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Aging State Detection of Viscoelastic Sandwich Structure Based on ELMD and Sensitive IA Spectrum Entropy

JINXIU QU[1] AND CHANGQUAN SHI[2]
[1]School of Mechanical and Electrical Engineering, Xi'an Technological University, Xi'an 710021, China
[2]State Key Laboratory for Manufacturing Systems Engineering, Xi'an Jiaotong University, Xi'an 710049, China

Corresponding author: Jinxiu Qu (ytuqjx@163.com)

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ABSTRACT Viscoelastic sandwich structure is playing an important role in mechanical equipment, but therein viscoelastic material inevitably suffers from aging which affects structural service performance and the whole performance of equipment. Therefore, the aging state detection of viscoelastic sandwich structure based on vibration response signal is essential for monitoring the health state of structure and guaranteeing the operation safety of equipment. However, the weakness of structural vibration response variation caused by material aging make this task challenging. In this paper, a novel method based on ensemble local mean decomposition (ELMD) and sensitive IA spectrum entropy is proposed for this task. As an adaptive nonlinear and non-stationary signal processing method, ELMD is introduced to decompose the structural vibration response signal, and a series of instantaneous amplitudes (IAs) are obtained. Then, the spectrum entropies of these IAs are developed to quantitatively assess the aging state of viscoelastic sandwich structure. However, the IA spectrum entropies have different sensitivities to the aging state. Therefore, the most sensitive IA spectrum entropy is selected with a distance evaluation technique to detect the aging state of viscoelastic sandwich structure. In order to demonstrate the effectiveness of the proposed method, the experimental device of a viscoelastic sandwich structure is designed, and different structural aging states are created through the accelerated aging of viscoelastic material. The results show the outstanding performance of the proposed method.

INDEX TERMS Ensemble local mean decomposition, IA spectrum entropy, feature selection, aging state detection, viscoelastic sandwich structure.

I. INTRODUCTION

Viscoelastic sandwich structure is a kind of composite structure consisting of elastic-solid layers and viscoelastic layers [1]–[3]. Due to the excellent energy dissipation performance of viscoelastic material, viscoelastic sandwich structure is playing an important role in the vibration absorption and noise reduction of mechanical equipment [4]–[6]. However, in the long-term service of viscoelastic sandwich structure, therein viscoelastic material, like rubber and silicone, will be aging gradually due to the influence of external environmental factors, such as temperature and humidity.

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Viscoelastic material aging will degrade the service performance of viscoelastic sandwich structure, and thus affect the operating safety of mechanical equipment. The aging degree of viscoelastic material is different, the health state of viscoelastic sandwich structure is different, which is defined the structure is in different aging states. Thus, the aging state detection of viscoelastic sandwich structure is essential to keep the structure service in health state and guarantee the mechanical equipment operating in safe situation.

The aging state detection of viscoelastic sandwich structure is within the scope of structural health monitoring. The vibration-based structural health monitoring has been attracting more and more attentions [7]–[10]. Especially, the data-driven method only using vibration response signals provides a convenient way, because it can realize online and nondestructive structural health monitoring. Viscoelastic sandwich structure can be regarded as a dynamic system composed of mass, stiffness and damping. Once the aging state change, the original dynamic model will change, and the vibration response signals will also change. That is, the vibration response signals of viscoelastic sandwich structure carry a wealth of feature information reflecting the structural aging state change. Therefore, the aging state detection of viscoelastic sandwich structure based on vibration response signals is a promising way. The major idea of this method is extracting sensitive feature information from the vibration response signal, and then identifying the aging state of viscoelastic sandwich structure using the extracted feature information. On the basis of this idea, in 2016, Qu et al. identified the aging state of viscoelastic sandwich structure based on adaptive second generation wavelet packet transform and multiwavelet support vector machine [11]. In 2019, Qu et al. identified the aging state of viscoelastic sandwich structure based on permutation entropy of dual-tree complex wavelet packet transform and generalized Chebyshev support vector machine [12]. However, these methods require a large number of training samples of different aging states, which restricts their practical engineering application. Therefore, constructing sensitive index, which is a monotone function of the aging state of viscoelastic sandwich structure, is a promising method for practical engineering application.

Since viscoelastic sandwich structure is a multilayer structure constituted of different materials, the vibration response signal is nonlinear and non-stationary. Moreover, the change of vibration response signal induced by the change of aging state is very weak. Therefore, it is urgent to extract more sensitive feature information from structural vibration response signal by means of advanced signal process method. Empirical mode decomposition (EMD) proposed by Huang *et al.* [13], is an adaptive time–frequency analysis method suitable for processing nonlinear and non-stationary signals. Based on the local characteristic time scales of a signal, EMD can decompose a complicated signal into a set of intrinsic mode functions (IMFs), which contain much important information than the original signal. In the last decade, EMD has been given great attention in the field of structural health monitoring [14]–[16]. However, the efficiency of the EMD method is confined by the problem of mode mixing.

Local mean decomposition (LMD) is a novel adaptive time–frequency analysis method developed by Smith [17], which has the similar principles with EMD. LMD can decompose a complicated signal into a set of product functions (PFs), and the envelope of a PF is instantaneous amplitude (IA). The differences between the two adaptive methods LMD and EMD are given in [18] where it is shown that LMD is superior to the EMD method in four aspects. At present, LMD is attracting considerable attention of researchers and has been widely investigated in the field of structural health monitoring, and it has been concluded that LMD is more suitable and performs better than EMD for structural health monitoring [19]–[23]. However, like EMD, LMD still faces mode mixing problem. Mode mixing which results from intermittent signal may severely distort the decomposition results of LMD and make them uninterpretable. To overcome this problem, ensemble local mean decomposition (ELMD) was proposed by Yang *et al.* [24], a noise-assisted data analysis method, can eliminate the mode mixing of LMD automatically by adding finite white noise to the investigated signal. Since ELMD is a major improvement on LMD, it has been applied in structural health monitoring [24]–[26] and presents better performance than ensemble empirical mode decomposition (EEMD) [27] and LMD. In this paper, the ELMD method is introduced to decompose the vibration response signal of viscoelastic sandwich structure into a set of PFs to highlight the feature information.

After decomposition of the vibration response signal with ELMD, another important task is to measure the dynamic characteristics of these PFs to identify the aging state of viscoelastic sandwich structure. Information entropy, as a measure of the average uncertainty about the information source, can be used to describe the dynamic characteristic of a signal quantitatively. Recently, it has been successfully applied in structural health monitoring [28]–[31]. Spectrum entropy, which is a kind of information entropy defined in the frequency domain and can be used to measure the complexity of the investigated signal in frequency domain. In this paper, IA spectrum entropy is developed based on ELMD and spectrum entropy to detect the aging state of viscoelastic sandwich structure. Generally, the IA spectrum entropies have different sensitivities to the aging state of viscoelastic sandwich structure. With a distance evaluation technique [32], the most sensitive one is selected as sensitive IA spectrum entropy to identify the aging state of viscoelastic sandwich structure.

In view of the above principles, a new method for the aging state detection of viscoelastic sandwich structure based on ELMD and sensitive IA spectrum entropy is proposed in this paper. First, the vibration response signal captured from viscoelastic sandwich structure is processed by ELMD, and a set of IA components are obtained. Second, the spectrum entropies of these IAs are calculated. Finally, the most sensitive IA spectrum entropy is selected from all IA spectrum entropies with distance evaluation technique to identify the aging state of viscoelastic sandwich structure. Experiments are carried out to validate the effectiveness and robustness of the proposed method.

The remainder of this paper is organized as follows. In section II, the theory and algorithm of ELMD is introduced. In section III, the IA spectrum entropy is constructed, and the method for selecting the sensitive IA spectrum entropy is introduced. In section IV, the procedure of the method based on ELMD and sensitive IA spectrum entropy is given. In section V, the proposed method is applied to the aging state detection of viscoelastic sandwich structure to validate its effectiveness and robustness. Conclusions are given in section VI.

II. ENSEMBLE LOCAL MEAN DECOMPOSITION

A. LOCAL MEAN DECOMPOSITION

As a novel adaptive time–frequency analysis method, LMD can decompose a complex multicomponent signals into a set of mono-component signals, so-called PFs. Each PF is the product of an envelope signal and a pure frequency modulated signal, the envelope signal is the instantaneous amplitude (IA) of this PF. Thus, LMD can directly derive IA without Hilbert transform (HT). For a given signal $x(t)$, the detailed LMD algorithm can be briefly described as follows.

Step 1: Determine all local extrema $n_{ij}(t_k)$, $k = 1, 2, \ldots, K$, where t_k is the index of extrema, $K$is the number of extrema, and the subscript i denotes the number of PF and j denotes the number of iterations.

Step 2: Compute the local mean $m_{ij}(k)$ and local local envelope amplitude $a_{ij}(k)$ of each two successive extrema as follows:

$$m_{ij}(k) = \frac{n_{ij}(t_k) + n_{ij}(t_{k+1})}{2} \tag{1}$$

$$a_{ij}(k) = \frac{\left|n_{ij}(t_{k+1}) - n_{ij}(t_k)\right|}{2} \tag{2}$$

Step 3: Assign the values of these local means and local amplitudes to the points between successive extreme points as their local means and local amplitudes. Moreover, the local means and the local amplitudes are smoothed by the use of moving averaging to form a smoothly varying continuous local mean function $m_{ij}(t)$ and a smoothly varying continuous local envelope function $a_{ij}(t)$, respectively.

Step 4: Separate the local mean function $m_{11}(t)$ from original signal$x(t)$, presented as:

$$h_{11}(t) = x(t) - m_{11}(t) \tag{3}$$

Then, $h_{11}(t)$ is divided by local envelope function $a_{11}(t)$, expressed as:

$$s_{11}(t) = h_{11}(t) / a_{11}(t) \tag{4}$$

This procedure needs to repeat until a purely frequency modulated signal s_{1n} is obtained, where n is the number of repetitions. This iterative process can be expressed as:

$$\begin{cases} h_{11}(t) = x(t) - m_{11}(t) \\ h_{12}(t) = s_{11}(t) - m_{12}(t) \\ \cdots \\ h_{1n}(t) = s_{1(n-1)}(t) - m_{1n}(t) \end{cases} \tag{5}$$

where

$$\begin{cases} s_{11}(t) = h_{11}(t) / a_{11}(t) \\ s_{12}(t) = h_{12}(t) / a_{12}(t) \\ \cdots \\ s_{1n}(t) = h_{1n}(t) / a_{1n}(t) \end{cases} \tag{6}$$

Step 5: Multiply all the smooth envelope estimation functions produced in the iterative process to obtain the corresponding IA as follows:

$$a_1(t) = a_{11}(t)\, a_{12}(t) \cdots a_{1n}(t) \tag{7}$$

The instantaneous phase (IP) and instantaneous frequency (IF) can be obtained as follows:

$$\varphi_1(t) = \arccos\left(s_{1n}(t)\right) \tag{8}$$

$$f_1(t) = \frac{f_s \mathrm{d}\varphi_1(t)}{2\pi \mathrm{d}t} \tag{9}$$

where, f_s is the sample rate. With the corresponding IA function and the final purely frequency modulated signal, the first PF is given by:

$$PF_1(t) = a_1(t)\, s_{1n}(t) \tag{10}$$

Step 6: Separate the first product function $PF_1(t)$ from the original signal $x(t)$ to form a new function $u_1(t)$. Thus, $u_1(t)$ is regarded as a new signal and processed in steps 1–4 repeatedly until $u_p(t)$ is a monotonic function or no more than five oscillations.

$$\begin{cases} u_1(t) = x(t) - PF_1(t) \\ u_2(t) = u_1(t) - PF_2(t) \\ \cdots \\ u_p(t) = u_{p-1}(t) - PF_p(t) \end{cases} \tag{11}$$

Finally, the original signal is reconstructed as:

$$s(t) = \sum_{i=1}^{p} PF_i(t) + u_p(t) \tag{12}$$

where $u_p(t)$ is the residual signal and p denotes the number of PFs.

Unfortunately, LMD suffers from mode mixing problem, which is shown as the oscillations of different time scales coexist in the same PF or the oscillations with the same time scale separate in different PFs. When mode mixing occurs, a PF can cease to have physical meaning, suggesting that there may be different physical processes improperly appeared in a mode, and then LMD is failure to reveal the dynamic characteristics of a signal.

B. ENSEMBLE LOCAL MEAN DECOMPOSITION

To overcome the problem of mode mixing in LMD, taking the same strategy as EEMD, Yang *et al.* [24] developed ELMD method. In the ELMD method, a PF is defined as the mean of an ensemble of trials. Each trial consists of the decomposition results of the signal plus a white noise with finite amplitude.

The principle of the ELMD algorithm is described as follows. The added white noise would populate the whole time–frequency space uniformly with the constituting components of different scales. When the inspected signal is added to this uniformly distributed white noise background, the components in different scales of the signal are automatically projected onto proper scales of reference established by the white noise in the background. Each of the noise-added decompositions includes the signal and the added white noise, thus each individual trial may certainly produce very noisy results. However, the noise of each trial is different among isolated trials. Therefore, it can be decreased or even completely canceled out in the ensemble mean of enough trials.

The ensemble mean is regarded as the true solution because finally the only persistent part is the signal as more and more trials are added in the ensemble. On the basis of this principle, for a given signal $x(t)$, the processes of the ELMD algorithm are shown as follows.

Step 1: Determine the number of ensemble trials M and the added noise amplitude A.

Step 2: Add a white noise series $n_m(t)$ with the given amplitude to the signal $x(t)$ and obtain a new signal:

$$x_m(t) = x(t) + n_m(t) \tag{13}$$

where $n_m(t)$ indicates the added white noise series in the mth trial, and $x_m(t)$ represents the noise-added signal of the mth trial.

Step 3: Decompose the noise-added signal $x_m(t)$ into a set of PFs using the LMD method mentioned above.

$$s_m(t) = \sum_{i=1}^{p} PF_{im}(t) + u_{pm}(t) \tag{14}$$

where PF_{im} denotes the ith PF of the mth trial, and p is the number of IMFs of each trial.

Step 4: Repeat steps 2–3 M times with different white noise series and get M sets of PFs.

Step 5: Calculate the ensemble means of corresponding PFs as:

$$PF_i(t) = \frac{1}{M}\sum_{m=1}^{M} PF_{im}(t) \tag{15}$$

where $PF_{i,m}(t)$ equals ith PF of mth trial. Report the final decomposition result.

It should be noted that, the number of ensemble trials and the added noise amplitude are the two parameters that need to be determined when the ELMD method is performed. However, there is no method reported in the literature how to choose the number of ensemble trials and the added noise amplitude.Wu et al. pointed out that an ensemble number of a few hundred can produce a very good result and the added noise with an amplitude of 0.2 time standard deviation of the investigated signal is chosen in most cases [27]. In addition, they also suggested that when the signal is dominated by high-frequency compositions the added noise amplitude should be smaller, and when the signal is dominated by low-frequency compositions the added noise amplitude should be bigger. In this paper, the number of ensemble trials and the added noise amplitude are determined according to previous studies and experimental experience.

III. SENSITIVE IA SPECTRUM ENTROPY

A. IA SPECTRUM ENTROPY

Viscoelastic sandwich structure can be taken as a dynamic system with mass, stiffness and damping. Once the structural aging state change, its original dynamic model will change, and its dynamic response signal will also change.

In information theory, information entropy expresses the average information provided by each symbol and the average uncertainty of the information source, and can provide useful information about the dynamic process. For a vibration response signal $\{x_i\}$, the mathematical description of information entropy is shown as follows:

$$IE = -\sum_{i=1}^{n} p_i \log p_i \tag{16}$$

where $\{p_1, p_2, \ldots, p_n\}$ are the probability density functions of signal amplitude, and n is the number of subintervals when the probability distribution p_i is calculated. Information entropy reflects the uniformity of probability distribution, and the most uncertain probability distribution has the maximum information entropy.

Suppose that $\{f_i\}$ is the frequency spectrum of the vibration response signal $\{x_i\}$ and calculate the probability density function $p(f_i)$. The spectrum entropy of $\{x_i\}$ can be defined as follows:

$$SE = -\sum_{i=1}^{n} p(f_i) \log p(f_i) \tag{17}$$

Spectrum entropy, as an alternative to information entropy, can measure the complexity of the measured signal in frequency domain, and can be used to describe the characteristics of the dynamic response signal quantitatively.

ELMD can decompose a dynamic response signal into a set of PFs with truly physical meaning, and the envelope of a PF is IA. IA spectrum entropy, which combines the merits of ELMD and spectrum entropy, is developed to detect the aging state of viscoelastic sandwich structure in this paper.

In order to calculate IA spectrum entropy, the vibration response signal of viscoelastic sandwich structure is processed by ELMD, and IAs $(IA_1, IA_2, \ldots, IA_n)$ are obtained. The spectrum entropy SE_i of each IA IA_i is calculated. Then, the IA spectrum entropies $SE_1, SE_2, \ldots, SE_n$ of the signal are obtained.

B. SELECTION OF SENSITIVE IA SPECTRUM ENTROPY

In fact, the IA spectrum entropies have different sensitivities to the aging state of viscoelastic sandwich structure. Some of them are sensitive and closely related to the structural aging state, but others are not. In this paper, a distance evaluation technique [32] is presented to evaluate the sensitivity of IA spectrum entropies, and the most sensitive one is selected to detect the aging state of viscoelastic sandwich structure.

Step 1: Calculating the inner-class average distance of the same aging state samples

$$\begin{aligned} d_{c,j} &= \frac{1}{M_c \times (M_c - 1)} \sum\nolimits_{l,m=1}^{M_c} \left| q_{m,c,j} - q_{l,c,j} \right| \\ l, m &= 1, 2, \ldots, M_c, \quad l \neq m \\ &\quad c = 1, 2, \ldots, C, \quad j = 1, 2, \ldots, J \end{aligned} \tag{18}$$

where M_c is the sample number of the kth aging state, and J is the IA spectrum entropy feature number of each sample,

C is the number of aging states, $q_{m,c,j}$ is the jth feature value of the mth sample in the cth aging state. Then getting the inner-class average distance of C aging states

$$d_j^{(w)} = \frac{1}{C}\sum\nolimits_{c=1}^{C} d_{c,j} \tag{19}$$

Step 2: Calculating the average feature value of all samples under the same aging state

$$u_{c,j} = \frac{1}{M_c}\sum\nolimits_{m=1}^{M_c} q_{m,c,j} \tag{20}$$

then obtaining the inter-class average distance between different aging state samples

$$d_j^{(b)} = \frac{1}{C\,(C-1)}\sum\nolimits_{c,e=1}^{C} \left|u_{e,j} - u_{c,j}\right| \\ c, e = 1, 2, \ldots, C, \quad c \neq e \tag{21}$$

Step 3: Calculating the ratio $d_j^{(b)}$ and $d_j^{(w)}$ and getting the distance evaluation factor

$$\alpha_j = d_j^{(b)} \Big/ d_j^{(w)} \tag{22}$$

Obviously, bigger $\alpha_j\,(j = 1, 2, \ldots, J)$ signifies that the corresponding IA spectrum entropy feature is better to separate the C aging states. Therefore, the most sensitive IA spectrum entropy feature can be selected according to the distance evaluation criteria α_j.

IV. THE PROPOSED AGING STATE DETECTION METHOD

In this paper, to realize the online and nondestructive aging state detection of viscoelastic sandwich structure, the aging state detection method on the basis of vibration response signals is carried out. Considering the nonlinearity and non-stationarity of vibration response signal, and the weakness of vibration response signal change induced by the structural aging state change, a new aging state detection method for viscoelastic sandwich structure based on ELMD and sensitive IA spectrum entropy is proposed in this paper. As an effective nonlinearity and non-stationary signal processing method, ELMD is introduced to process the vibration response signal to highlight feature information, and the IA spectrum entropy is developed to detect the structural aging state. The flow chart of the proposed method is illustrated in Fig. 1. The main steps of the method are given as follows.

(1) Collect the vibration response signals of viscoelastic sandwich structure with different aging states.
(2) Decompose the vibration response signals into a set of PFs by using ELMD. The first four PFs, which include the most dominant signal components, are chosen and used to extract the aging state feature information.
(3) Calculate the spectrum entropies of the IAs of PFs, and the four IA spectrum entropies of a signal are obtained and recorded as $SE_1, SE_2, \ldots, SE_4$.
(4) Calculate the sensitivity factors of the four IA spectrum entropies based on the distance evaluation technique.
(5) Select the IA spectrum entropy with the biggest sensitivity factor as the sensitive IA spectrum entropy.

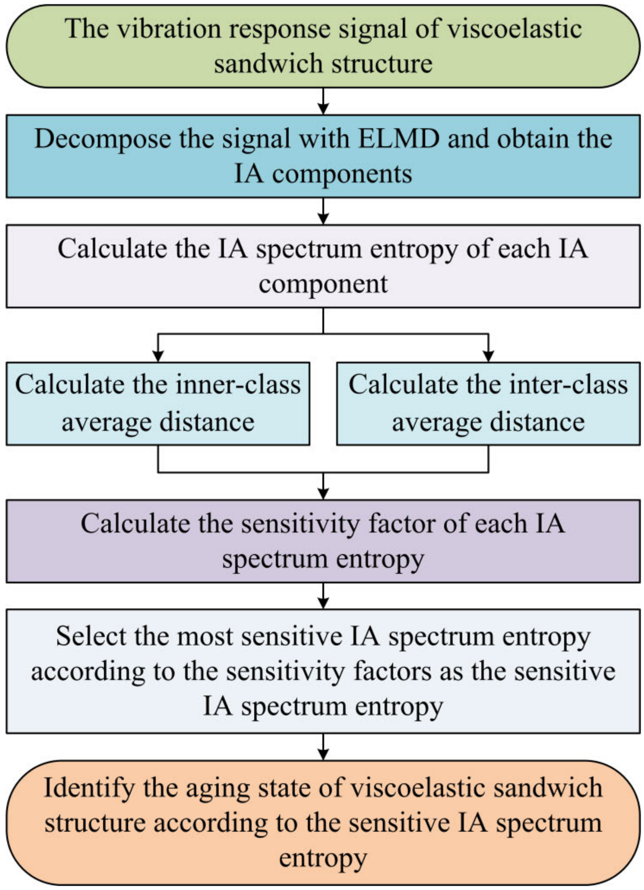


FIGURE 1. **The flow chart of the proposed method.**

(6) Identify the aging state of viscoelastic sandwich structure based on the sensitive IA spectrum entropy.

V. EXPERIMENTAL VALIDATION

In order to verify the effectiveness of the proposed method, a case study in regard to the aging state detection of a viscoelastic sandwich structure is carried out in this section. In this case study, the experimental device of a viscoelastic sandwich structure is designed firstly. Then, the hot oxygen accelerated aging experiment of viscoelastic material is carried out in an aging chamber. Finally, the impulse excitation experiment of viscoelastic sandwich structure in different aging states are performed by replacing the viscoelastic layers with different aging degrees, and the structural vibration response signals are collected to identify the structural aging states.

A. THE DESIGN OF EXPERIMENTAL DEVICE

To prepare the different aging states of viscoelastic sandwich structure, according to engineering practice and experiment requirement, the experimental device of a viscoelastic sandwich structure is designed. This experimental device possesses the capability to regulate structural preload, and can conveniently replace the viscoelastic layers. In addition, the experimental device not only can perform the excitation experiments under free and constraint situations, but also can facilitate radial sensor placement. Schematic diagram and physical photo of the experimental device are shown in Fig. 2(a) and Fig. 2(b), respectively.

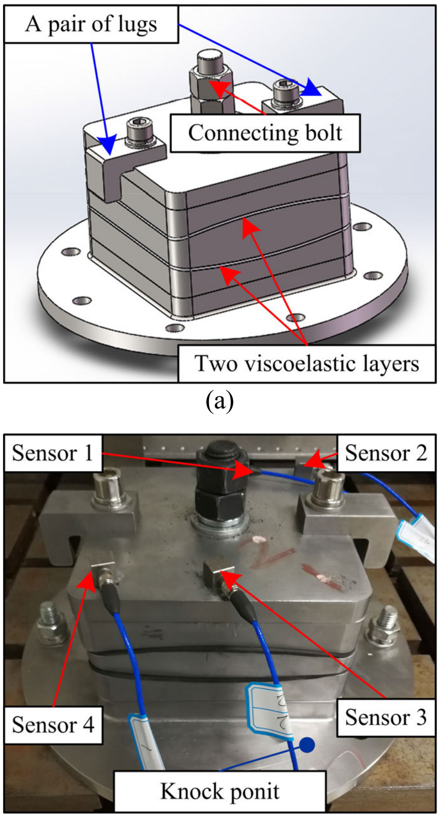


FIGURE 2. The experimental device. (a) The schematic diagram and (b) the physical photo.

It can be seen from Fig. 2 that the designed experimental device is a bolted connection structure and primarily constituted of multiple metal layers with two viscoelastic layers embedded in. Therein viscoelastic layers are made from nitrile butadiene rubber and used for structural vibration absorption and noise reduction. In addition, there is a connecting bolt to generate preload for compressing metal layers and viscoelastic layers, and the size of preload can be regulated by means of a torque spanner. Furthermore, the excitation experiment under constraint situation can be performed by fixing chassis, and the excitation experiment under free situation can be carried out by hanging a pair of lugs. Moreover, the whole structure presents square, which can facilitate radial sensor placement.

B. HOT OXYGEN ACCELERATED AGING EXPERIMENT

The aging state of viscoelastic sandwich structure is mainly referred to the aging degree of viscoelastic material. In engineering practice, the aging of viscoelastic material is a time consuming process, it is impossible to achieve natural aging within a short time. In order to accelerate the aging process, the customized viscoelastic material specimens are input into an aging chamber for hot oxygen accelerated aging. The aging chamber has such functions as temperature control and continuous air blast. In the aging chamber, a hot oxygen environment with high temperature and high wind speed is produced. The environmental parameters are shown in Tab. 1, where air temperature is set as 115°C, air circulation is forced by the fans and air humidity is in normal level. Moreover, the duration of aging is used to describe the aging degree of viscoelastic material.

TABLE 1. The environmental parameters of accelerated aging chamber.

Parameter	Temperature (°C)	Humidity	Air speed
Setting	115	Normal	Forced wind

The placement of viscoelastic material specimens in aging chamber is in a hanging and hierarchical manner, as shown in Fig. 3. Moreover, to ensure that the hot air of aging chamber is circulated, the aging degree of viscoelastic material specimens is uniform and the two neighboring specimens are not stick together, the distance between two neighboring specimens is at least 10 mm, and the distance between the edge specimen and the chamber wall is not less than 70 mm. In aging chamber, there are three kinds of viscoelastic material specimens, as shown in Fig. 3. In particular, the specimens A are the tensile specimens used to carry out tensile property test. The specimens B are the compressive specimens used to perform compressive property test. The specimens C are the viscoelastic layers imbedded in viscoelastic sandwich structure.

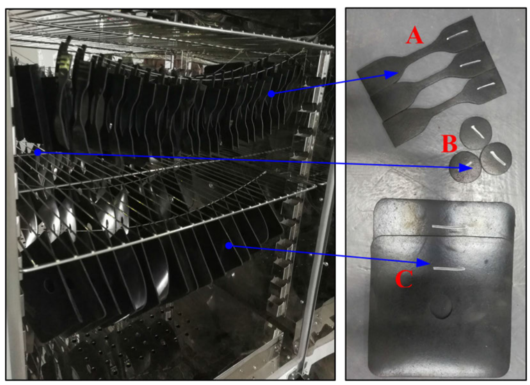


FIGURE 3. Viscoelastic material specimens and their placement.

According to sampling plan, a group of viscoelastic material specimens which consist of three tensile specimens, three compressive specimens and two viscoelastic layers, are taken out from aging chamber, when the aging time is 0, 1, 3, 5, 6, 7 and 8 days, respectively. In this way, seven groups of viscoelastic material specimens with different aging days are finally obtained.

To inspect the aging degree of the viscoelastic material with different aging days, with tensile and compressive specimens, tensile and compressive properties are tested by means of a testing system, as shown in Fig. 4(a). It can be seen from Fig. 4(a) that, this testing system mainly consists of a microcomputer control electronic universal testing machine and the matched testing software. By replacing the clamp device of testing machine, this testing system can carry out the required tensile and compressive property tests. The adopted tensile and compressive clamp devices are displayed in Fig. 4(b) and Fig. 4(c), respectively.

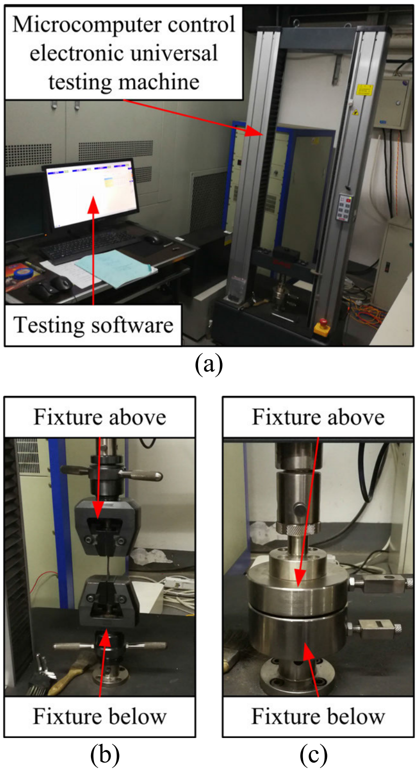


FIGURE 4. The property test of viscoelastic material. (a) Testing system, (b) tensile clamp device and (c) compressive clamp device.

As for the tensile property test of tensile specimens with certain aging days, the length, width and thickness of the working range of tensile specimens are respectively 20 mm, 6 mm and 2 mm, and test result is the average of normal fracture specimens. In accordance with national standard, the tensile properties of the seven groups of tensile specimens with different aging days are tested when tensile rate is set to be 100 mm/min, and corresponding tensile elasticity modulus are displayed in Fig. 5(a).

As for the compressive property test of compressive specimens with certain aging days, the thickness and diameter of compressive specimens are respectively 2 mm and 30 mm, and test result is the average of three specimens. According to national standard, the compressive properties of the seven groups of compressive specimens with different aging days are tested when the amount of compression and compression rate are respectively set to be 1 mm and 0.5 mm/min, and corresponding compressive elasticity modulus are presented in Fig. 5(b).

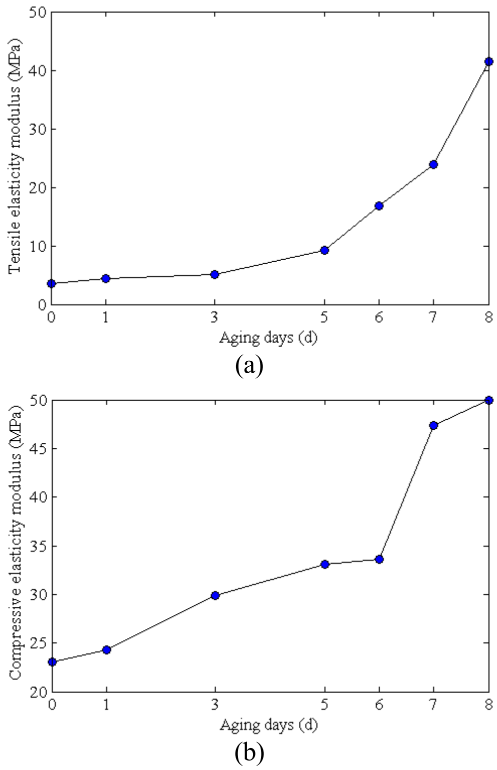


FIGURE 5. The property test results of viscoelastic material. (a) Tensile elasticity modulus and (b) compressive elasticity modulus.

It can be seen from Fig. 5 that, with the increment of aging days, both the tensile elasticity modulus and the compressive elasticity modulus of viscoelastic material gradually increase. This indicates that the aging degree of viscoelastic material gradually deepens with the increase of aging days. Moreover, it can be seen from Fig. 5(b) that the compressive elasticity modulus mutates from the sixth to the seventh aging day. This is because, in the early stage of aging, the molecular structure of viscoelastic material is principally crosslinking reaction and the aging rate is stable. However, in the later stage of aging, the molecular structure of viscoelastic material is mainly fracture reaction and the aging speed is accelerated. These analysis results imply that the hot oxygen accelerated aging experiment is highly effective to change the properties of viscoelastic material.

C. IMPULSE EXCITATION EXPERIMENT

Seven aging states of viscoelastic sandwich structure can be prepared by replacing the viscoelastic layers with seven aging degrees. After the replacement of viscoelastic layers, the preload generated by connecting bolt should be kept the same, which is determined to be about 7500 N, and the corresponding tightening torque of torque spanner is about 25 N $\cdot$ m. This is because the embedded viscoelastic layers mainly suffer from compressive stress, and under this preload, the compressive elasticity modulus of viscoelastic material with different aging days changes obviously. The aging time of viscoelastic layers for each structural aging state is displayed in Tab. 2, and the seven structural aging states are denoted by AS1-AS7, respectively. From Tab. 2, it can be seen that the aging degrees of viscoelastic layers in seven structural aging states are gradually deepening.

TABLE 2. The aging state description of viscoelastic sandwich structure.

Aging state number	Aging time (Day)	Label
Aging state 1	0	AS1
Aging state 2	1	AS2
Aging state 3	3	AS3
Aging state 4	5	AS4
Aging state 5	6	AS5
Aging state 6	7	AS6
Aging state 7	8	AS7

When viscoelastic sandwich structure is in different aging states, in order to capture the corresponding vibration response signals, an experimental system is built for impulse excitation experiment. As shown in Fig. 6, the experimental system mainly constituted of the experimental device of viscoelastic sandwich structure pasted with acceleration sensors (The sensitivity is 100 mv/g and the measuring range is 50 g), an advanced data acquisition and analysis system by ECON and a force hammer.

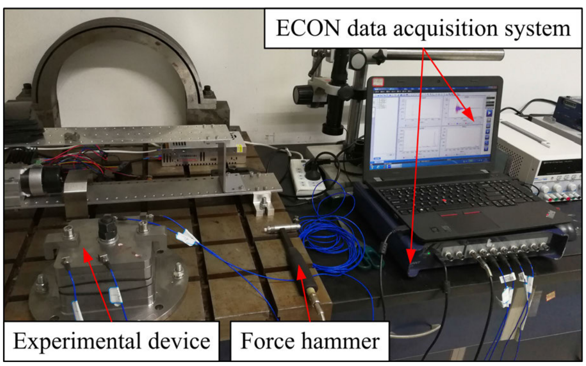


FIGURE 6. The impulse excitation experimental system.

In order to meet engineering practice and make the collected data serve a broader purpose, the experimental device of viscoelastic sandwich structure is fixed at a base, and four acceleration sensors are mounted on the surface of viscoelastic sandwich structure, as shown in Fig. 2(b). The impulse excitation generated by force hammer in vertical direction is imposed on the experimental device of viscoelastic sandwich structure in each of aging states. The knock point is shown in Fig. 2(b). Under the impulse excitation, the vibration response signals of viscoelastic sandwich structure in all aging states are measured by the corresponding acceleration sensors and then stored by the data acquisition system. The sampling frequency is set to 10240 Hz. For each measure point, seven data subsets corresponding to seven structural aging states are obtained. Each data subset consists of 10 samples. Each sample contains 2048 data points.

The vibration response signals of viscoelastic sandwich structure in seven aging states are shown in Fig. 7. It can be seen from Fig. 7 that when viscoelastic sandwich structure is in different aging states, the difference between the vibration response signals is very weak. It is impossible to identify the different structural aging states using vibration response signals directly. Therefore, to identify the different aging states of viscoelastic sandwich structure accurately, it is very essential to develop an effective method to extract the feature information from these vibration response signals which is sensitive to the different structural aging states.

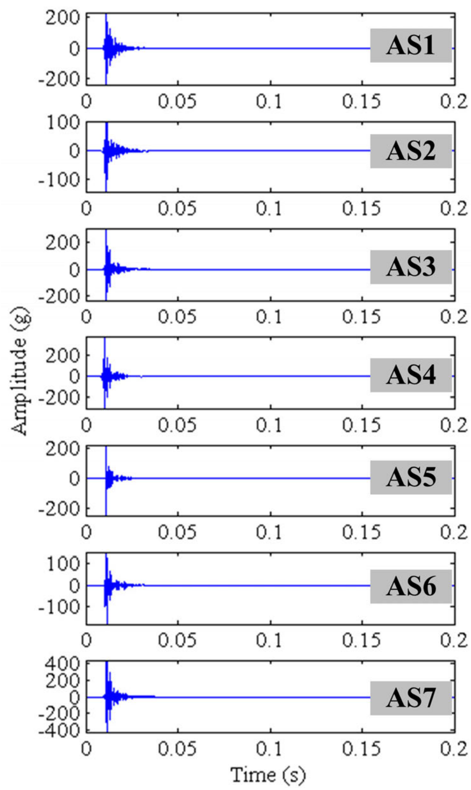


FIGURE 7. Vibration response signals of the seven structural aging states.

D. AGING STATE DETECTION RESULT

To fulfill the task of the aging state detection of viscoelastic sandwich structure using vibration response signals, a novel method based on ELMD and sensitive IA spectrum entropy is proposed in this paper. The vibration response signals from sensor 3 are applied to demonstrate the effectiveness of the proposed method. The proposed method only needs to use the data from one sensor, so it can also be validated using the vibration response signals from other sensors.

In order to extract effective feature information reflecting the different structural aging states, the collected vibration response signals are first decomposed into a set of PFs

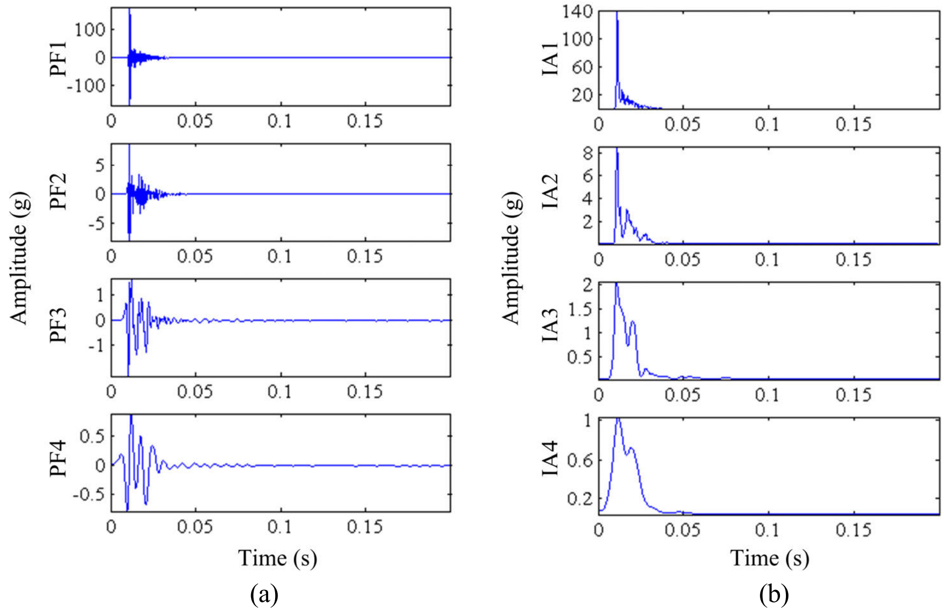


FIGURE 8. The decomposition result of ELMD. (a) The four PFs and (b) the four IAs.

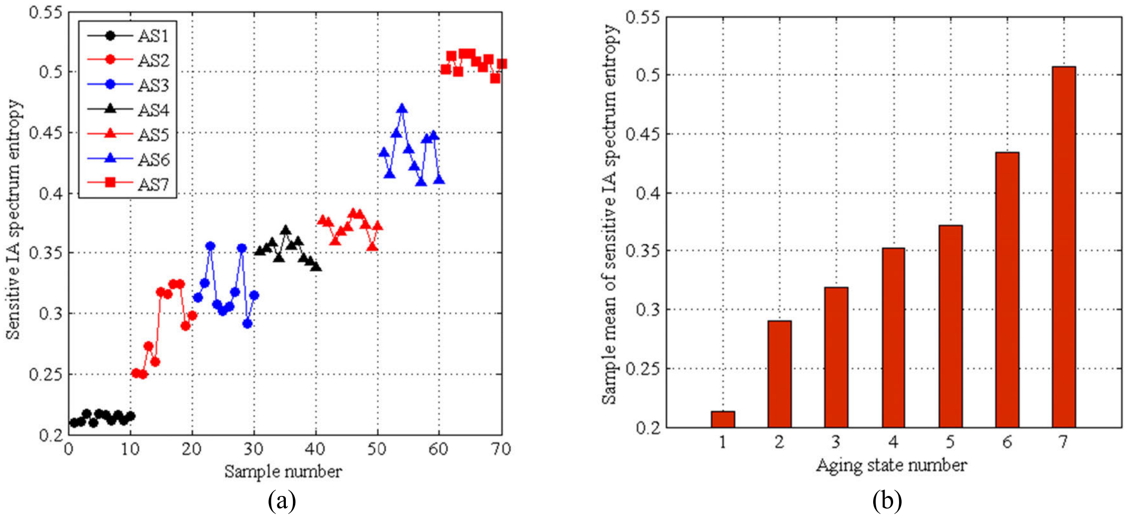


FIGURE 9. The aging state identification result of the proposed method. (a) Sensitive IA spectrum entropies of samples under different aging states and (b) sample mean of sensitive IA spectrum entropies under different aging states.

by the ELMD method, in which the added noise amplitude is set as 0.2 time standard deviation of the signal and the ensemble number is set as 100. The first four PFs of one vibration response signal are respectively shown in Fig. 8(a), and the corresponding four IAs are respectively shown in Fig. 8(b). Then, the spectrum entropies of the IAs are calculated, the sensitivity factors of these IA spectrum entropies are calculated, and the most sensitive one is selected.

Finally, the sensitive IA spectrum entropy is used to identify the aging state of viscoelastic sandwich structure. The identification result is shown in Fig. 9. It can be seen from Fig. 9 that the sensitive IA spectrum entropy can effectively distinguish among different aging states, each aging state is clustered well, and there are only few sample overlaps among different aging states. Moreover, the sample mean of sensitive IA spectrum entropies monotonically increases with the change of aging degree of the viscoelastic material from low to high, which means that the more serious of viscoelastic material aging is, the bigger the detection index is. Thus, the sample mean of sensitive IA spectrum entropies on aging state samples can be used as an index to quantitatively identify the aging state of viscoelastic sandwich structure. The above analysis results show that, the proposed method can effectively identify the aging state of viscoelastic sandwich structure.

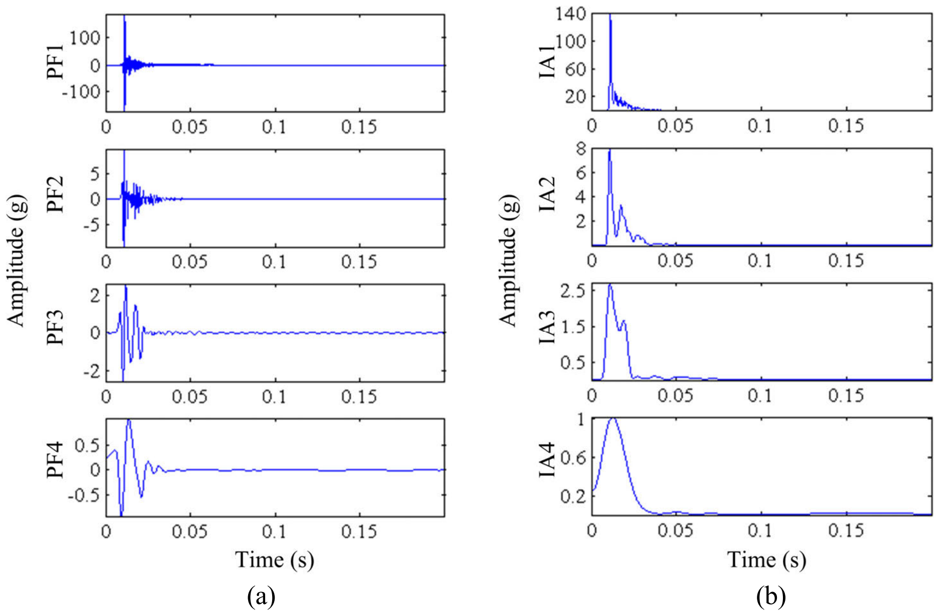


FIGURE 10. The decomposition result of ELMD. (a) The four PFs and (b) the four IAs.

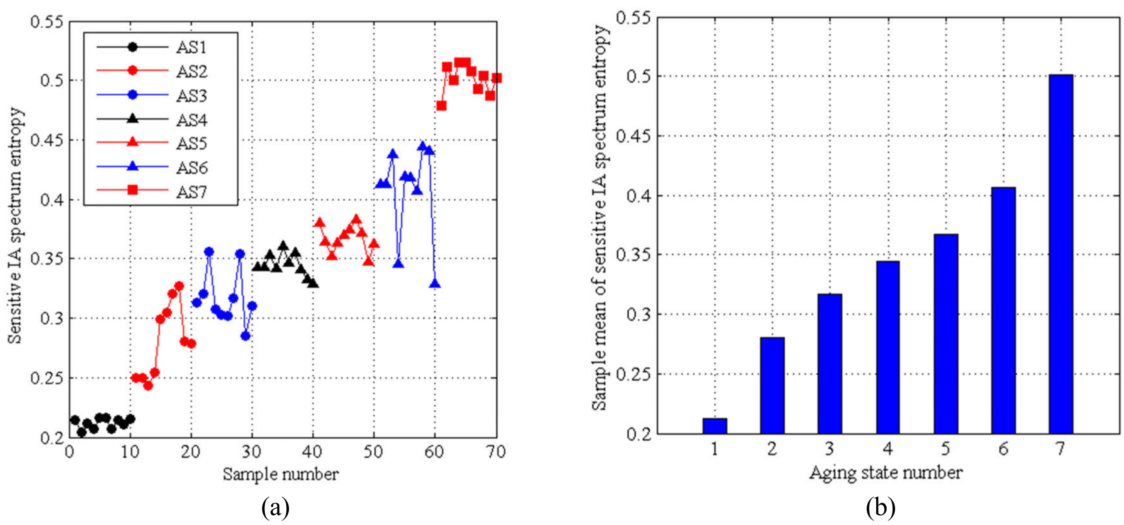


FIGURE 11. The aging state identification result of the LMD based method. (a) Sensitive IA spectrum entropies of samples under different aging states and (b) sample mean of sensitive IA spectrum entropies under different aging states.

In order to validate the superiority of the proposed method, the LMD based method (LMD and sensitive IA spectrum entropy) is used to identify the aging state of viscoelastic sandwich structure. Firstly, the collected vibration response signals are first decomposed into a set of PFs by the LMD method. The first four PFs of one vibration response signal are respectively shown in Fig. 10(a), and the corresponding four IAs are respectively shown in Fig. 10(b). Then, the spectrum entropies of the IAs are calculated, the sensitivity factors of these IA spectrum entropies are calculated, and the most sensitive one is selected. Finally, the sensitive IA spectrum entropy is used to identify the aging state of viscoelastic sandwich structure. The identification result is shown in Fig. 11. It can be seen from Fig. 11 that the sample mean of sensitive IA spectrum entropies based on the LMD method also increases with the increase of viscoelastic material aging time and also can identify the aging state of viscoelastic sandwich structure. However, compared with the proposed method, there are more sample overlaps among the seven aging states, and the clustering effect of each aging state is poorer. Therefore, the proposed method is more effective than the LMD based method in the aging state detection of viscoelastic sandwich structure.

In order to further compare the two methods of the proposed method and the LMD based method, the standard deviations of sensitive IA spectrum entropies on each aging

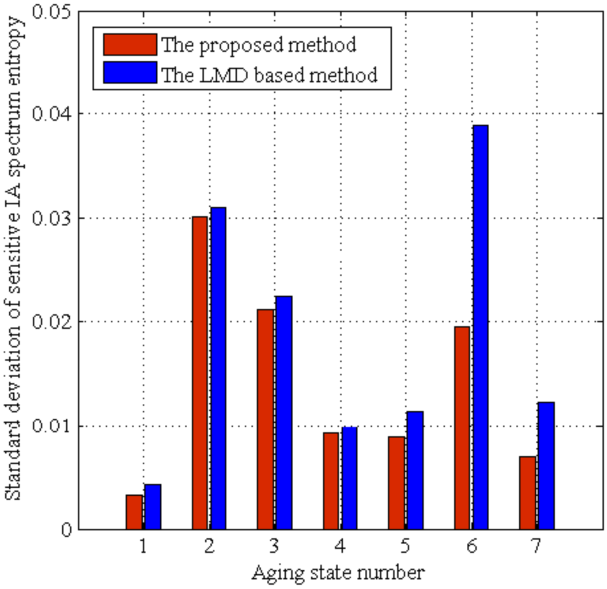


FIGURE 12. The standard deviations of sensitive IA spectrum entropies based on the proposed method and the LMD based method.

state samples are also calculated and displayed in Fig. 12, respectively. The standard deviation of sensitive IA spectrum entropies on aging state samples can reveal the robustness of the method, the smaller the standard deviation is, and the better the robustness of the method is.

It can be seen from Fig. 12 that, the standard deviations of sensitive IA spectrum entropies on seven aging state samples of the LMD based method are all significantly larger than those of the proposed method, which means that the robustness of the proposed method is better than that of the LMD based method. This again shows that the proposed method is more effective than the LMD based method in the aging state detection of viscoelastic sandwich structure.

To further validate the superiority of the proposed method, the EEMD based method (EEMD and sensitive IMF Hilbert envelope spectrum entropy) is used to identify the aging state of viscoelastic sandwich structure. First of all, the collected vibration response signals are first decomposed into six IMFs by the EEMD method, in which the added noise amplitude is set as 0.2 and the ensemble number is set as 100. The six IMFs of one vibration response signal are respectively shown in Fig. 13(a). After that, Hilbert envelope demodulation is performed on these IMFs, the corresponding six Hilbert envelope (HE) signals are respectively shown in Fig. 13(b), and for each IMF, the spectrum entropy is calculated based on the frequency spectrum of HE signal. Furthermore, the sensitivity factors of these IMF Hilbert envelope spectrum entropies are calculated, and the most sensitive one is selected. In the end, the sensitive IMF Hilbert envelope spectrum entropy is used to identify the aging state of viscoelastic sandwich structure. The identification result is shown in Fig. 14.

It can be seen from Fig. 14 that, compared with the proposed method, there are a lot of sample overlaps among different aging states, the clustering effect of each aging state is very poor, and the sample mean of sensitive IMF Hilbert envelope spectrum entropies is not monotonically

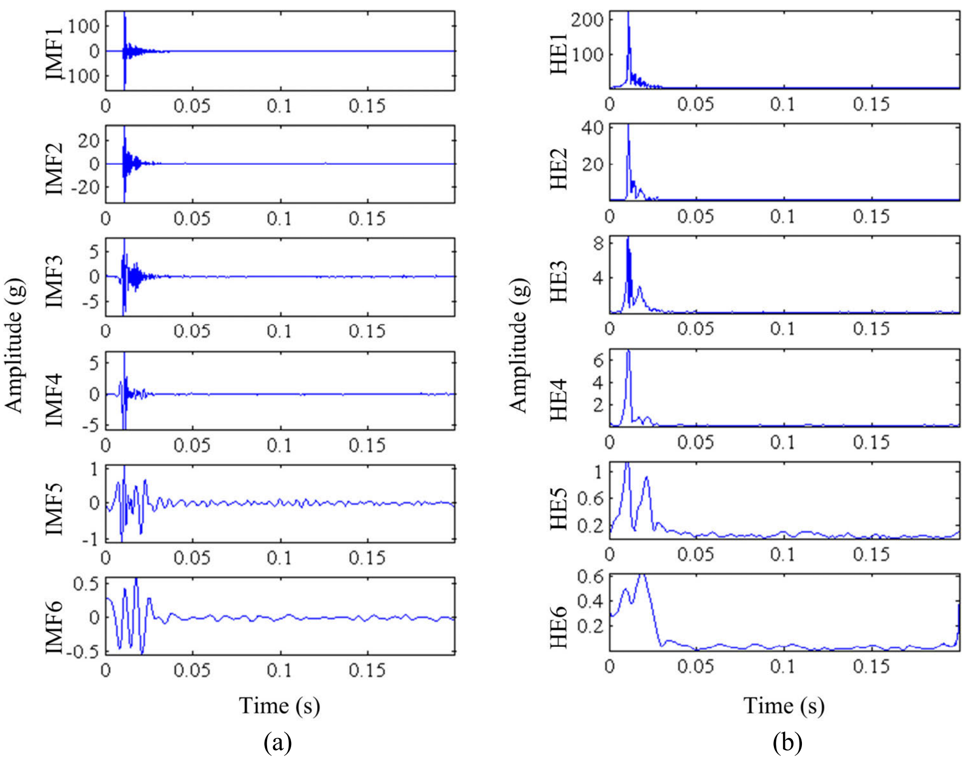
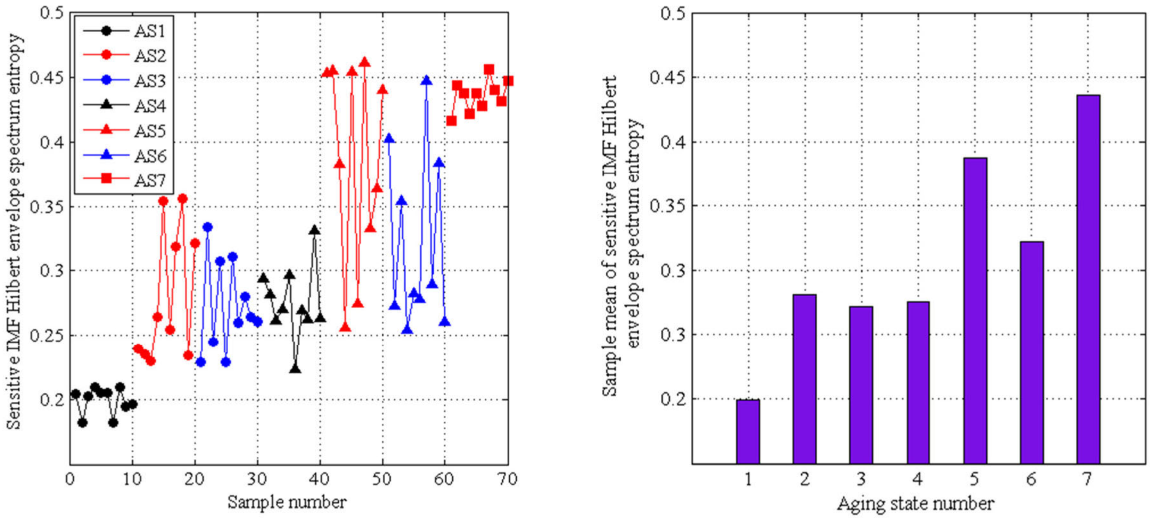


FIGURE 13. The decomposition result of EEMD. (a) The six IMFs and (b) the six HEs.



(a) (b)

FIGURE 14. The aging state identification result of the EEMD based method. (a) Sensitive IMF Hilbert envelope spectrum entropies of samples under different aging states and (b) sample mean of sensitive IMF Hilbert envelope spectrum entropies under different aging states.

increasing with the increment of aging degree of the viscoelastic material. These analysis results suggest that the EEMD based method cannot accurately identify the aging state of viscoelastic sandwich structure, and the proposed method is more effective than the EEMD based method in the aging state detection of viscoelastic sandwich structure.

VI. CONCLUSION

By analyzing the vibration response signals, this paper presents a new method based on ELMD and sensitive IA spectrum entropy to detect the aging state of viscoelastic sandwich structure. First, ELMD is introduced to decompose the vibration response signals captured from viscoelastic sandwich structure into a series of PFs. Then, the spectrum entropies of all IAs are calculated to measure the dynamic characteristics of these IAs. Finally, the sensitive IA spectrum entropy is selected to identify the structural aging state, and the mean value of sensitive IA spectrum entropies is used as an index to quantitatively assess the aging state of viscoelastic sandwich structure.

In order to validate the effectiveness of the proposed method for the aging state detection of viscoelastic sandwich structure, the experimental device of a viscoelastic sandwich structure is designed, and the different structural aging states are prepared by performing hot oxygen accelerated aging experiment on viscoelastic material. The impulse excitation experiment of all structural aging states is performed and the corresponding vibration response signals are collected to be analyzed. The identification results shown that the proposed method can effectively identify the aging state of viscoelastic sandwich structure. The proposed method is more superior to the detection methods based on LMD and EEMD. Thus, a much more effective method is provided in this paper for the aging state identification of viscoelastic sandwich structure.

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JINXIU QU was born in Heze, Shandong, China, in 1988. She received the B.S. degree in mechanism design, manufacturing, and automatization from Yantai University, Shandong, China, in 2010, and the Ph.D. degree in mechanical engineering from Xi'an Jiaotong University, Xi'an, China, in 2015. She is currently a Lecturer with the School of Mechanical and Electrical Engineering, Xi'an Technological University, Xi'an. Her research interests include structural health monitoring, mechanical fault diagnosis, dynamic response signal processing, the fault diagnosis of mechanical equipment, and the health monitoring of complex structures.

CHANGQUAN SHI was born in Weifang, Shandong, China, in 1987. He received the B.S. degree in mechanism design, manufacturing and automatization from Yantai University, Shandong, China, in 2010, and the M.S. degree in mechanical engineering from Xi'an Jiaotong University, Xi'an, China, in 2013, where he is currently an Engineer with the State Key Laboratory for Manufacturing System Engineering. His research interests include the design of mechanical structures and the dynamics analysis of mechanical structures.