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Impact Damage Identification for Composite Material Based on Transmissibility Function and OS-ELM Algorithm

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Abstract: A method is proposed based on the transmissibility function and the Online Sequence Extreme Learning Machine (OS-ELM) algorithm, which is applied to the impact damage of composite materials. First of all, the transmissibility functions of the undamaged signals and the damage signals at different points are calculated. Secondly, the difference between them is taken as the damage index. Finally, principal component analysis (PCA) is used to reduce the noise feature. And then, input to the online sequence limit learning neural network classification to identify damage and confirm the damage location. Taking the amplitude of the transmissibility function instead of the acceleration response as the signal analysis for structural damage identification cannot be influenced by the excitation amplitude. The OS-ELM algorithm is based on the ELM (Extreme Learning Machine) algorithm, in-creased training speed also increases the recognition accuracy. Experiment in the epoxy board shows that the method can effectively identify the structural damage accurately.

Keywords: Impact damage, transmissibility function, OS-ELM.

1 Introduction

Composite materials with high specific strength, high specific stiffness, long fatigue life and corrosion resistance and light weight, etc., are widely used in the aerospace field, the automotive industry and a variety of related engineering structures [Sun and Gu (2017); Sun, Zhang, Qian et al. (2013)]. However, some impact damage (such as bird collisions, stone parts dropping, drop hammer impact, etc.) will inevitably occur in the actual use and maintenance of the composite material because the composite material has no significant strength in the thickness direction, Load-sensitive, particularly vulnerable to lateral impact leading to matrix cracks, fiber breakage and delamination and a series of damage [De

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Angelis, Men, Almond et al. (2012); Rogge and Leckey (2013); Long, Yao and Zhang (2015)]. When the composite material is impacted, the human eye does not recognize and detect such impact damage due to its laminating and energy absorbing properties, resulting in material property changes and serious safety hazards [Zhao, Xu and Guo (2017)]. Therefore, damage identification of composite impact damage is indispensable.

In this paper, the transmissibility of undamaged signals and damage signals at different points is used as the damage index, use the PCA compression feature processing input to the OS-ELM neural network classification to identify damage and confirm the damage location. ELM [Huang, Zhu and Siew (2006)] is proposed by Huang Guangbin to solve the single hidden layer neural network algorithm. Compared with SVM and traditional neural network, the training speed of ELM is very fast, which requires less artificial disturbance and strong generalization ability for heterogeneous data sets. Although the algorithm is fast learning, the generalization ability is good, but it takes the batch mode, that is, all the data is processed before adding to the network to learn once, thus wasting a lot of time. In this paper, the online sequence ELM algorithm [Liang, Huang, Sarathandran et al. (2006)] is presented in 2006. OS-ELM shows that the learning speed is fast and the generalization performance is good in the large data set. Therefore, combined with previous studies [Chen, Diao and Ren (2014); Lu, Jiang, Jia et al. (2015); Zhao, Wu, Zhang et al. (2018)], this paper uses the transmissibility function input to the OS-ELM neural network, can be identify damage very effectively and rapidly.

2 Transmissibility function principle

Construct the damage index, with n degrees of freedom system of differential equations of vibration:

$$M\ddot{x}_{(t)}+C\dot{x}_{(t)}+Kx_{(t)}=f(t) \tag{1}$$

Where, $x(t)$, $\dot{x}(t)$ and $\ddot{x}(t)$ are the n-order displacement, velocity and acceleration arrays respectively; M, C and K are the $\mathrm{n}\times n$ order real symmetric matrices of mass, damping and stiffness of the system; $f(t)$ is the external load. Fourier Transform of Eq. (1) to get next order frequency response matrix of vibration system:

$$X(\omega)=H(\omega)F(\omega) \tag{2}$$

Where,

$$H(\omega)=(K-\omega^2M+i\omega C)^{-1} \tag{3}$$

For the vibration system frequency response function matrix, $\mathrm{n}\times n$ order.Acceleration array is:

$$A(\omega)=-\omega^2H(\omega)F(\omega) \tag{4}$$

Assuming that the only excitation applied to structure k is Fourier transform, the excitation array may be:

$$F(\omega)=\{0_{1,}0_2,...F_k(\omega),...,0_n\}^T \tag{5}$$

By substituting Eq. (4) into Eq. (5) is reduced to:

$$A(\omega) = -\omega^2 F_{k(\omega)} H_{k(\omega)} \tag{6}$$

Suppose the acceleration response of external excitation is transmitted from i to j, and the acceleration transfer rate function is defined as the ratio of two responses:

$$T_{\mathrm{ij}}(\omega) = \frac{A_i(\omega)}{A_j(\omega)} = \frac{-\omega^2 h_i(\omega) F(\omega)}{-\omega^2 h_j(\omega) F(\omega)} = \frac{h_i(\omega) F(\omega)}{h_j(\omega) F(\omega)} \tag{7}$$

By substituting Eq. (5) into Eq. (7) $T_{\mathrm{ij}}(\omega)$ is reduced to:

$$T_{\mathrm{ij}}(\omega) = \frac{H_{ik}(\omega)}{H_{jk}(\omega)} \tag{8}$$

Where, $H_{\mathrm{ik}}(\omega)$ and $H_{\mathrm{jk}}(\omega)$ are entries of the FRF.

The damage index defined in this paper is termed “difference transmissibility function and is defined as differences between transmissibility functions of the damaged structure and transmissibility functions of the undamaged structure given as:

$$\mathit{D}\mathrm{iffice}\, T_{ij}(\omega) = T_{\mathrm{ij}}^{d}(\omega) - T_{ij}^{ud}(\omega) \tag{9}$$

Where, $T_{ij_{ij}}^{\mathrm{ud}}(\omega)$ is the transmissibility function from the undamaged structure and $T_{ij_{ij}}^{d}(\omega)$ is the transmissibility function from the damaged structure, the $\mathit{D}\mathrm{iffce}\,\mathrm{T}_{\mathrm{ij}}(\omega)$ for PCA compression noise reduction processing, then input to the OS-ELM neural network .

3 OS-ELM algorithm principle

Based on the ELM algorithm, the OS-ELM algorithm is proposed, and the training speed and generalization performance are further improved. According to the ELM principle, the OS-ELM algorithm can be described as follows:

Step 1: Initialize the stage.

Given the activation function g, the number of hidden nodes is L, giving a short initial training set $Z_0 = \{(x_i, t_i)\}_{i=1}^{P_0} \in P_0 \times L$, and $P_0 > L$.

Randomly select the input weight and hidden layer threshold in the range of [-1, 1].

Calculate the output matrix of the initial hidden layer:

$$H_0 = \begin{bmatrix} G(\mathrm{w}_1 x_1 + b_1) & \dots & G(\mathrm{w}_{\mathrm{L}} x_1 + b_L) \\ . & & . \\ . & \dots & . \\ . & & . \\ G(\mathrm{w}_1 x_{P_0} + b_1) & \dots & G(\mathrm{w}_{\mathrm{L}} x_{P_0} + b_L) \end{bmatrix}_{P_0 \times L} \tag{10}$$

Calculate the initial output weight $B^{(0)} = N_0 H_0^T T_0$, where, $N_0 = (H_0^T T_0)^{-1}, T_0 = [t_1, .. t_{P_0}]^T$;

Take k=0, where, k represents the number of data segments sent to the network.

Step 2: Online learning stage.

The output matrix H_{k+1} of the hidden layer node is calculated for the k+1th data segment:

$$H_{k+1} = \begin{bmatrix} G(w_1 x_1 + b_1) & \dots & G(w_L x_1 + b_L) \\ . & & . \\ . & \dots & . \\ . & & . \\ G(w_1 x_{P_{k+1}} + b_1) & \dots & G(w_L x_{P_{k+1}} + b_L) \end{bmatrix}_{P_{k+1} \times L} \tag{11}$$

Calculate the output weights $B^{(k+1)}$.

$$N_{k+1} = N_k - N_k H_{k+1}^T (I + H_{k+1} N_k H_{k+1}^T)^{-1} H_{k+1} N_k \tag{12}$$

$$B^{(k+1)} = B^{(k)} + N_{k+1} H_{k+1}^T (T_{k+1} - H_{k+1} B^{(k)}) \tag{13}$$

Take k = k + 1 and return to the online learning phase (1).

4 Experimental study

4.1 Experimental setup and steps

(1) In this experiment, composite epoxy board, 4 pzt sensors, digital acquisition card (ni-usb4431), impact hammer (Lc-01), charge amplifier (Ye5852) were used to collect the signal of the epoxy board without damage and the damage signal after impact. Firstly, an impact hammer is used to impact the epoxy board, the charge signal is used to amplify the response signal, and then the data acquisition system is produced by using Labview, and the damaged response signal is collected by the data acquisition card. The experimental platform is shown in Fig. 1(a), the arrangement of the sensors and the coordinate axis is shown in Fig. 1(b), where the circles represents the sensors

(2) Transmissibility function is calculated by Fourier Fransform, subtract the transmissibility function from the health state under the damage state of each point to obtain the difference transmissibility function as the damage index.

(3) Use the PCA data compression capabilities to reduce the size of the damage index.

(4) The damage characteristic index after compression in Step (3) is used to identify the structural damage by using the classification recognition function of OS-ELM algorithm.

(a) (b)

Figure 1: The experimental platform (a). The sensors and coordinate axis location (b)

4.2 Experimental results and analysis

In this experiment, the accelerometer was installed on the drop hammer body of the dropping hammer impact tester, the free fall of the hammer body collided with the composite material, and the acceleration response was obtained. The acceleration responses of points 1, 2, 3 and 4 are selected for damage identification. The acceleration responses of points 1, 2, 3 and 4 are selected for damage identification. The sampling frequency of acceleration response is 1000 kHz. Taking the acceleration response of point 10 as a virtual input and the acceleration responses of points 1, 2, 3 and 4 as outputs, the transmissibility function of the two points 1-4, 2-4, 3-4 before and after the structural damage was calculated respectively. The transmissibility functions T_{1-4}^{ud}, T_{2-4}^{ud} and T_{3-4}^{ud} of undamaged signals are defined as H1, H2 and H3 respectively. Similarly, the transmissibility functions T_{1-4}^{d}, T_{2-4}^{d} and $T_{3\text{-}4}^{\mathrm{d}}$ of damage signals are defined as D1, D2 and D3 respectively. Their spectrum is shown in Fig. 2.

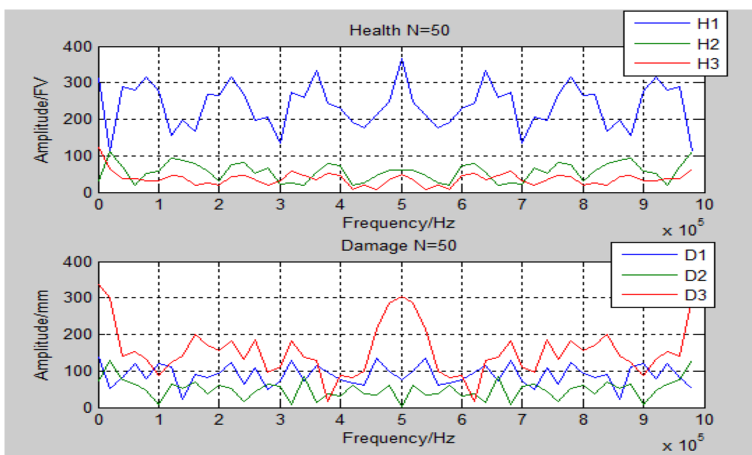

Figure 2: Transmissibility function spectrum of health and damage signals

From the Fig. 2, it is observed that significant changes in the transmissibility associated with different damage states. That is, changes in the amplitude, shape and position of the frequency peak, the amplitude-frequency characteristics of the damaged structure and the undamaged structure signal are extracted, and the difference between them is taken as damage index, and then do the PCA feature processing, select the first four features input to the OS-ELM to identify damage. Finally, the damage coordinate positions are shown in Tab. 1. OS-ELM neural network can more accurately identify damage, and the predicted output close to the expected output.

The characteristic data is input into the SVM and ELM neural network classifiers, and compared with the OS-ELM in this paper. The optimal parameters for each classifier are selected to obtain the performance comparison of the classifiers as shown in Tab. 2 and Tab. 3.

From Tab. 1, OS-ELM classification accuracy and ELM, SVM basically the same, indicating that the algorithm can be used for composite impact damage identification. By comparing the training time of the three classifiers, the classification efficiency of OS-ELM is far greater than the other two classifiers. As can be seen from Tab. 3, ELM consumes about 5 times the OS-ELM. This is because OS-ELM adopts the continuous training mode, and requires fewer nodes in hidden layer, so the time complexity of the algorithm is obviously reduced and the classification efficiency is improved.

Therefore, the transmissibility of undamaged signals and damage signals at different points is used as the damage index, use PCA compression feature processing input to the OS-ELM neural network classification to identify damage and confirm the damage location. The experiment concluded: This method is feasible, and the overall performance is excellent.

Table 1: Damage identification coordinates

	Damage location	
Sequence	X	Y
1	-2.6645	1.5233
2	1.2458	2.9867
3	1.6768	3.6770

Table 2: Three kinds of classifier classification accuracy comparison

Classifier	Training accuracy	Testing accuracy	Number of nodes
SVM	1. 000 0	0. 967 0	30
ELM	0. 991 0	0. 949 5	280
OS-ELM	0. 995 0	0. 965 0	30

Table 3: Three kinds of classifier time consumption comparison

Classifier	Training time/s	Testing time/s	Number of nodes
SVM	16. 296 9	0. 100 0	30
ELM	0. 087 5	0. 009 4	280
OS-ELM	0. 015 6	0. 001 6	30

5 Conclusion

In this paper, transmissibility function and OS-ELM neural network are used to study the impact damage of composite materials. If the input vector of the network is constructed directly by using the transmissibility function, the dimension of the input vector is too large, which leads to problems such as difficult network convergence and poor stability. Therefore, the transmissibility of undamaged signals and damage signals at different points is used as the damage index, use PCA compression feature processing input to the OS-ELM neural network classification to identify damage and confirm the damage location. The experiment verifies the feasibility of this method and can determine the location of damage well.

Because this method uses the acceleration response data for structural damage localization directly, it does not need excitation information, modal parameters and structural finite element model, so it is more suitable for the structure health monitoring.

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