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The application of Shuffled Frog Leaping Algorithm to Wavelet Neural Networks for acoustic emission source location

Xinmin Cheng [a,*], Xiaodan Zhang [b], Li Zhao [b], Aideng Deng [b], Yongqiang Bao [b], Yong Liu [c], Yunliang Jiang [a]

[a] School of Information and Engineering, Huzhou Teachers College, Huzhou, Zhejiang, 313000, China
[b] School of Information Science and Engineering, Southeast University, Nanjing, Jiangsu, 210096, China
[c] Institute of Cyber-Systems and Control, Zhejiang University, Hangzhou, Zhejiang, 310027, China

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A B S T R A C T

When using acoustic emission to locate the friction fault source of rotating machinery, the effects of strong noise and waveform distortion make accurate locating difficult. Applying neural network for acoustic emission source location could be helpful. In the BP Wavelet Neural Network, BP is a local search algorithm, which falls into local minimum easily. The probability of successful search is low. We used Shuffled Frog Leaping Algorithm (SFLA) to optimize the parameters of the Wavelet Neural Network, and the optimized Wavelet Neural Network to locate the source. After having performed the experiments of friction acoustic emission's source location on the rotor friction test machine, the results show that the calculation of SFLA is simple and effective, and that locating is accurate with proper structure of the network and input parameters.

1. Introduction

The Time Difference Of Arrival (TDOA) location method is a usual approach to locate the position of a fault using the acoustic emission technology [1–3] in the fault location. The TDOA location method detects the time differences of arrival at different sensors from homologous acoustic emission signals, and calculates the source location in accordance using the space array between the sensors.

When we use the signals measured above the default threshold of the acquisition system to calculate the arrival time, the latter not only depends on the parameters of acoustic emission instrumentations, e.g. the position of transducers, frequency dispersion, attenuation, noise interference, and other factors, but also depends on the experience of the operator. In order to decrease the impact of man-made factors, it is important to design a smart algorithm for source locating [4–6].

In the intelligent algorithms, the Neural Network is a usual and effective method, and it is with the characteristics of self-organizing, self-adaptive, self-learning, and better robustness. With the rational structure of the network, right input samples, and enough training samples, this method can provide the precise activity of the acoustic emission [7–9].

This paper introduces the Wavelet Neural Network module, uses the Shuffled Frog Leaping Algorithm (SFLA) [10–12] instead of the traditional decreasing gradient algorithm, optimizes the parameters of the network, and implements the acoustic emission source location method. The experimental results show that its accuracy and efficiency are much higher than those of traditional positioning methods.

* Corresponding author.
E-mail address: chengxinmin@yahoo.cn (X. Cheng).

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2. Shuffled Frog Leaping Algorithm

In a d-dimensional target searching space, D frogs (solutions) are randomly generated to compose initial population. The i-th frog represents a potential solution of the problem $X_i = (x_{i1}, x_{i2}, \ldots, x_{id})$. Frogs are arranged from good to bad according to their fitness values to divide the whole population into N sub-populations. Among them, the frog ranked 1st is assigned into the 1st sub-population, the one ranked 2nd into the 2nd sub-population, the one ranked Nth into the Nth sub-population, the one ranked $N+1$ into the 1st sub-population, the one ranked $N+2$nd into the 2nd sub-population, and the sequence continues until all frogs have been assigned.

Every sub-population is used for local area deep searching, that is for each sub-population, the worst individual X_{w}, the best one X_{b}, and the global best one X_{g} of the sub-population in each iteration are determined first. The update operation is applied only to the current worst individual X_{w}, which is described as:

$$\Omega_i = \mathrm{rand}() * (X_{\mathrm{b}} - X_{\mathrm{w}}) \quad (-\Omega_{\max} \leqslant \Omega_i \leqslant \Omega_{\max}) \tag{1}$$

$$\text{new}\, X_{\mathrm{w}} = X_{\mathrm{w}} + \Omega_i \tag{2}$$

where rand() represents random number uniformly distributed between 0 and 1, $\Omega_{\max}$ represents the maximum of update steps allowed. If the fitness value of new X_{w} is better, X_{w} will be replaced. If it is not improved, X_{b} in Eq. (1) and Eq. (2) is replaced with X_{g}. Then, the new update strategy is:

$$\Omega_i = \mathrm{rand}() * (X_{\mathrm{g}} - X_{\mathrm{w}}) \quad (-\Omega_{\max} \leqslant \Omega_i \leqslant \Omega_{\max}) \tag{3}$$

$$\text{new}\, X_{\mathrm{w}} = X_{\mathrm{w}} + \Omega_i \tag{4}$$

If the fitness value of new X_{w} is still not improved, then a new X_{w} will be generated randomly. We then repeat this update operation until the update number is satisfied. After the local area deep-searching of all sub-populations has been finished, all frogs in the whole sub-population are mixed and reordered into sub-population and the worst individual in each sub-population is replaced. The fitness values of all individuals are changed as a consequence. Therefore, we may reorder the population according to the new fitness values from the highest value to the lowest one, and the corresponding individual frogs can be assigned into N sub-groups in the same way as the first time. Then, the local area deep-searching are processed until satisfying the number of mixed iterations.

3. Wavelet Neural Network

The main idea of Wavelet Neural Networks (WNN) [13–15] consists in using the wavelet function as a neuronal activation function and relating the wavelet to the BP network. Since wavelet transform has a good local time-frequency feature and multi-resolution analysis capability, Wavelet Neural Network performs well for identification and approximation to any functions.

The wavelet transform should satisfy $\psi(t) \in L^2(R)$, where $L^2(R)$ is the square integrable space of real numbers, and it is an energy-limited signal space. $\Psi(\omega)$ denotes the Fourier transform of $\psi(t)$, and it should satisfy:

$$c_\psi = \int_R \frac{|\Psi(\omega)|}{|\omega|} \,\mathrm{d}\omega < \infty \tag{5}$$

where $\psi(t)$ is the basic wavelet or mother wavelet. After stretching and shifting, we can get a wavelet sequence:

$$\psi_{a,b}(t) = |a|^{-1/2} \psi\left(\frac{t-b}{a}\right), \quad a, b \in R;\ a \neq 0 \tag{6}$$

where a is the stretching factor, and b is the shift factor. If the function $f(t) \in L^2(R)$, the wavelet transform of $f(t)$ is defined as:

$$W_f(a,b) = \langle f, \psi_{a,b} \rangle = |a|^{-1/2} \int_R f(t) \psi\left(\frac{t-b}{a}\right) \mathrm{d}t \tag{7}$$

Its inverse transform is defined as:

$$f(t) = \frac{1}{C_\psi} \int_R \frac{1}{a^2} W_f(a,b) \psi\left(\frac{t-b}{a}\right) \mathrm{d}a \,\mathrm{d}b \tag{8}$$

The discrete form of $f(t)$ is:

$$f(t) = \sum_{i=1}^{k} \omega_i \psi\left(\frac{t-b_i}{a_i}\right) \tag{9}$$

where k is the number of wavelets.

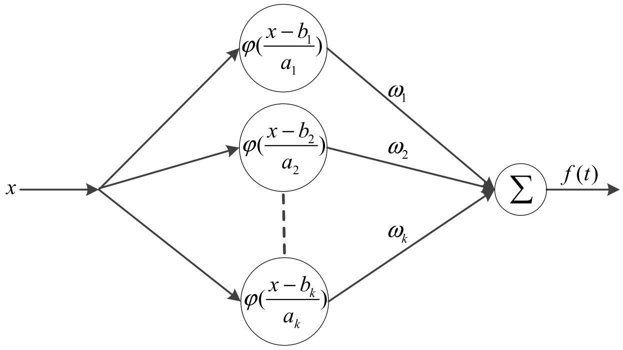


Fig. 1. The structure of the wavelet network.

Table 1
Algorithm: SFLA-based parameter learning.

Step 1: Decide the model dimensions according to the hidden layers and the wavelet neural network parameters.
Step 2: Prepare the pairwise training data.
Step 3: Initialize the population, calculate the fitness of each individual, if the fitness satisfies the required accuracy, go to step 5.
Step 4: Find the worst individual and replace it according to SFLA algorithm; if the best individual satisfies the required accuracy, go to step 5, otherwise repeat step 4 until the required accuracy is satisfied.
Step 5: Output the optimized parameters and implement the wavelet neural network.

The diversity and the complexity of the wavelet function construction decide the diversity and the complexity of the wavelet network structure. At present, the majority of scholars have adopted compact structures. Practically, we generally make the number of hidden layers one, which is a triple layer of neural networks with a single hidden layer. In Eq. (9), a signal function $f(t)$ can be fitted by the wavelet in the form of linear superposition, the network structure as Fig. 1, where ω_i is the weight between the hidden layer and the output layer, and $\psi(\frac{t-b_i}{a_i})$ is the output value of the input node. The required parameters include the number of hidden nodes k, scale factor a_i, shift factor b_i and the weight between the hidden layer and output layer ω_i.

4. The application of the Shuffled Frog Leaping Algorithm in Wavelet Neural Network

In the BP Wavelet Neural Network, the most common learning algorithm is BP algorithm, which is based on gradient information to adjust the connection weights. It may easily fall into local extreme points. SFLA has a characteristic of fast convergence and high robustness, global search capability. If it is used to optimize the neural network connection weights, we can overcome the local extreme points of the BP neural network. In addition, the proposed algorithm improves the convergence rate of neural networks with a pan-neural network capability and learning ability.

When using SFLA to train neural networks, we firstly define the vector position of the frog. As shown in Fig. 1 for the wavelet neural network, the number of frogs is initialized at 40, and the vector position of each particle is:

$$x(i) = [\omega_{i1}, \dots, \omega_{ij}, a_{i1}, \dots, a_{ij}, b_{i1}, \dots, b_{ij}], \quad i = 1, 2, \dots, 40 \tag{10}$$

where j is the number of hidden layer neurons. The fitness function for the neural network is the mean square error indicator, and the formula is given as follows:

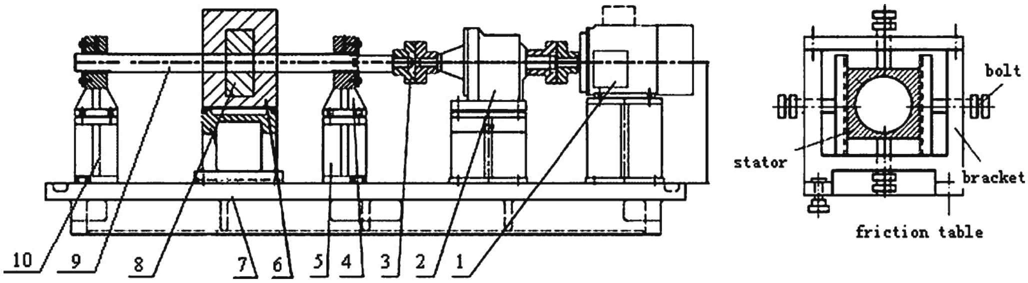
$$J(k,i) = \sum_{m=1}^{n} \left(y_{m,i} - \hat{y}_{m,i}^{k}\right)^2, \quad k = 1, 2, \dots, N \tag{11}$$

where $J(k,i)$ is the i-th frog fitness value after k iterations, n is the number of training samples, $y_{m,i}$ is the ideal output value for the network after the m-th sample input of the i-th particle, $\hat{y}_{m,i}^{k}$ is the practical output value for the network after the m-th sample input of the i-th particle, k is the iteration number, and N is the maximum number of iterations.

For clarity, we summarize the algorithm of SFLA based parameter learning in Table 1.

5. Experiment analysis

The test bed of rotor system acoustic emission friction is shown in Fig. 2. The input voltage of the motor is used to regulate the rotational speed. The semi-flexible shaft connects the electric motor with the shaft section, and the sliding bearing chock supports the rotor. A mobile friction device is installed at the base of the test bed. The mobile friction device is located in the space between shaft blocks 1 and 2. A retractable bolt is installed on the side of the screw along the center



1, electric motor; 2, acceleration box; 3, shaft joint; 4, bearing; 5, shaft block 1; 6, friction table; 7, base; 8, turntable; 9, axle; 10, shaft block 2

Fig. 2. Test bed of rotor friction acoustic emission.

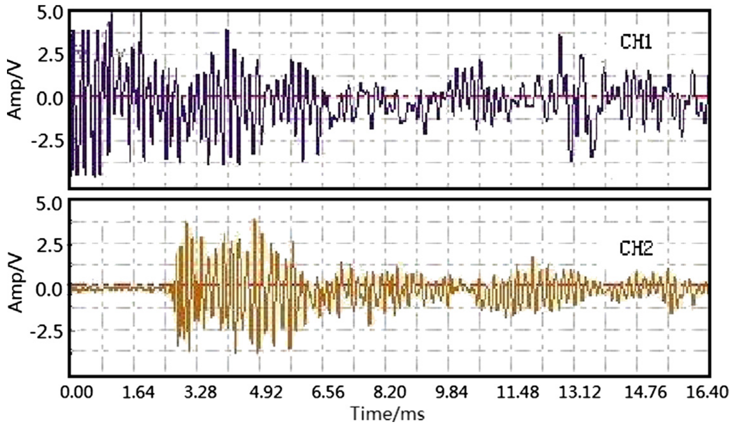


Fig. 3. Two-way acoustic emission signals from the friction.

of the radial axis and the acoustic emission signals will be excited from the friction between the rotors by adjusting the bolts.

The SR150 sensor is adopted for experiments, its frequency range covers from 20 kHz to 300 kHz. The A/D resolution of the AE collection card is 12 bits. The two acoustic emission sensors are installed separately on the shaft blocks 1 and 2, and the space coordinates are $(x_1, y_1) = (0, 0)$ and $(x_2, y_2) = (50, 0)$. The acoustic emission is on the shaft and its distance away from the sensor is set at 20 cm. We set the sampling frequency at 1 MHz, the number of points at 16 384. Fig. 3 displays the acoustic emission signals received by the two sensors when the rotors are rubbing. When friction happens, the AE event will occur. Thus, the number of AE events depends on the friction time. More than 10 events were used at every location.

We get two-way signals' amplitude and energy, and use the ratio between the coordinates of the sensor and the received signal energy as the input of the neural network. In the experiment, we set the rotating shaft as the x-axis, while the y-axis is perpendicular to the direction of the rotating shaft. The direction of acoustic emission signals is on the x-axis, and the neuron output number of the network is 1.

We rub the rotors twenty times and use the data as the input of the network to train the neural network. From the Fig. 4, if the number of hidden layer neurons is lower than 10, the network is not stable and the correct rate of the output is volatile. As the number of hidden layer neurons increases, both the network and the correct rate of the output will be stable. We set the number of hidden layer neurons at 10 for the accuracy and efficiency of the network.

We use the above network to carry out experiments at five different locations of rotor friction. The results give us the information about the performance of SFLA and the wavelet neural network. Network prediction results and actual results are listed in Table 2.

The wavelet neural network with the SFLA makes the correct rate high. The error rate is below 3%. As shown in Table 2, the error rates are irregular, which is due to that the fact the training samples are not enough. Some unsuitable parameters of the network also bring about the high error rates. Besides, the lack of de-noising makes the output error inevitable.

6. Conclusions

In this paper, a new algorithm called SFLA is proposed and is used in place of the traditional gradient descent method. Through optimizing the parameters of the wavelet neural network, using the characteristic parameters of acoustic emission, and setting the ratio of the sensor coordinates to signal energy as a neural network input, SFLA performs well when applied

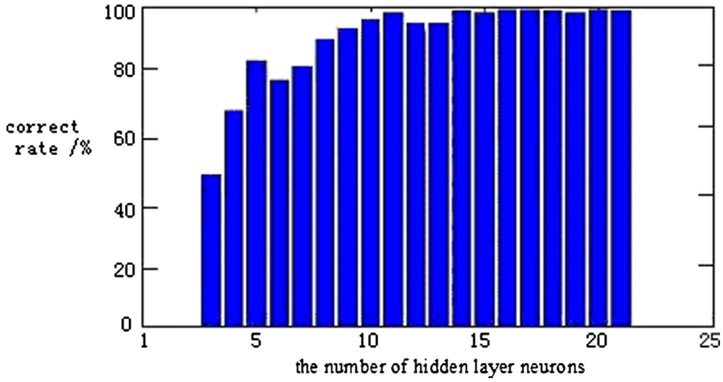


Fig. 4. The relationship between the correct rate and the hidden layer.

Table 2
Network prediction results and actual results.

Actual results (away from the sensor 1)/cm	Network prediction results (cm)	Error rate (%)
5	5.12	2.40
15	14.89	0.73
25	25.03	0.12
35	34.51	1.40
45	44.37	1.40

to acoustic emission source location. Besides, the obtained error variance when increasing the number of hidden layer neurons helps us to determine the optimal number of hidden layer neurons.

The experimental results on the test bed of the rotor system show that the above-designed network is not only good at predicting of the acoustic emission source location, but also displays a satisfying efficiency. However, as a new approach to acoustic emission source location, there may be many other application fields, such as high-temperature detection, geological seismic monitoring, fault localization of the complex structure, rock AE signal analysis, sound source classification, and so on. Besides, SFLA may encounter the local minimum problem. These will be our on-going work for further investigation.

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