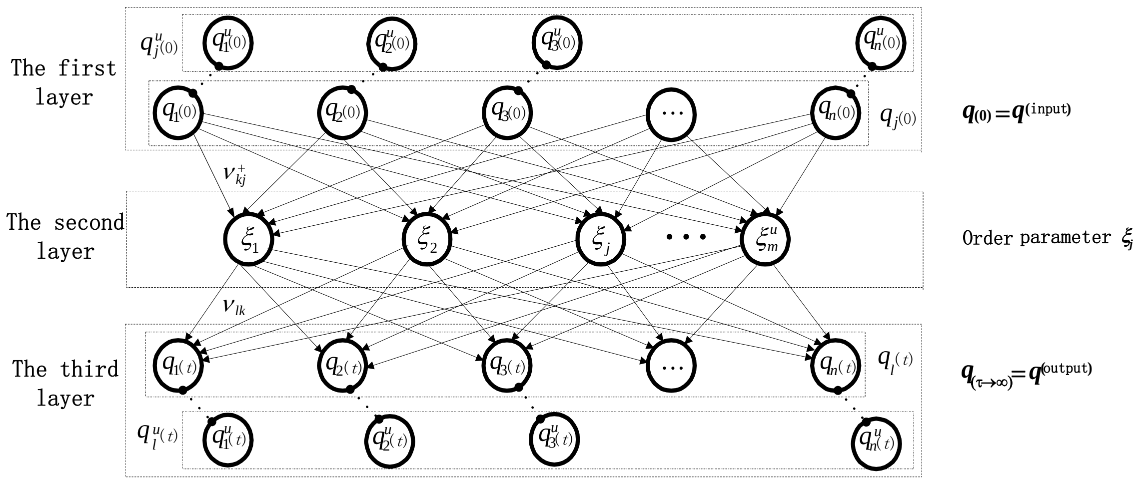



Fig. 3 Realization Diagram based on Modified SNN

## 3. Experimental setup

In the experimental platform section, the PZTs, was used as both actuator and sensor to inspect the integrity of frame structures. The detection objective is to identify different damage structural conditions of a frame model building. Fig. 4 depicts the frame structure health monitoring system in Smart Materials and Structures Laboratory at University of Houston. The platform was mainly constructed using a two-story steel frame structure model, dSPACE, amplifier and signal processing system. The dSPACE hardware system integrated analog-to-digital and digital-to-analog, which can provide useful synchronization function for the input signals and output signals.The two-story steel frame structure model is shown in Fig. 5. It was made of beam elements, floor elements, base element and brackets. Their dimension values are showed in Table 1.All the elements were assembled by using screw nuts and bolts. In this frame structure, there are two PZT patches to be used, as shown in Fig. 6. The larger PZT patch, which has two-layer rectangular bending structure, was surface-bonded on either side of the support beam near the base end. It was used as an actuator to excite the frame structure and enable vibration. The smaller PZT patch was surface-bonded at another support beam near the base bottom and acted as a sensor. The sensor provided the feedback signal for the active detection algorithm. The inner side of PZT patch was glued tightly on the beam surface with the nonconductive epoxy glue, and the outer side was also covered with the nonconductive epoxy glue to prevent damage, such as water. The physical properties of two PZTs are shown in Table 2, while Fig. 7 depicts the response power spectral density of the frame structure model within 500Hz and 100Hz. It is known that the first five resonant frequencies of the frame structure model exist within 100Hz, which is enough to fully expose the dynamics of the structures and will instruct the choice of sweep signal frequency range of the following experiments.

Table 1 Frame Structure Model Parameters

| Name | Value | Amount |
|---|---|---|
| Beam Element | $330\times50.8\times1.27$ mm$^3$ | 4 |
| Floor Element | $254\times50.8\times2.54$ mm$^3$ | 2 |
| Base Element | $279.4\times50.8\times7.62$ mm$^3$ | 1 |
| Bracket Element | $46.8\times25.4\times2.54$ mm$^3$ | 10 |

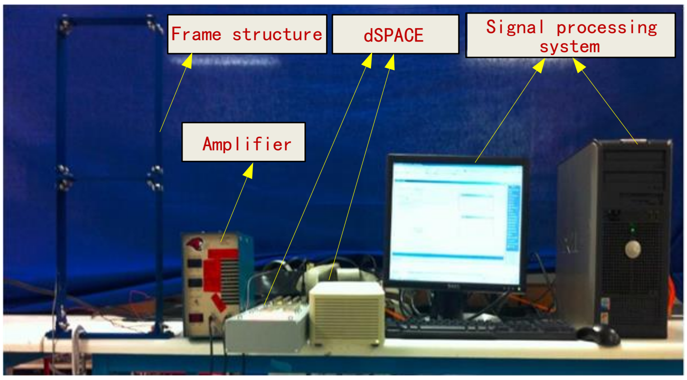



Fig. 4 Experimental Platform

Table 2 PZT Patch Properties

| Symbol | Quantity | PZT actuator | PZT sensor |
|---|---|---|---|
| L×w×t | Dimensions | 70×30×0.25 $mm^3$ | 10×10×0.25 $mm^3$ |
| $d_{33}$ | Strain coefficient | $5.93\times10^{-10}$ C $N^{-1}$ | $5.93\times10^{-10}$ C $N^{-1}$ |
| $d_{31}$ | Strain coefficient | $-2.74\times10^{-10}$ C $N^{-1}$ | $-2.74\times10^{-10}$ C $N^{-1}$ |
| $\rho_p$ | PZT density | 7500 $kgm^{-3}$ | 7500 $kgm^{-3}$ |
| $E_p$ | Young's modulus | $6.3\times10^{10}$ N $m^{-2}$ | $6.3\times10^{10}$ N $m^{-2}$ |

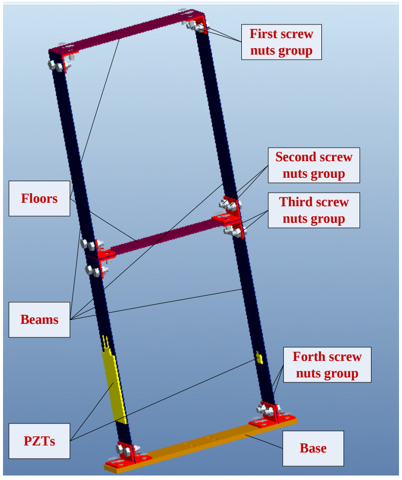
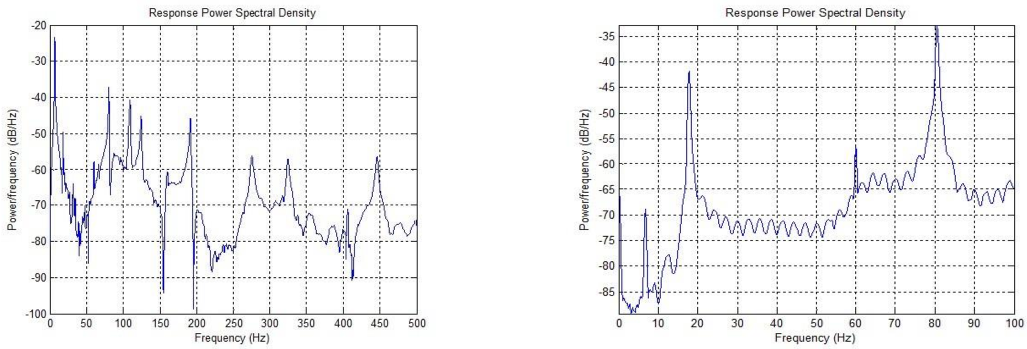



Fig. 5 Frame Structure Model

(a) Piezoelectric Actuator

(b) Piezoelectric Sensor

Fig. 6 Zoomed In Images of Piezoelectric Actuator and Sensor




(a) Power Spectral Density Response within 500Hz (b) Power Spectral Density Response within 100Hz

Fig. 7 Frequency Response Characteristics of the Frame Structure Model

## 4. Experimental results and analysis

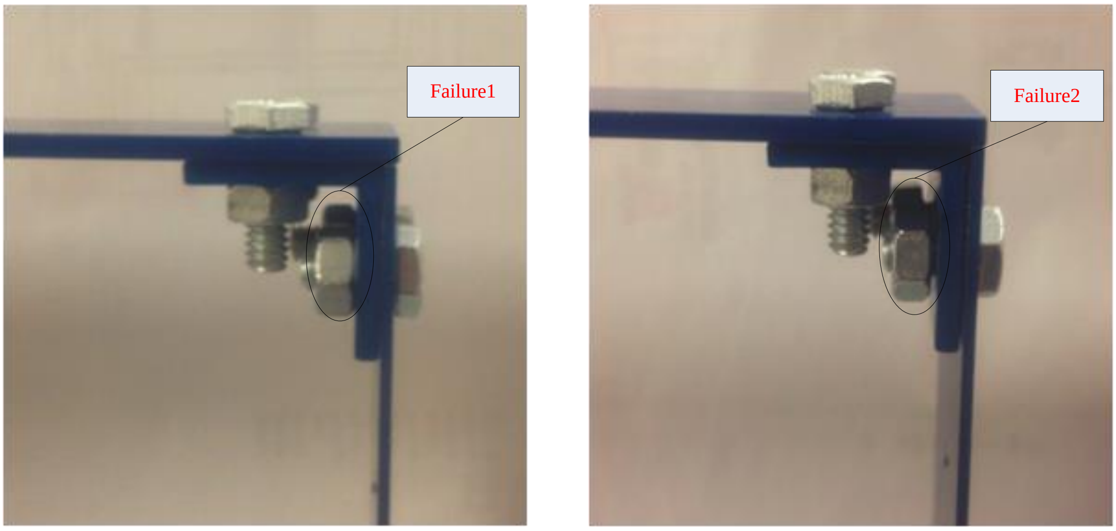
Upon excitation, the active actuator can generate a changing mechanical strain in response to an applied electric field, and cause the frame structure to vibrate. Once possible defects of the frame structure appear, analysis can be performed for the frame structural conditions. In this experiment section, any loose screw nuts or bolts may cause damage to the structure, and should be identified. The experiments were performed with dSPACE real-time control system for excitation and data acquisition. The experiments were mainly carried out in three situations, including structural condition identification in different damage degrees, under disturbance environments and noise environments.

### *4.1 Identification experiments for structural conditions in different damage degrees*

For the same type of fault structural condition, each screw nut was subject to different levels of looseness during the structural operation. The first degree of looseness was identified as Failure1 while the second degree was then called Failure2. This is evident in the corresponding failures depicted in Figs. 8(a) and 8(b), respectively. In this experiment, health monitoring of a frame structure with two different degrees of Failure1 and Failure2 was used as example to validate the proposed SDDM.

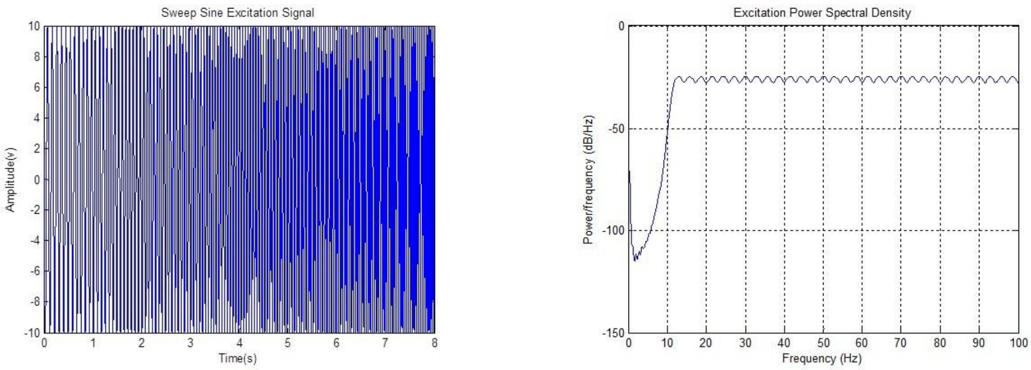
#### *4.1.1 Experiment for existing structural conditions in different damage degrees*

Four initial structural conditions were implemented, including (1) Healthy, (2) Fault1, where the first group of screw nuts is loose, (3) Fault2, where the second group of screw nuts is loose, and (4) Fault3, where the third group of screw nuts is loose. The specific location of each group of screw nuts is shown in Fig. 5. For each structural condition, the sweep sine signal was applied to the actuator patch through the dSPACE digital-to-analog and amplifier. Additionally, the vibration signal of frame structure was obtained from the sensor patch through the dSPACE analog-to-digital. According to the frequency response characteristics of the frame structure from Fig. 6, thefrequency range of the applied sweep sine excitation was determined from 0.1 Hz to 100 Hz and its period was 50 seconds, as depicted in Fig. 9.




(a) Degree of Looseness without Preload (b) *Looseness Degree with one Thread*

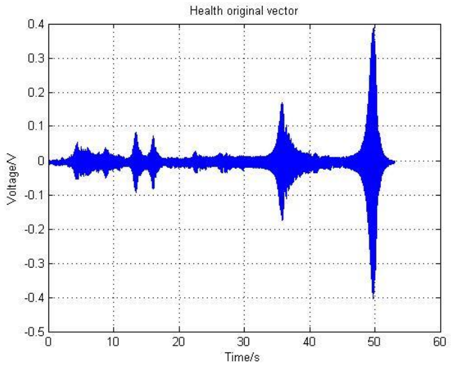
Fig. 8 The Different Looseness Degree of Screw Nut and Bolt in the same Damage Condition



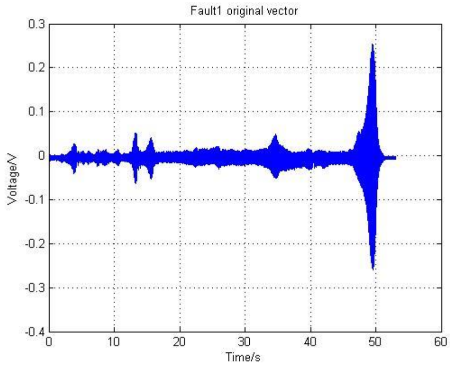

(a) Segmental Signal of Sweep Sine Signal (b) Power Spectrum Density of Sweep Sine Signal

Fig. 9 Sweep Sine Signal

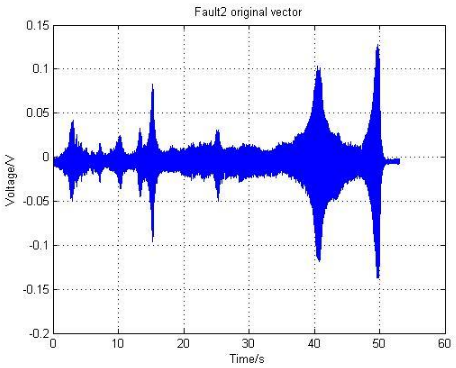
It should be noted that the sampling frequency of each structural condition signal is 1000 Hz. After ceasing the excitation operation, because the structural vibration can be stopped after a certain delay, the sampling period of each structural condition signal lasted a total of 53s, in order to reflect completely and correctly the signals for every structural condition. That is to say there are 53,000 characteristic values for every existing structural condition. The records of four existing structural conditions were obtained for the healthy condition, Fault1, Fault2 and Fault3 at the Failure1, respectively, which are shown in Fig. 10.



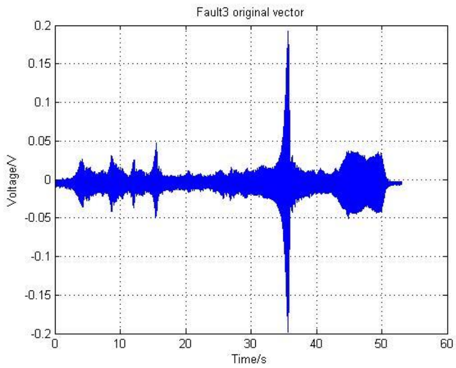

(a) Original Vector Signal of Healthy Condition




(b) Original Vector Signal of Fault1



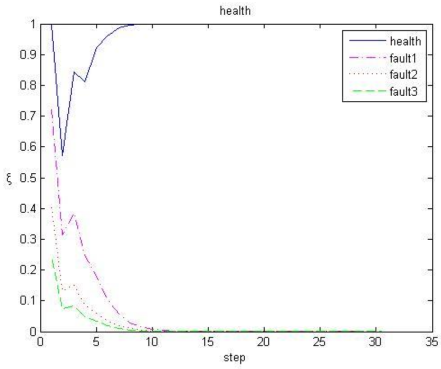

(c) Original Vector Signal of Fault2



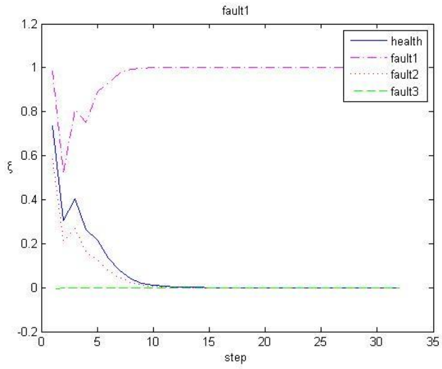

(d) Original Vector Signal of Fault3

Fig. 10 Corresponding Original Vectors of Four Structural Conditions

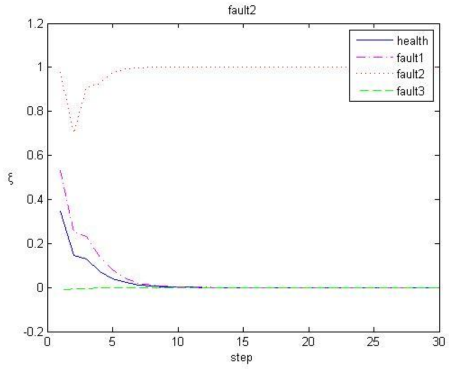
To verify the identification performance, the four53-second signals of the healthy condition, Fault1, Fault2 and Fault3at the Failure2 were treated as to-be identified signals. By implementing the competitive process module of SDDM, the corresponding order parameter evolution of each existing structural condition was shown in Fig. 11. Fig. 11(a) indicates the identification course when a to-be identified signal of health condition was provided. Blue color represented the healthy condition, plotted by order parameter iterative steps on the horizontal axis and order parameter values on the vertical axis. The initial values of order parameters corresponding to the four structural conditions are 0.9986, 0.7219, 0.4020 and 0.2456, which were acquired according to Eq. (23). After 30 iteration steps gained from Eq. (16), the order parameter of healthy condition wins with iterative error value at 2.2204e-016, which was obtained by means of Eq. (25), while the rest 3 order parameters of structural conditions are all 0.Thus, the healthy condition was indeed identified correctly based on Eq. (24). Figs. 11(b)-11(d) represent the identification courses of the to-be identified signals in Fault1, Fault2 and Fault3 respectively. Furthermore, Table 3 shows the identification performance results of the four courses. Results show that the proposed SDDM can identify every defined structural condition rapidly and correctly regardless of different damage degree for the same type structural condition.



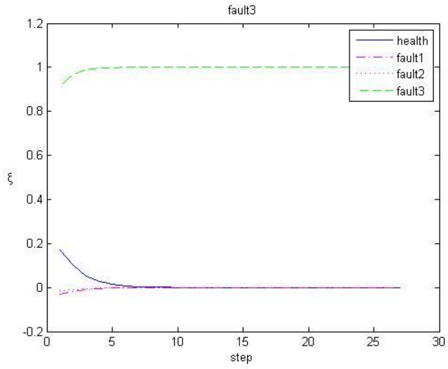

(a) The Identification Process of Healthy Condition




(b) The Identification Process of Fault1




(c) The Identification Process of Fault2




(d) The Identification Process of Fault3

Fig. 11 The Identification Course of Different Order Parameters in Different Failure Degree

Table 3 Performance and result of recognition in different failure degree

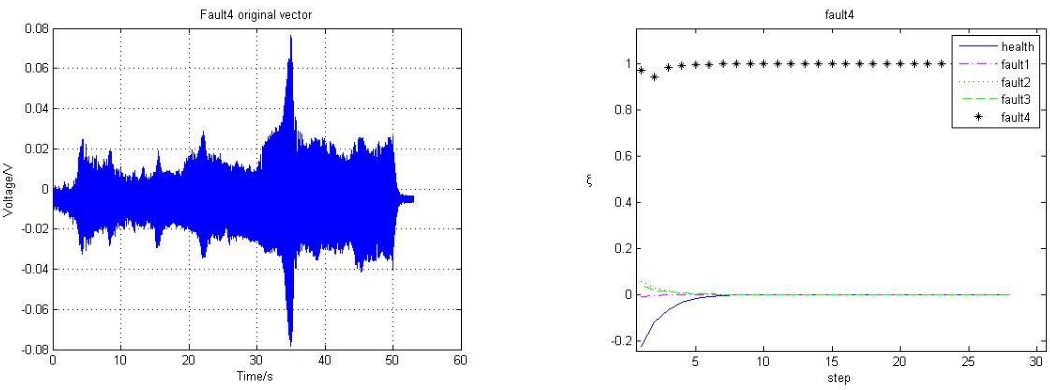
| Structural condition | $\varepsilon(0)$ | $\psi$ | $l$ | $\Gamma$ |
|---|---|---|---|---|
| health | 0.9986, 0.7219, 0.4020, 0.2456 | 2.2204e-016 | 30 | T |
| Fault1 | 0.7344, 0.9831, 0.5833, -0.0088 | 1.1102e-016 | 31 | T |
| Fault2 | 0.3484, 0.5306, 0.9750, -0.0123 | 1.1102e-016 | 29 | T |
| Fault3 | 0.1704, -0.0282, -0.0144,0.9174 | 2.2204e-016 | 26 | T |

#### *4.1.2 Online updated damage structural condition experiment in different damage degree*

A new structural condition may appear if one structural condition cannot be identified from the original OV set. The following experiment verifies the online updated damage condition performance of the proposed methodology. First, a new damage condition was set, which involves the fourth loose group of screw nuts called Fault 4.The location of the fourth screw nuts group can be found in Fig. 5. A 53-second signal of the Fault4 in the Failure1 was collected online as the new OV, which is shown in Fig. 12(a). Fig. 12(a) indicates that time domain signal of this Fault4 has greatly weakened peaks between 30 to 40sand different energy distribution comparing with the former 4 OVs of structural conditions. The update process module of SDDM was then implemented to add the OV of Fault4 to form a new OV set described as Eq. (4). Then the new AV set can be got on the basis of Eqs. (19) and (20). Finally, another 53-second signal of the Fault4 condition in the Failure2 was collected online as the to-be identified signal. Fig. 12(b) shows the corresponding order parameter evolution of the Fault4.Numerically, Table 4 shows the online damage condition update performance. Clearly, Fault4 can be identified correctly after 27 iteration steps, without affecting the proper identifications of the healthy condition, Fault1, Fault2 and Fautl3 in the new OV set. By comparing Table 3 to Table 4, it is observed that after adding Fault4 condition into the OV set, the initial value number of order parameters increases to 5 with significant changes. Each identification course has declined slightly in iterative steps. Results indicate that the proposed online updated damage condition in SDDM is feasible. As a supplemental function of SDDM, the online damage condition update has the capability to find new damage conditions sensitively and add it into the OV set. By using this function, it will be convenient to detect new damage structural conditions in time and provide alerts in time.

Table 4 Recognition Performance in Different Damage Degree with Updated Condition

| Structural condition | $\varepsilon(0)$ | $\psi$ | $L$ | $\Gamma$ |
|---|---|---|---|---|
| healthy | 0.9974, 0.0007, -0.0017, 0.0035,0.0022 | 3.3307e-016 | 20 | T |
| Fault1 | 0.0555, 0.9188, 0.0498, -0.0031,-0.0200 | 1.2405e-016 | 25 | T |
| Fault2 | -0.0689, 0.0264, 0.9902, 0.0036,-0.0094 | 1.2303e-016 | 25 | T |
| Fault3 | -0.0919, 0.0611, -0.0072,0.9565,-0.0384 | 2.2204e-016 | 25 | T |
| Fault4 | -0.2266,-0.0077,0.0571,0.0413,0.9718 | 1.1102e-016 | 27 | T |



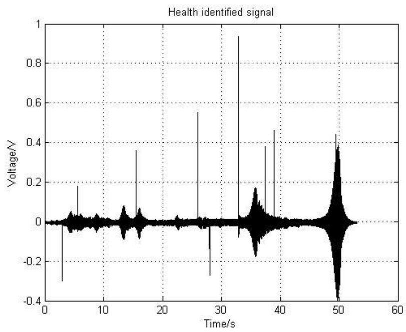

(a) Original Vector Signal of Online Fault4 (b) The Identification Process of Fault4

Fig. 12 Online Updated Fault4 and Its Identification Course in Different Damage Degree

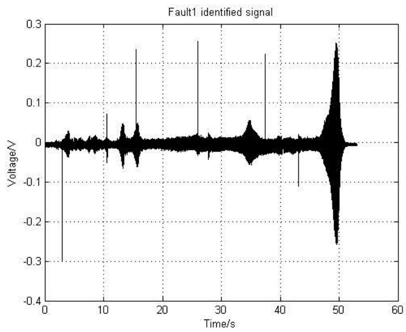
### *4.2 Identification experiments for structural conditions under disturbance environment*

#### *4.2.1 Experiment for existing structural conditions in disturbance environment*

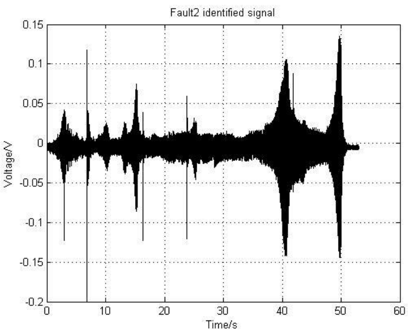
Considering that the frame structures are likely to be influenced by stochastic disturbances, a new experiment should then test the anti-disturbance ability of the proposed SDDM. In this experiment, the frame structure maintains the same five previous structural conditions, which are the healthy condition, Fault1, Fault2, Fault3, and Fault4. For each structural condition, the same sweep sine excitation and sample frequency at 1000 Hz were applied to the frame structure to record signals of different structural conditions.



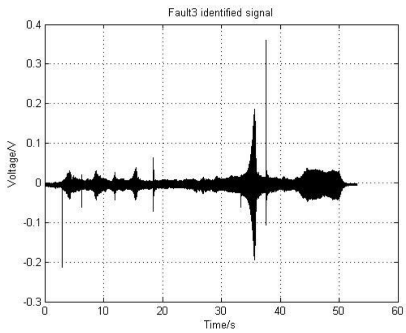

(a) To-be Identified Signal of Healthy Condition



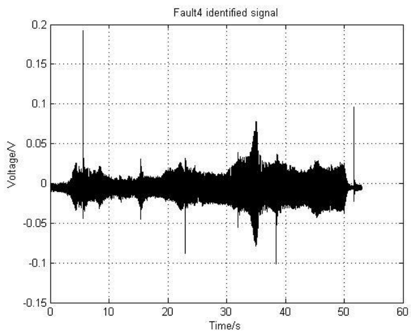

(b) To-be Identified Signal of Fault1




(c)To-be Identified Signal of Fault2




(d) To-be Identified Signal of Fault3

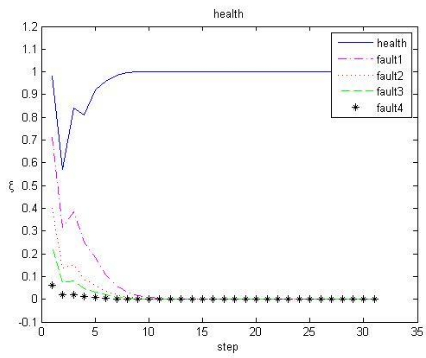



(e) To-be Identified Signal of Fault4

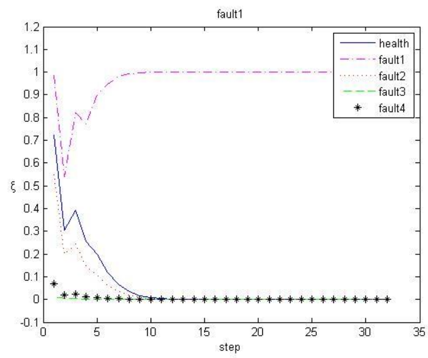
Fig. 13 Corresponding to-be Identified Signals of Five Structural Conditions

A total of 5 records were obtained for the five structural conditions in the Failure1, in which each structural condition has 1 record with one circle. Each record lasted 53s. The OVs of five structural conditions were acquired accordingly. As shown in Fig. 13, random knocking disturbances were induced into the to-be identified signals of the healthy condition, Fault1, Fault2, Fault3 and Fault4. That is, the to-be identified signals have been subjected to random interference and will be identified by comparing to the baseline.

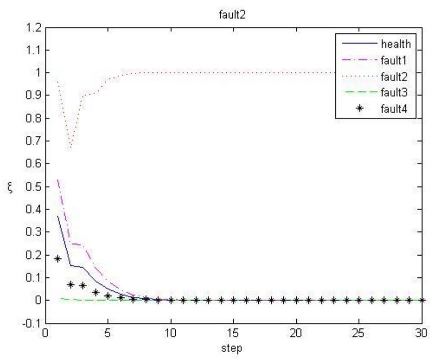
It can be observed that the amplitudes of knocking signals were dramatically larger than that of the vibration range generated by the PZT actuator patch. Furthermore, random knocking signals possess a wide frequency range to affect the identified signals. Additionally, the SDDM was implemented to engage these signals in a similar competitive process. The corresponding order parameter evolutions of the healthy condition, Fault1, Fault2, Fault3 andFault4areshown in Fig. 14. Additionally, Table 5 presents the numerical identification performance results. Fig. 14 and Table 5 show that the healthy condition, Fault1, Fault2, Fault3 and Fault4 were identified correctly and efficiently within 28-31 iteration steps. Consequently, it was demonstrated that importing disturbance signals has little effect on the identification performance because random disturbances cannot change the signal structure of every structural condition in nature. The results confirm the promising disturbance rejection ability of the proposed method.



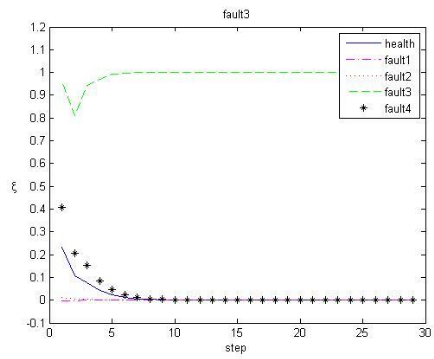
(a) The Identification Process of Healthy Condition



(b) The Identification Process of Fault1

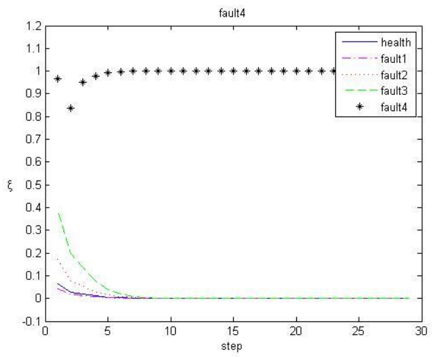


(c) The Identification Process of Fault2



(d) The Identification Processof Fault3

Continued-




(e) The Identification Process of Fault4

Fig. 14 Identification Process of Different Order Parameters under Disturbance Environment

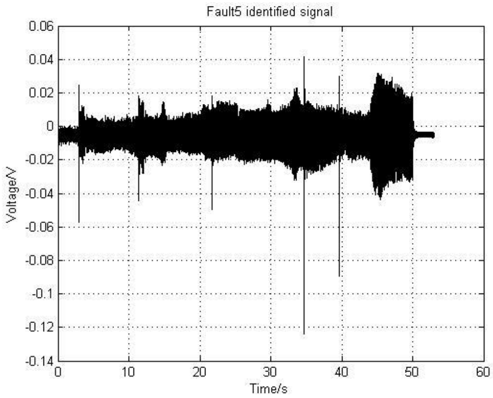
Table 5 Recognition Performance in Disturbance Environment

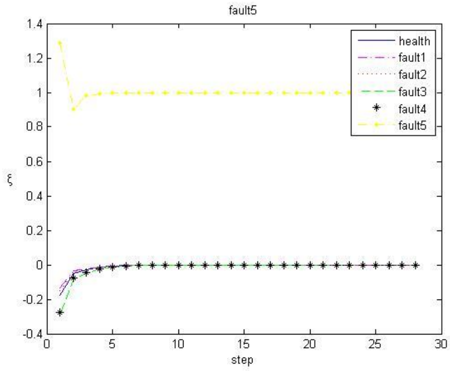
| Structural condition | $\varepsilon(0)$ | $\psi$ | $L$ | $\Gamma$ |
| --- | --- | --- | --- | --- |
| health | 0.9829,0.7109,0.3987,0.2344,0.0623 | 2.2204e-016 | 30 | T |
| Fault1 | 0.7218, 0.9850,0.5483,0.0120,0.0689 | 1.1102e-016 | 31 | T |
| Fault2 | 0.3706,0.5289,0.9585,0.0072,0.1831 | 1.1202e-016 | 29 | T |
| Fault3 | 0.2327,-0.0035,0.0132,0.9634,0.4062 | 1.1102e-016 | 28 | T |
| Fault4 | 0.0639,0.0420,0.1707,0.03880,0.9677 | 1.1402e-016 | 28 | T |

#### *4.2.2 Online updated damage structural condition experiment in disturbance environment*

In reality, the damage structural condition of frame structures may occur in more than one screw nut group simultaneously. One additional damage condition is that the looseness of first and the fourth group of screw nuts (called Fault5) in Failure1 was added online in this experiment to test the identification ability of the proposed method for online updated damage condition in disturbance environments. A 53-second signal of the Fault5with random disturbances in the Failure1 was collected online as the new OV. And the another to-be identified signal of Fault5 was then comprised of a 53-second signal with different disturbances as shown in Fig. 15(a). Also, the order parameter evolution of Fault5 is shown in Fig. 15(b), while the corresponding identification performance is expressed in last row of Table 6.

Order parameter initial values of each structural condition were respectively -0.1787,-0.1324,-0.150,-0.2942,-0.2752 and 1.2893. Fault5' siterative error was 1.1102e-016 and the number of iterative steps was 27. In the case of adding the new damage condition, the former correctly tested identified signals of healthy condition, Fault 1, Fault 2, Fault 3 and Fault 4 were tested again on the basis of the newly formed 6 OV set. And the testing results also presented correct. Following the testing, the results indeed confirmed the initial analysis. Table 6 also fully confirmed identification performances of all structural conditions. This experiment demonstrated that the online updated damage condition in disturbance environments did not affect the existing condition identifications, and possesses a strong ability of anti-disturbance.




(a) To-be Identified Signal of Online Fault5 (b) The Identification Process of Fault5

Fig. 15 To-be Identified Updated Fault5 and Its Identification Course under Interference

Table 6 Recognition Performance of Online Updated Fault5 in Disturbance Environment

| Structural condition | $\xi(0)$ | $\psi$ | $L$ | $\Gamma$ |
|---|---|---|---|---|
| healthy | 0.9846,-0.0051,0.0016,-0.0065,-0.0060,0.0079 | 1.1204e-016 | 22 | T |
| Fault1 | 0.0133,0.9894,-0.0067,0.0209,0.0337,-0.0216 | 1.1306e-016 | 24 | T |
| Fault2 | -0.0297,0.0006,0.9550,-0.0087,-0.0212,0.0418 | 2.2204e-016 | 24 | T |
| Fault3 | -0.0132,0.0137,-0.0018,0.9538,0.0126,0.0123 | 1.4202e-016 | 23 | T |
| Fault4 | 0.0035,0.0001,-0.0151,-0.0097,0.9641,0.0129 | 1.4106e-016 | 23 | T |
| Fault5 | -0.1787,-0.1324,-0.150,-0.2942,-0.2752,1.2893 | 1.1102e-016 | 27 | T |

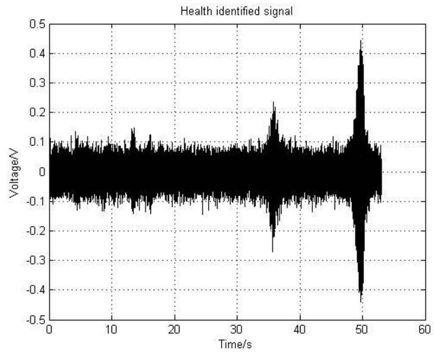
However, online updated damage conditions in disturbance environment should not be too excessive. This is because the online updated damage condition is now assumed to be the OV in the new settings. However, it is not truly the real OV. The extravagant number of structural conditions with disturbance environment may not distinguish the newly added structural conditions well and could increase the possibility of incorrect identification.

### *4.3 Identification experiments for structural conditions under noisy environment*

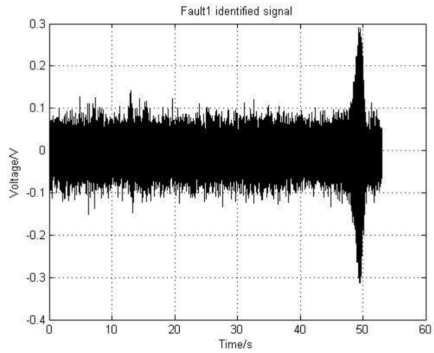
#### *4.3.1 Experiment for existing structural conditions in noisy environment*

The low-frequency measurement for frame structures is relatively more prone to contamination by ambient vibration noise than those of high frequency ones [12]. The experiment should test the anti-noise ability of the proposed SDDM. The structure has six initial conditions as seen in Section 4.2.2, which include the healthy condition, Fault1, Fault2, Fault3, Fault4 andFault5. Additionally in this experiment, the six OVs from Section 4.2.2 were regarded as the OV set. To verify the identification performance in noisy environment, each 53-secondsignal with White Gaussian Noise

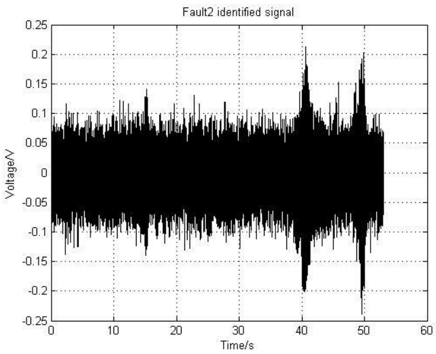
(WGN) of the healthy condition, Fault1, Fault2, Fault3 and Fault4 in Failure1 acquired online was treated as the corresponding to-be identified signal. According to the actual situation, the Signal Noise Ratio (SNR) was set to 30.The to-be identified signals of the healthy condition, Fault1, Fault2, Fault3 and Fault4 are shown in Fig. 16. It is observed that peripheral noise differs with random knocking disturbance mainly in signal type as well as amplitude. It can therefore be inferred that most of the useful identified signals were submerged in the noise.



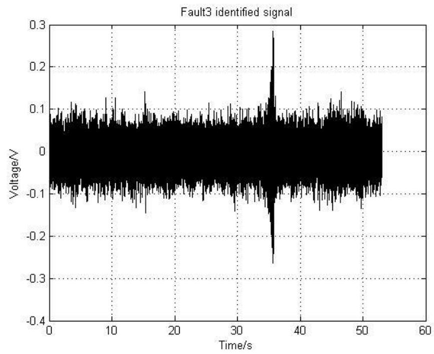

(a) To-be Identified Signal of Healthy Condition



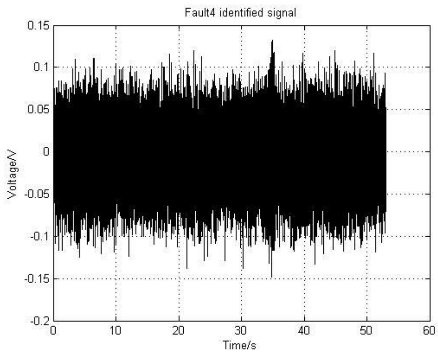

(b) To-be Identified Signal of Fault1




(c) To-be Identified Signal of Fault2



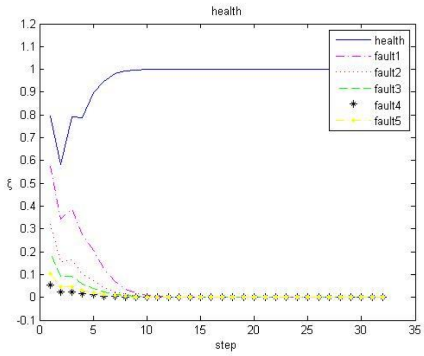

(d) To-be Identified Signal of Fault3



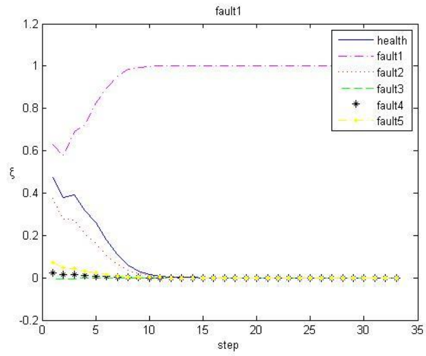

(e) To-be Identified Signal of Fault4

Fig. 16 Corresponding Identified Signals of Five Structural Conditions (SNR=30)

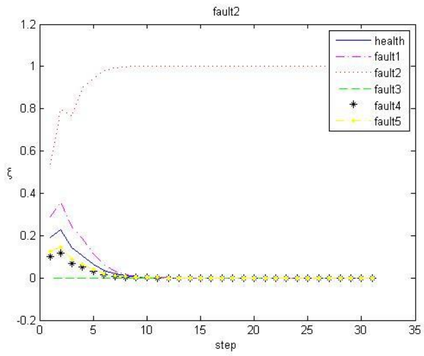
By implementing SDDM for the competitive process, the corresponding order parameter evolution of each structural condition can be seen as shown in Fig. 17. Furthermore, Table 7 numerically shows the identification performances of the healthy condition, Fault1, Fault2, Fault3 and Fault4 in the noisy environment. Clearly, their identification results are completely accurate. However, the identification course of the healthy condition, Fault1, Fault2, Fault3 and Fault4 in the noisy environment has increased slightly iterative steps than in disturbance environment, while still maintaining a high identification speed.



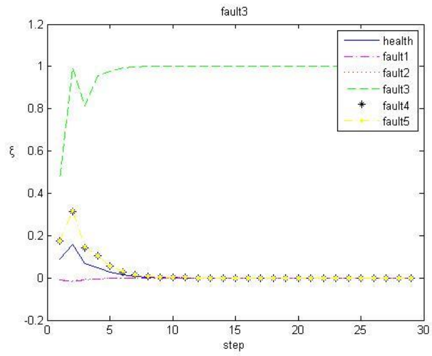

(a) The Identification Process of Healthy Condition



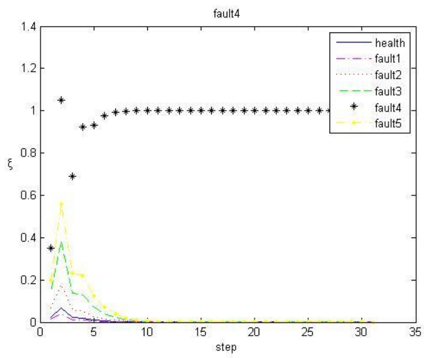

(b) The Identification Process of Fault1




(c) The Identification Process of Fault2




(d) The Identification Process of Fault3




(e) The Identification Process of Fault4

Fig. 17 Identification Process of Different Order Parameters under Noisy Environment (SNR=30)

Table 7 Recognition Performance in Noisy Environment (SNR=30)

| Structural condition | $\xi(0)$ | $\psi$ | $L$ | $\Gamma$ |
|---|---|---|---|---|
| healthy | 0.7955,0.5730,0.3185,0.1935,0.0544,0.0952 | 1.1202e-016 | 31 | T |
| Fault1 | 0.4722,0.6295,0.3735,-0.0064,0.0242,0.0704 | 1.1303e-016 | 32 | T |
| Fault2 | 0.1877,0.2887,0.5314,-0.0002, 0.0938,0.1239 | 1.1406e-016 | 30 | T |
| Fault3 | 0.0859,-0.0131,-0.0077,0.4653,0.1792,0.1792 | 2.2204e-016 | 29 | T |
| Fault4 | 0.0245,0.0139,0.0659,0.1402,0.3483,0.2003 | 1.1102e-016 | 23 | T |

When the SNR was reduced to 10, the corresponding order parameter evolutions of the healthy condition, Fault1, Fault2, Fault3 and Fault4 are shown in Fig. 18. Presented in Table 7, the first five rows of the set depict the identification performances of the respective order parameter evolutions previously mentioned. It can be seen that all the initial values of order parameters are larger with 30 in SNR than 10, which indicates that the evolutionary trend of all the order parameters was more obvious with an SNR of 30 (as set in the beginning) rather than a setting of 10. Despite the choice of 30 or 10 as the SNR setting, their ultimate identification results were correct following the analysis, as the results displayed close identification errors and a similar number of iterative steps. Results demonstrate that the proposed method possesses strong anti-noise ability.

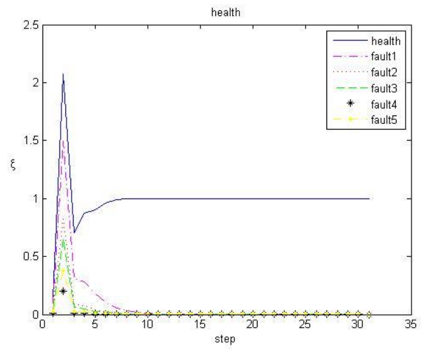
#### *4.3.2 Experiment for existing structural conditions in noisy environments with disturbance*

In some cases, the interference and noise may exist simultaneously. The coexistence of noise and disturbance can mask more useful information for each structural condition at a great extent. On the basis of section 4.3.1, disturbances were added into the noisy environment with a SNR of 10 to test the Fault5 identification performance in the experiment.

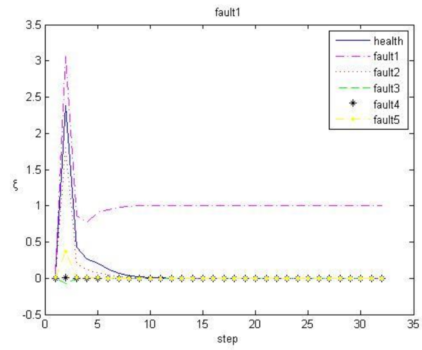
Table 8 Recognition Performance of Fault5 in Noisy Environment with Disturbance

| Structural condition | $\xi(0)$ | $\psi$ | $L$ | $\Gamma$ |
|---|---|---|---|---|
| healthy | 0.1289,0.0956,0.0535,0.0270,0.0057,0.0104 | 2.2204e-016 | 30 | T |
| Fault1 | 0.0626,0.0813,0.0492,-0.0038,0.0020,0.0028 | 2.1202e-016 | 31 | T |
| Fault2 | 0.0180,0.0274,0.0603,-0.0046,0.0085,0.0044 | 3.1102e-016 | 25 | T |
| Fault3 | 0.0144,0.0036,0.0003,0.0479,0.0195,0.0156 | 4.4409e-016 | 24 | T |
| Fault4 | -0.0027,-0.0062,0.0093,0.0153,0.0443,0.0274 | 2.3306e-016 | 27 | T |
| Fault5 | 0.0005,-0.0006,0.0057,0.0191,0.0128,0.0242 | 1.1102e-016 | 29 | T |

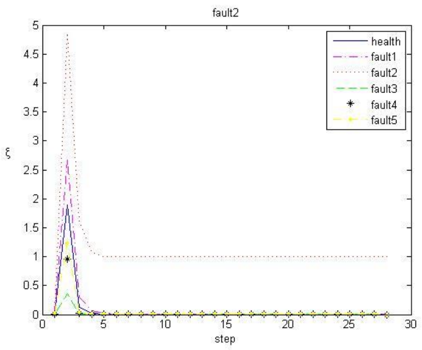
Fig. 19(a) shows the to-be identified signal of Fault5 in coexisting environments of disturbance and WGN with 10 in SNR. Implementing competitive process module of SDDM, the corresponding identification course is shown in Fig. 19(b), parameters of identification performance are shown in the last line of Table 8. Initial values of order parameters were 0.0005, -0.0006, 0.0057, 0.0191, 0.0128 and 0.0242. Iterative error was1.1102e-016 and iterative steps equaled 29. The identification process turns out correct. Results show that damage structural conditions can be identified correctly as well as rapidly under the coexisting of noisy and disturbance environments for the existing structural conditions.



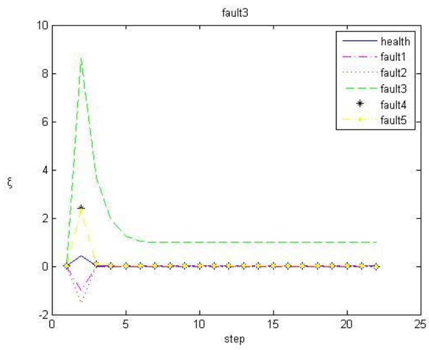

(a) The Identification Process of Healthy Condition



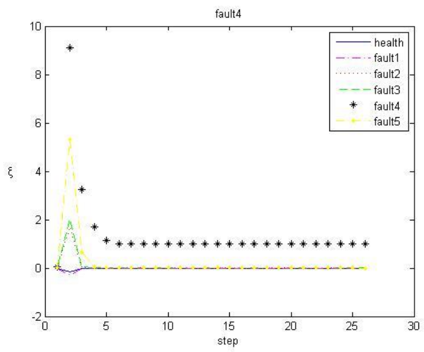

(b) The Identification Process of Fault1




(c) The Identification Process of Fault2

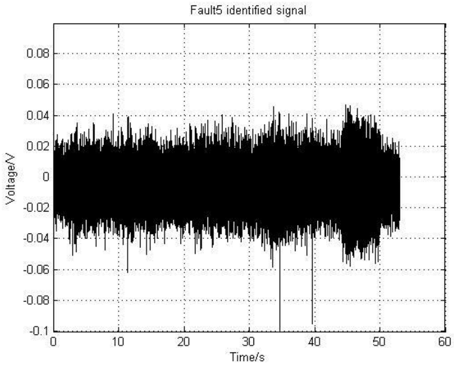



(d) The Identification Process of Fault3

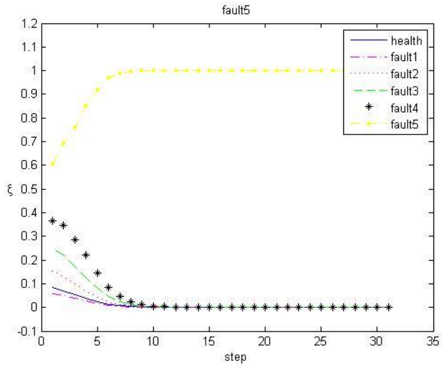



(e) The Identification Process of Fault4

Fig. 18 Identification Process of Different Order Parameters under Noisy Environment(SNR=10)




(a) To-be Identified Signal of Fault5




(b) The Identification Process of Fault5

Fig. 19 The Identification Course of Different Order Parameters under Noisy Environment with Disturbance

## 5. Conclusions

Through the implementation of Synergetics to SHM for frame structures, the innovative damage detection method using piezoceramic actuators and sensors was proposed in this paper. The method employed vibration modes with a limited frequency range including the first resonant frequencies in low frequency to detect minor damage of frame structures, which can decrease sampling rate and greatly reduce the data number of each structural condition. Moreover, because of the high sensitivity of the PZT patches for small differences among structural conditions, each 53-second circle signal online acquired for each structural condition in frame structures can be directly treated as an original vector (OV), which can be compared to adopting time series clustering strategy to achieve the OV set for other structures, such as pipe structures. The proposed method can greatly enhance the operating convenience and the identification accuracy. Self-organization competitive process is easily realized in the modified SNN based on top-bottom structure to avoid non-uniqueness and non-maneuverability of dynamic activity starting from bottom-top structure. The competitive networked action was controlled by the strict mathematics ratiocination to rapid convergence. The indexing system of identification performance was established to check the evolution state of all the order parameters qualitatively and quantitatively. Updated processes were convenient in detecting new damage caused by dynamic varying vibration and provided alerts in time. Experimental results for the frame structure model indicate that the proposed method can identify various structural conditions with a fast identification speed facing the uncertainty problem in different damage degrees, under noisy and disturbance environments, it can be seen that the proposed method is very useful for efficient control for the frame structures. However, implementing online updated damage structural conditions as the OVs under noisy environments for frame structures should not be set in too low SNR. This is because lower SNR may change the signal structure of new structural conditions and increase the possibility of misjudgment. Therefore, it can be universally solved through implementing a filter for online updated damage structural condition as a new OV in noisy circumstance with low SNR.

This paper mainly focused on the frame structures as experimental subjects to verify the proposed Synergetics based Damage Detection Method (SDDM) using piezoceramic transducers. Other similar large structures can be studied in future research, such as transmission tower structures and truss structures.

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