ISSN 1027-5495. Functional Materials, 23, No.2 (2016), p. 331-336
doi:http://dx.doi.org/10.15407/fm23.02.331

Acoustic emission source positioning research of 3D braided composite material based on the wavelet network

Su Hua, Zhang Ning, Zhang Tianyuan

Tianjin Polytechnic University, Binshui Road 399, Xiqing District, Tianjin, 300387, P.R. China

The acoustic emission detection technology is used to position the acoustic emission source of 3D braided composite material. Through comprehensive utilization of the characteristic parameters of acoustic emission signals, the wavelet neural network (WNN) is used to conduct damage positioning and computation, and by combining the shuffled frog leaping algorithm (SFLA), it can improve the convergence performance. Through experiment comparison with traditional positioning computation method, after optimization with the frog leaping algorithm, the wavelet network acoustic emission source positioning method can effectively improve the precision of damage positioning.
Keywords: Three-dimensional (3D) Braided Composites, shuffled frog leaping algorithm (SFLA),Wavelet Neural Network (WNN), Acoustic Emission Source Positioning

Технология детектирования акустической эмиссии используется для определения положения источника акустической эмиссии трехмерных композитных материалов с упрочняющей оплеткой. Путем всестороннего использования характеристических параметров сигналов акустической эмиссии, вейвлет-нейросети используются для определения и позиционирования дефекта, а комбинируя с алгоритмом неупорядоченных прыжков лягушки, можно улучшить сходимость. Путем сравнения экспериментов с традиционным методом расчета позиционирования, после оптимизации алгоритмом прыгающей лягушки, метод вейвлет-нейросетей для позиционирования источника акустической эмиссии может эффективно повысить точность определения положения дефекта.

Дослідження позиціонування джерела акустичної емісії тривимірних композитних матеріалів зі зміцнювальним оплетенням на основі вейвлет-мереж. *Су Хуа, Чжан Нін, Чжан Тяньюань*

Технологію детектування акустичної емісії використано для визначення положення джерела акустичної емісії тривимірних композитних матеріалів зі зміцнювальним оплетенням. Шляхом всебічного використання характеристичних параметрів сигналів акустичної емісії, вейвлет-нейромережі використовують для визначення та позиціонування дефектів, а завдяки поєднанню з алгоритмом невпорядкованих стрибків жаби можна покращити сходження. Шляхом порівняння експериментів з традиційним методом розрахунку позиціонування, після оптимізації алгоритмом стрибків жаби, метод вейвлет-нейромереж для позиціонування джерела акустичної емісії може ефективно підвищувати точність визначення положення дефектів.

1. Introduction

The acoustic emission source positioning is an important work of acoustic emission detection technique, which is an important index to evaluate the acoustic emission detection, and its accuracy reflects whether the position obtained through acoustic emission detection is consistent with the actual position where the defect is found. How to increase the position-

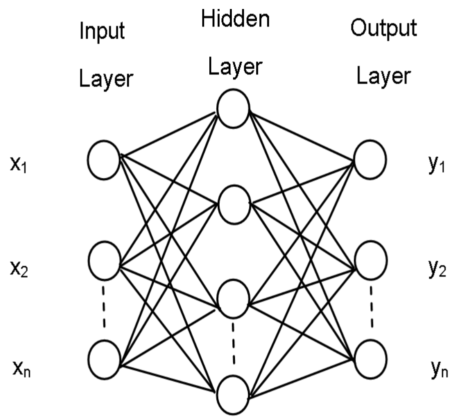

Fig. 1. Three-layers network structure

ing accuracy of acoustic source and maximally reduce missed or false positioning is an important task during acoustic emission source positioning. Due to different aeolotropic sound velocity, the application of tradition geometrical time-difference positioning method for aeolotropic composite material is restricted. In recent years, in accordance with the aeolotropy of composite material, several acoustic emission source positioning methods based on geometrical time-difference positioning method have been developed. For instance, after fitting aeolotropic wave velocity, it can be used as known parameter, and added to the classic geometrical positioning method and virtual wave front method [1,2,3].

The acoustic emission signal from composite material during loading can include all information of composite material damage, such as the location of damage source, damage model and degree. It has broad application prospects to use the acoustic emission technology to detect the structure of composite material.

This paper proposes an acoustic emission detection method of optimized wavelet neural network (WNN) based on the shuffled frog leaping algorithm (SFLA). By combining acoustic emission and WNN, this paper conducts theoretic analysis and specific experiment research on the acoustic emission source positioning of 3D braided composite material.

2. WNN based on shuffled frog leaping algorithm

2.1 Wavelet network

The wavelet neural network (WNN) is the product by combining the wavelet analysis theory and neural network theory. The wavelet transform (WT) conducts multi-scale analysis of signal through scale expansion and translation, which can effectively extract local information of signal; the neural network has the characteristics of self-learning, self-adaption and fault tolerance, which is also a common function approximator. The elements and whole structure of WNN are determined in accordance with the wavelet analysis theory, which can avoid the blindness of BP neural network in structural design. In addition, it has stronger learning ability and higher accuracy, and for the same learning task, the WNN has simpler structure and faster convergence rate. [7,8] This paper chooses a compact WNN, and its structure is as shown in Fig.1.

Dimension design for input and output. The dimension of input and output should be determined in accordance with the problem that needs to be solved and data expression method. In order to conduct accurate positioning of the source of acoustic emission signal, in addition to obtaining traditional time of arrival, we also need to comprehensively consider the sound wave information such as energy, amplitude and counts to conduct positioning training in a clearer and more comprehensive way. Because all the input signals are simulation signals, which requires sampling before training, the dimension of input layer should be determined in accordance with the sampling point number of waveform, which should be finally determined by coordinating the positioning accuracy. The dimension of output layer should also be determined in accordance with actual requirement. The dimension of output layer should also be determined with actual requirement. This paper mainly studies the source positioning of acoustic emission signal, so the node number of input layer is set as 8, and the nerve cell number at output layer is set as 2, which are the abscissa and ordinate respectively.

Excitation function. By combining the characteristics of damage acoustic emission signal of 3D braided composite material, this paper chooses the Morlet wavelet as the network excitation function:

$$\psi(x) = \cos(1.75x)\exp(-0.5x^2) \qquad (1)$$

Through translation and expansion of $\psi(x)$, we can obtain the $j(j = 1,2,...,J)^{\text{th}}$ wavelet function on the hidden layer of WNN:

$$\psi_j(x) = \frac{1}{\sqrt{|a_j|}}\psi\left(\frac{x-b_j}{a_j}\right) a_j, b_j \in \Re \qquad (2)$$

Hidden layer and node selection. The node number on hidden layer is very important to the performance of whole network. If the number is too low, the network won't obtain adequate information from the sample, which cannot sufficiently reflect the internal rule of sample, and it will further reduce the network's generalization ability; if the number is too high, it will increase the network's learning time, which will cause the decrease in convergence rate. At present, there is no explicit analytic expression that can be used to select node number of hidden layer, which is generally determined by combining the actual problem through multiple experiments. By combining the actual situation, in accordance with the error precision requirement, this paper sets the node number of hidden layer as 17.

2.2 SFLA

The shuffled frog leaping algorithm (SFLA) is a population-based cooperative search method inspired by biological emulation in the nature[6]. Its basic idea is: F frogs form the initial frog population, in which, the solution of ith frog in S dimension solution space can be expressed as $X_i = (x_1, x_2, \dots x_s,)$. Then, sort individual frogs in the initial frog population in descending order in accordance with the adaptive value, and find the optimal solution P_x for the initial frog population. Later, divide the frog population into m sub-populations, and each sub-population contains n frogs, which satisfy the relation $F = m \times n$. When the first frog enters the first sub-population, the second frog enters the second sub-population, the m^{th} frog enters the m^{th} sub-population, and the $(m + 1)^{th}$ frog enters the first sub-population, until all frogs have entered the specified sub-population. In Formula (3), j refers to the j^{th} frog, while P_j refers to the probability of the j^{th} frog being chosen. Then, we can find the best solution P_b and worst solution P_w in the sub-population; in accordance with Formulas (4) and (5), we can conduct local deep search to each sub-population [7,8].

$$P_j = 2(n+1-j)/[n(n+1)], j = 1, 2, \dots, n \quad (3)$$

$$S = Rand() \times (P_b - P_w) \quad (4)$$

$$P_{nw} = P_w + S \ , (-S_{\max} \le S \le S_{\max}) \quad (5)$$

In Formula (4), *Rand*() refers to a random number between 0 and 1; S refers to the frog's leap step size, which is a reasonable difference value; S_{max}: maximum step size of each movement made by single frog; P_{nw} refers to the updated P_w. If P_w is in a feasible solution space, calculate corresponding fitness of P_{nw}. If the corresponding fitness of P_{nw} is less optimal than the corresponding fitness of P_w replace P_b in Formula (4) with P_x to update P_w; if there still is no progress, randomly generate a new frog to replace P_w. Otherwise, repeat the update process until it reaches the preset local iterations LS. After completing deep search of various sub-populations, remix and sort the frogs in the frog population; then, divide the frog population into various sub-populations to continue local search, until it satisfies any preset condition to stop the algorithm.

In this paper, the SFLA is used to optimize the WNN, the initial operation parameters are set as:

F: the population size is 100, which refers to the total quantity of individuals contained in the population.

m: the sub-population size is 20.

S_{max}: the maximum step size of each movement made by single frog is 20.

LS: the local evolution times are 10.

SF: the glocal evolution times are 400.

3. Experimental

3.1 Experimental sample

The TORAYCCA@ T300 carbon fiber (12K) is used as the reinforced fiber for the plate specimen of 3D braided composite material. The braided structure of fabricated part is four-step 1×1 3D 5-direction braided structure, and the basis material is TDE86# epoxy resin. The resin transfer molding (RTM) process is used for curing molding, and the sample has a thickness of (5±0.1)mm. In the experiment, 6 samples of the same size (35cm×20cm×5mm) are chosen and divided into Group A and Group B, with 3 samples in each group; Group A is used in the lead-break experiment, while Group B is used in the damage positioning experiment.

3.2 Four-probe array plane positioning method

This test adopts the four-probe array plane positioning method to position the acoustic emission source, as shown in Fig.2.

Arrange the four probes into a rhombus on the surface of test piece, the time difference of probes S_1 and S_3 in receiving the acoustic emission signals is Δt_x, while the time difference of probes S_2 and S_4 in receiving the acoustic emission signals is Δt_y. The distance between S_1 and S_3 is a, while the distance between S_2 and S_4 is b, and the wave velocity is V. Therefore, the AE source is located at the intersection point $Q(X,Y)$ between two curves, and the coordinate expressions are as shown in Formulas (6) and (7).

$$X = \frac{\Delta t_x V}{2a} \left(\Delta t_x V + 2\sqrt{\left(X - \frac{a}{2} \right)^2 + Y^2} \right) \quad (6)$$

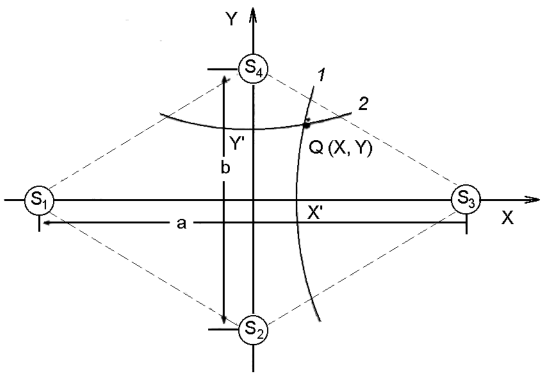

Fig. 2. Four-probe array AE source positioning method

$$Y = \frac{\Delta t_y V}{2b}\left(\Delta t_y V + 2\sqrt{\left(Y - \frac{a}{2}\right)^2 + X^2}\right) \quad (7)$$

3.3 Result and analysis of simulative lead-break experiment

Conduct four-point positioning experiment to the plate test piece of 3D four-direction braided composite material in Group A.

Fig.3 shows the diagram of four-direction plane lead-break experiment, and the four sensors are arranged into a rhombus. The standard lead-break experiment is used to simulate the source which generates the acoustic emission signals, and take the average value of three responses. In the experiment, with the rhombus center as the origin, and the coordinates of four sensors are (0,15); (0,–15); (–30,0) and (30,0) respectively. Select four test points with the coordinates of (15,10), (–15,–10), (–5,5) and (5,–5) respectively, conduct 3 experiments at each test point, and calculate the average value.

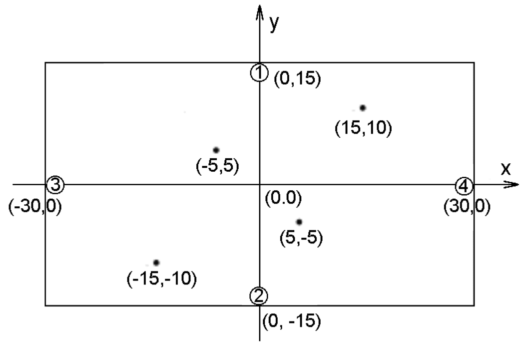

Fig.3 Sensor layout on the plate test piece of 3D four-direction braided composite material during lead-break experiment

Use traditional mathematical morphology to conduct filtering processing of the experiment data obtained above; then, use the correlation analysis method to extract critical values of time difference; conduct computation to obtain the coordinate location of acoustic emission signals. In the meantime, for the convenience of comparison, the positioning analysis method that combines the WNN and SFLA is adopted, which integrates multiple other parameters, including the time difference parameter, into the positioning algorithm to obtain better positioning result. Because the experiment results of test pieces in Group A are close, Test piece 1is used as the example to analyze the experiment result. Table 1 shows the experiment data of Test piece 1. *n* accordance with the experiment results, we can see that when single parameter time difference is used to position the test point, even after mathematic morphological filtering and correlation analysis, its positioning accuracy is still low. The absolute average error of its abscissa is 2.1 cm, while

Table 1 Four-point positioning result comparison for Test piece 1 in Group A

Four-point positioning comparison of 3D braided composite material										
Test point (cm)			WNN + SFLA positioning method				Correlation analysis method			
			Positioning value (cm)		Error (cm)		Positioning value (cm)		Error (cm)	
No.	*x*	*y*	*x*	*y*	*x*	*y*	*x*	*y*	*x*	*y*
1	15	10	16.5	11.6	1.5	1.6	12.7	12.1	2.3	2.1
2	15	10	13.4	11.3	1.6	1.3	13.1	12.4	1.9	2.4
3	15	10	16.4	11.5	1.4	1.5	12.5	12.5	2.5	2.5
4	–15	–10	–13.7	–8.7	1.3	1.3	–13.5	–8.7	1.5	1.3
5	–15	–10	–16.4	–11.6	1.4	1.6	–12.4	–7.9	2.6	2.1
6	–15	–10	–13.5	–11.5	1.5	1.5	–12.6	–7.6	2.4	2.4
7	5	–5	6.3	–3.6	1.3	1.4	3.2	–6.8	1.8	1.8
8	5	–5	6.8	–3.5	1.8	1.5	2.9	–7.1	2.1	2.1
9	5	–5	3.8	–3.8	1.2	1.2	2.8	–6.9	2.2	1.9
10	–5	5	-3.4	6.5	1.6	1.5	–3.2	6.6	1.8	1.6
11	–5	5	-6.3	6.4	1.3	1.4	–2.9	7.1	2.1	2.1
12	–5	5	-3.5	6.5	1.5	1.5	–3.0	7.2	2	2.2

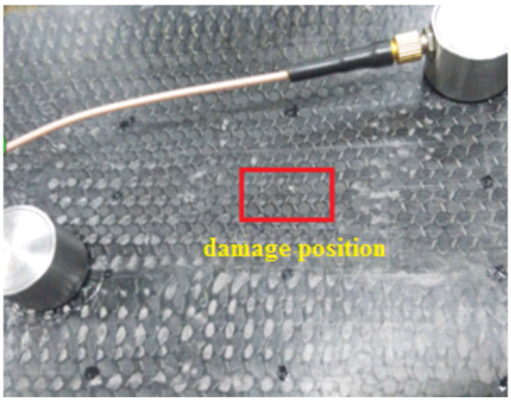

Fig. 4. Damage position of 3D braided composite material

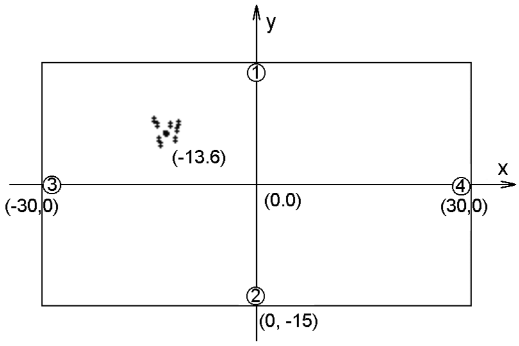

Fig.5 Actual damage position comparison of 3D braided composite material

absolute average error of its ordinate is 2.04, which is caused by the anisotropy of composite material in acoustic wave propagation velocity. In the meantime, the unique characteristics of braided angle also affect the measured value of velocity of the acoustic emission signals, while this also directly affects the measurement precision of time difference, which causes big error. When the WNN and SFLA are combined to process data and conduct positioning analysis, the absolute average error of its abscissa is 1.45cm, while absolute average error of its ordinate is 1.44. We can see that the positioning error has declined by 5mm, and the positioning accuracy has been significantly improved.

3.4 Result and analysis of damage positioning experiment of 3D braided composite material

Test pieces in Group B is chosen for the experiment, and for the convenience to compare the test results, we artificially created a dotted surface damage on each test piece in advance, as shown in Fig.4. We place the sensors on the coordinates of (0,15); (0,–15); (–30,0) and (30,0) respectively. In this paper, Test piece 1 in Group B is chosen for analysis. After causing dotted damage at coordinate (–13, 6) on the test piece surface, stress is imposed on the test piece for 8 consecutive times through the impact test machine, and the acoustic emission signals are measured and recorded. By adopting the positioning method that combines WNN and SFLA, the coordinate position of damage is calculated, as shown in Table 2.

Table 2 Actual damage positioning results of Test piece1 in Group B

Times	Actual co-ordinates (cm)		Computed coordinates (cm)		Error (cm)	
	x	y	x	y	x	y
1	–13	6	–11.5	7.7	1.5	1.7
2	–13	6	–11.4	7.3	1.6	1.3
3	–13	6	–14.8	4.7	1.8	1.3
4	–13	6	–14.4	4.4	1.4	1.6
5	–13	6	–11.2	7.5	1.8	1.5
6	–13	6	–11.6	4.9	1.4	1.1
7	–13	6	–14.4	7.6	1.4	1.6
8	–13	6	–14.5	7.4	1.5	1.4

In accordance with the acoustic emission positioning experiment of 3D braided composite material, we can see that based on the traditional positioning method, by adding morphological filtering, correlation processing and related neural network technology based on SFLA, we can filter the mechanical noise, conduct multi-factor determination of relative time difference and study the multi-parameter self-learning positioning method, and great results have been achieved. During the damage positioning, the absolute average error of its abscissa is 1.45cm, while absolute average error of its ordinate is 1.44, which is consistent with the error range of Group A during lead-break experiment. The damage assessment points present even distribution with the damage point as the center, as shown in Fig.5. In Fig.5, the round spot represents the actual damage position, while the asterisk represents the neural network and frog leaping tagged position. In accordance with Fig.5, we can see that by adopting the positioning method that combines WNN and SFLA, the positioning accuracy has been significantly improved.

4. Conclusion

During acoustic emission positioning research on the damage of 3D braided composite material, through experiemnt, it can verify that: by adopting the positioning method that combines WNN and SFLA, the positioning accuracy has been significantly improved. Compared to the traditional positioning analysis method, the positioning error has declined by 5mm on average.

Due to the impact of various factors of 3D braided composite material on the extraction of acoustic emission signals, such as its braided angle, fiber saturated level and resin infiltration/curing, it cannot realize accurate positioning of damage.

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