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RESEARCH ARTICLE

Hybrid algorithm combining genetic algorithm with back propagation neural network for extracting the characteristics of multi-peak Brillouin scattering spectrum

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Abstract In this study, a hybrid algorithm combining genetic algorithm (GA) with back propagation (BP) neural network (GA-BP) was proposed for extracting the characteristics of multi-peak Brillouin scattering spectrum. Simulations and experimental results show that the GA-BP hybrid algorithm can accurately identify the position and amount of peaks in multi-peak Brillouin scattering spectrum. Moreover, the proposed algorithm obtains a fitting degree of 0.9923 and a mean square error of 0.0094. Therefore, the GA-BP hybrid algorithm possesses a good fitting precision and is suitable for extracting the characteristics of multi-peak Brillouin scattering spectrum.

Keywords fiber optics, Brillouin scattering spectrum, genetic algorithm (GA), back propagation (BP) neural network, multi-peak spectrum

1 Introduction

Optical fiber sensing based on Brillouin scattering spectrum [1] has gained increasing attention in recent years. The traditional Brillouin scattering spectrum reveals a single peak only. Our previous study developed the genetic algorithm quantum-behaved particle swarm optimization (GA-QPSO) algorithm, which shows certain superiority in fitting single-peak Brillouin scattering spectrum [2]. However, in long-distance optical fiber sensing systems, the metrical data of Brillouin scattering spectrum at certain points of optical fiber reveal multiple peaks [3]. In special conditions, the multi-peak Brillouin spectrum is used to discriminate the intersecting sensitivity related to the changes in temperature and strain [4]. An ideal feature extraction algorithm should accurately identify the amount and position of peaks in multi-peak spectrum and correctly plot the consecutive fitting curve. The feature extraction algorithm for single-peak spectrum is obviously unsuitable for multi-peak Brillouin scattering spectrum.

Liang et al. [3] proposed a method of interval segmentation and nonlinear regression method based on the least square method for extracting the characteristics of multi-peak Brillouin scattering spectrum. Zhao et al. [5] proposed a method in which the Brillouin scattering spectrum containing multiple peaks is divided into several single-peak signals first, and then every curve is fitted separately using the Levenberg-Marquardt algorithm. The abovementioned methods can fit multi-peak Brillouin scattering spectrum, but they need to divide the multi-peak spectrum into single-peak signals first prior to the fitting. If too many peaks are revealed or the peaks are too weak, then the accuracy of the position of each peak will be significantly compromised and the calculation process will be complicated. In addition, the segmentation calculation will ignore the relational information between peaks. Aiming at the aforementioned problems, a new hybrid algorithm combining genetic algorithm (GA) with back propagation (BP) neural network (GA-BP) was proposed in this study for extracting the features of multi-peak Brillouin scattering spectrum.

2 Fitting principle of multi-peak Brillouin scattering spectrum

A phenomenon of spectral broadening, such as the Doppler

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broadening and collision broadening, caused by frequent collisions between luminous particles and other particles usually occur in the practical Brillouin scattering optical system [6]. After such a change process, the Brillouin scattering spectrum will lose its ideal Lorentzian spectral profile [7], approach to a Gaussian spectral line, and finally relocate itself somewhere in the middle [8].

In this study, the Pseudo-Voigt function was expressed as a weighted combination of Gaussian and Lorentzian functions [9] and was used as the primary function of unimodal Brillouin scattering spectrum.

$$f_{\mathrm{B}}(v) = k\frac{(\Delta v_{\mathrm{B1}}/2)^2}{(v-v_{\mathrm{B}})^2 + (\Delta v_{\mathrm{B1}}/2)^2} + (1-k)\exp\left[-2.773\left(\frac{v-v_{\mathrm{B}}}{\Delta v_{\mathrm{B2}}}\right)^2\right], \tag{1}$$

where v is the Brillouin frequency, k is the linear weight coefficient, v_{B} is the Brillouin center frequency shift, Δv_{B1} is the Lorentz spectral linewidth, and Δv_{B2} is the Gaussian spectral linewidth. The primary function of multi-peak Brillouin scattering spectrum should be the sum of many primary functions of Brillouin scattering spectrum.

$$g_{\mathrm{B}}(v) = \sum_{i=1}^{M} f_{\mathrm{B}i}(v), \tag{2}$$

where M is the amount of current peak of multi-peak Brillouin scattering spectrum, and $f_{\mathrm{B}i}(v)$ is the corresponding unimodal primary function of each peak.

3 Basic principle of hybrid optimization algorithm

3.1 BP neural network

BP neural network is one of the most widely used neural network models at present [10], and it is a multilayer feed forward neural network for training according to the error BP algorithm. The BP neural network model is shown in Fig. 1.

The model relations are described as follows:

$$O_1 = f_1(W_1 \times x + b_1), \tag{3}$$

$$O_2 = f_2(W_2 \times O_1 + b_2), \tag{4}$$

where x is the sample signal input, W_1 refers to the weights between the input layer and hidden layer, W_2 refers to the weights between the hidden layer and output layer, b_1 is the thresholds of nodes in the hidden layer, b_2 is the thresholds of nodes in the output layer, O_1 is the output of the hidden layer, and O_2 is the output of the output layer. f_1 and f_2 are the delivery functions of BP neural network. f_1 is the tansig(x) function, which is called the S model tangent function; f_2 is the linear function.

The learning process of BP neural network includes the forward propagation of the sample signal and the backward propagation of errors. In the forward propagation, the input sample signal passes through the transfer function of each layer, and this signal is modified by weights and thresholds. The calculated results are obtained in the output layer. The system error is generated by the actual output and expected value, and this error is in accordance with the network link path shown in Fig. 1. The system error will conduct the backward propagation. The weights and thresholds are modified progressively using the error negative gradient descent method. Finally, a set of updated weights and thresholds is obtained. The alternating process of forward and back propagation runs in cycles until the network error meets the requirements of system, and then the BP neural network learning terminates.

3.2 Hybrid optimization algorithm

BP neural network uses the steepest descent method for the backward propagation of errors and modifies the weights according to the negative gradient direction of the error function [11]; thus, BP neural network easily falls into the local minimum state. GA is an iterative optimization algorithm with a certain adaptive capability such that it can improve the global search capability of the system [12]. Therefore, a hybrid optimization algorithm called GA-BP was proposed in this study. In this method, the initial value of weights and thresholds in the BP neural network algorithm can be obtained accurately. The fall of BP neural network into the local minimal state can also be avoided.

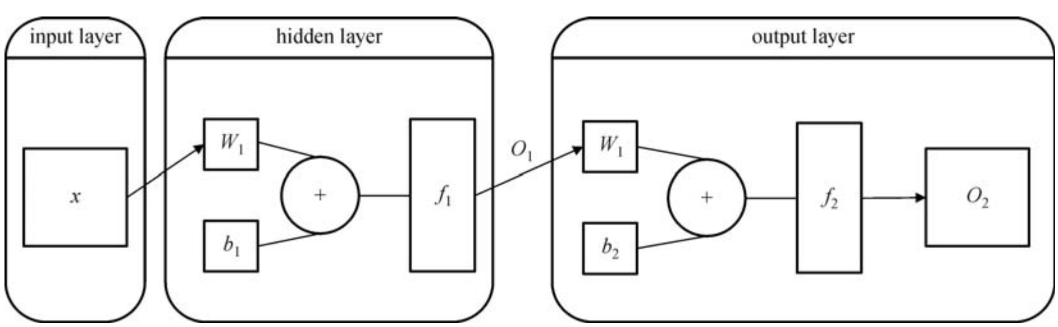

Fig. 1 BP neural network model

The flow diagram of the GA-BP hybrid algorithm is shown in Fig. 2.

The specific steps of the GA-BP hybrid algorithm are as follows.

Step 1: Determine the network topology such as the amount of the input layer, hidden layer, and output layer, and the number of nodes in each layer. Initialize the value of weights and thresholds to provide the basis for the code length in GA.

Step 2: Use GA to encode the initial values of BP neural network and then initialize the population and produce the chromosomes. Use the error produced by the network output value and expected value as the fitness value.

Step 3: Apply the fitness value to the evaluation index. Use the roulette wheel method to select the chromosomes in the population such that a new better population can be obtained. Introduce the chromosomes with better fitness value into the new population.

Step 4: After the selection operation, use the crossover operation as the current chromosomes in the population. Consequently, the information exchange and location between each chromosome can be sufficiently updated such that better chromosomes can be derived.

Step 5: After the crossover operation, the mutation operation for the current chromosomes can produce excellent chromosomes in the population. Accordingly, the global search capability of GA and the convergent speed of GA to the global optimal solution can be improved.

Step 6: Calculate the fitness value of the current chromosomes again. Compare the fitness value of the same chromosome in different genetic ages, and the individual optimal solution is the chromosome with a better fitness value in the population; sort the fitness value of all chromosomes in the same genetic age, and the global optimal solution is the chromosome with the best fitness value in the population.

Step 7: If the global optimal solution meets the system requirements or the algorithm achieves the number of evolutionary iteration, then stop the GA part to output the global optimal solution. Otherwise, repeat Steps 3–6.

Step 8: When the GA part terminates, the global optimal solution corresponds to the chromosome, which contains all the weights and thresholds of the optimized BP neural network. For the write operation, the optimized weights and thresholds are assigned to the BP neural network algorithm.

Step 9: Use the BP neural network algorithm optimized by GA in the forward propagation of the sample signal. The BP of errors is used to modify and further optimize the weights and thresholds.

Step 10: If the error value of BP neural network meets

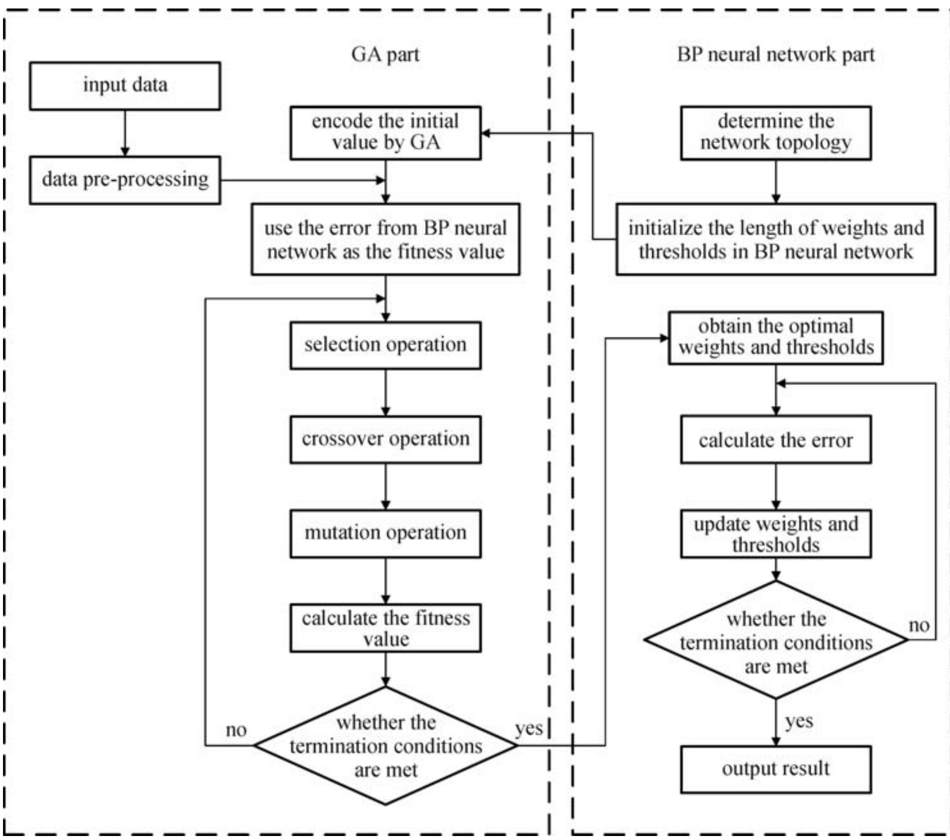

Fig. 2 Flow diagram of the GA-BP hybrid algorithm

the system requirements, then the BP neural network algorithm stops and outputs the final result. Otherwise, repeat Step 9.

4 Simulation analysis of the GA-BP hybrid algorithm

The data of multi-peak Brillouin scattering spectra under different circumstances were processed using the GA-BP hybrid algorithm to determine its feasibility and applicability for fitting multi-peak Brillouin scattering spectrum. Suppose that the linewidth $\Delta\nu_{B1} = \Delta\nu_{B2} = 40$ MHz. White Gaussian noise was added to the system to simulate the actual measurement environment. The data of multi-peak Brillouin scattering spectrum were fitted with signal-to-noise ratios (R_{sn}) of 20, 25, and 30 dB. The fitting results are shown in Fig. 3 and Table 1.

Assume that the R_{sn} values are 20, 25, and 30 dB, and the multi-peak Brillouin scattering spectra are fitted in different conditions. The fitting curve with 25 dB is shown in Fig. 4, and the overall fitting results are shown in Table 2.

Figures 3–4 and Tables 1–2 show that the GA-BP hybrid algorithm can accurately identify the amount and position of peaks in multi-peak spectrum. Moreover, the algorithm can correctly plot the consecutive fitting curve of multi-peak Brillouin scattering spectra, which are based on the input samples with different R_{sn} values and linewidths. The fitting results with three different values of R_{sn} show that the Brillouin frequency shift error of each peak was small and decreased with the increase in R_{sn}. The Brillouin frequency shift errors of each peak with 30 dB were 0.6, 0.5, and 0.8 MHz, respectively. By use of the new hybrid algorithm, a better fitting degree (R^2) was obtained, and the mean square errors (MSEs) under different conditions were all less than 0.1. The results show that the GA-BP hybrid algorithm is feasible and applicable for the feature extraction of multi-peak Brillouin scattering spectrum.

The superiority of the GA-BP hybrid algorithm to three other methods including particle swarm optimization (PSO) algorithm, GA-QPSO algorithm, and BP neural network was tested with $R_{sn} = 30$ dB. The fitting curve is shown in Fig. 5, and the overall fitting results are shown in Table 3.

Figure 5 and Table 3 show that, compared with the three other algorithms, the GA-BP hybrid algorithm obtained the maximum fitting degree of 0.9899 and the minimum MSE of 0.0186; however, its running time was the maximum at 11.53 s.

5 Experimental results and analysis

The principle diagram of the distributed optical fiber Brillouin scattering spectrum system is shown in Fig. 6.

Figure 6 shows that the light emitted by laser (DFB-LD) is divided into two paths through the optical fiber coupler. One path is the probe light, and the other is the reference light. The probe light is modulated into pulse light waves using the acousto-optic modulator (AOM). Given that the pulse light is weak, the waves of this light are amplified using the erbium-doped fiber amplifier (EDFA). The amplified light will then enter into the sensing optical fiber through the polarization controller (PC) and the circulator. The reference light passes through the microwave source and electro-optic modulator (EOM), which is controlled by direct current (DC) stabilized power supply to be modulated. To meet the frequency response range of photoelectric detector, a coherent operation must also be

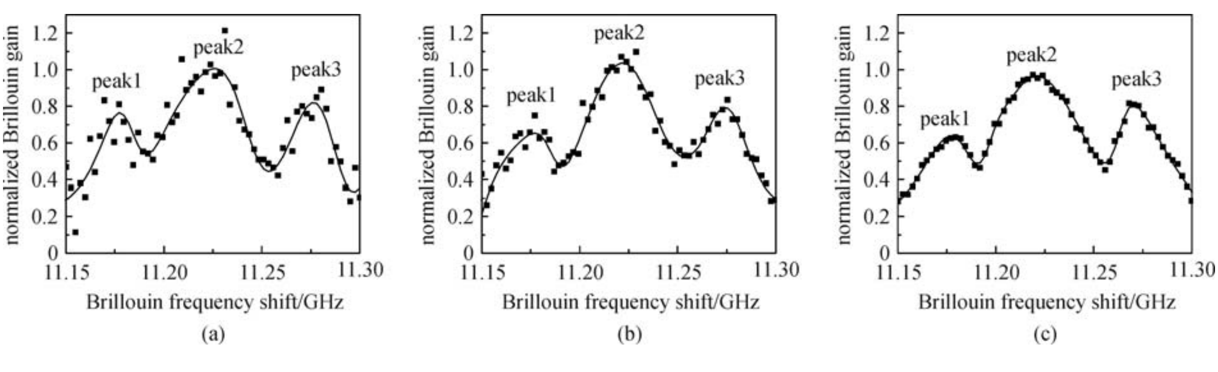

Fig. 3 Comparison of fitting results among three different values of R_{sn}: (a) $R_{sn} = 20$ dB; (b) $R_{sn} = 25$ dB; and (c) $R_{sn} = 30$ dB

Table 1 Fitting results among three different values of R_{sn}

R_{sn}/dB	R^2	MSE	Brillouin frequency shift error/MHz		
			peak1	peak2	peak3
20	0.8240	0.0912	1.4	1.5	1.3
25	0.9275	0.0540	1.0	1.1	1.0
30	0.9899	0.0186	0.6	0.5	0.8

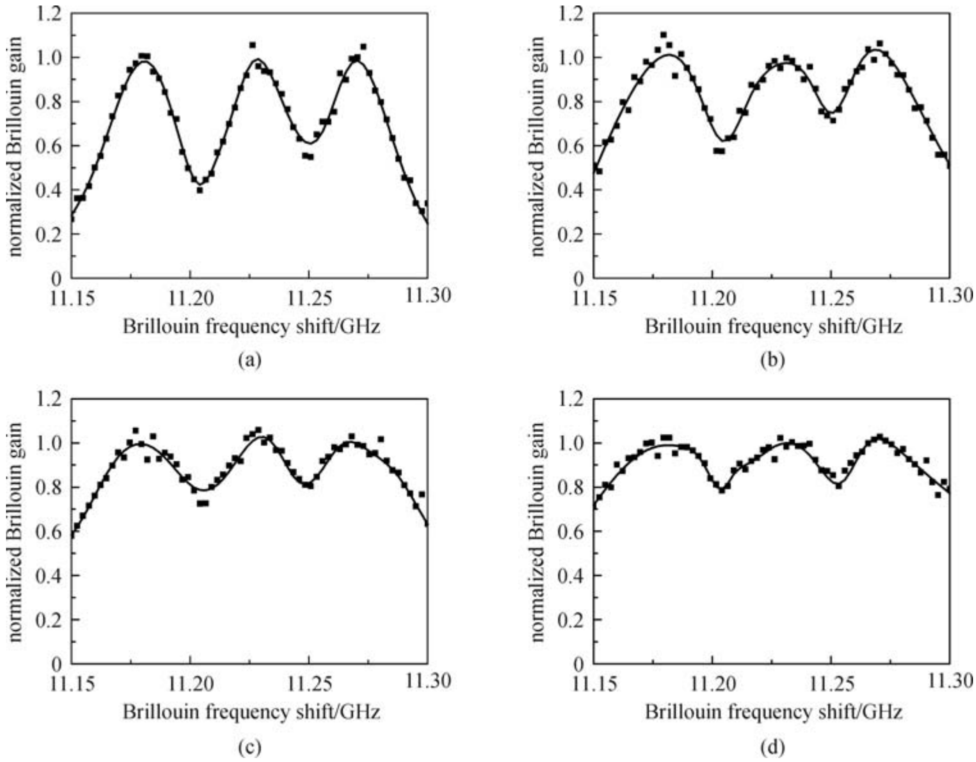

Fig. 4 Fitting results of multi-peak Brillouin scattering spectrum in different conditions: (a) $\Delta\nu_{B1} = \Delta\nu_{B2} = 40$ MHz; (b) $\Delta\nu_{B1} = \Delta\nu_{B2} = 60$ MHz; (c) $\Delta\nu_{B1} = \Delta\nu_{B2} = 80$ MHz; and (d) $\Delta\nu_{B1} = \Delta\nu_{B2} = 100$ MHz

Table 2 Fitting results of different parameters

R_{sn}/dB	linewidth/MHz	R^2	MSE
20	40	0.8681	0.0913
	60	0.8345	0.0741
	80	0.9576	0.0724
	100	0.8515	0.0740
25	40	0.9814	0.0297
	60	0.9550	0.0337
	80	0.9314	0.0297
	100	0.9047	0.0240
30	40	0.9690	0.0380
	60	0.9552	0.0328
	80	0.9121	0.0341
	100	0.9083	0.0294

conducted between the modulated light from the polarization scrambler (PS) and the Brillouin backscattering signal that returns from the circulator. The double balance photoelectric detector (DBPD) changes the optical signals after coherent operation into electrical signals. Finally, the digital acquisition (DAQ) system is used to obtain the experimental data of Brillouin scattering spectrum.

In the experiment, the length of the ordinary single-mode fiber was measured at 30 km. At its 25 km location, the heating box was applied to heat the two sections of optical fiber with 100 m length of 100 m apart. The heating temperatures were 50°C and 80°C. The rest of the fiber was placed in a room temperature environment at 25°C. The measured multi-peak Brillouin scattering spectrum went through the photoelectric conversion and was collected by the high-speed data acquisition card. The experimental data of multi-peak Brillouin scattering spectrum collected by the operations described above were used as a sample and processed by the PSO algorithm, GA-QPSO algorithm, BP neural network, and GA-BP hybrid algorithm. The fitting curves are shown in Fig. 7, and the fitting results are shown in Table 4.

Figure 7 and Table 4 show that the basis function of PSO algorithm or GA-QPSO algorithm had only one parameter of the central frequency shift of the Brillouin scattering spectrum. When processing the experimental data containing multiple center frequency shifts of Brillouin scattering spectrum, the PSO algorithm or GA-QPSO algorithm can only randomly select one center frequency shift as a benchmark at the beginning of population initialization and then carry on with the fitting. Therefore, the fitting effect of the two algorithms to the multi-peak Brillouin scattering spectrum was weak. BP neural network can fit the multi-peak Brillouin scattering spectrum completely. However, during the correction process of the weights and thresholds in the network BP, the BP neural network algorithm easily falls into the local minimum state. Furthermore, the algorithm can only conduct a deep search on the peak on

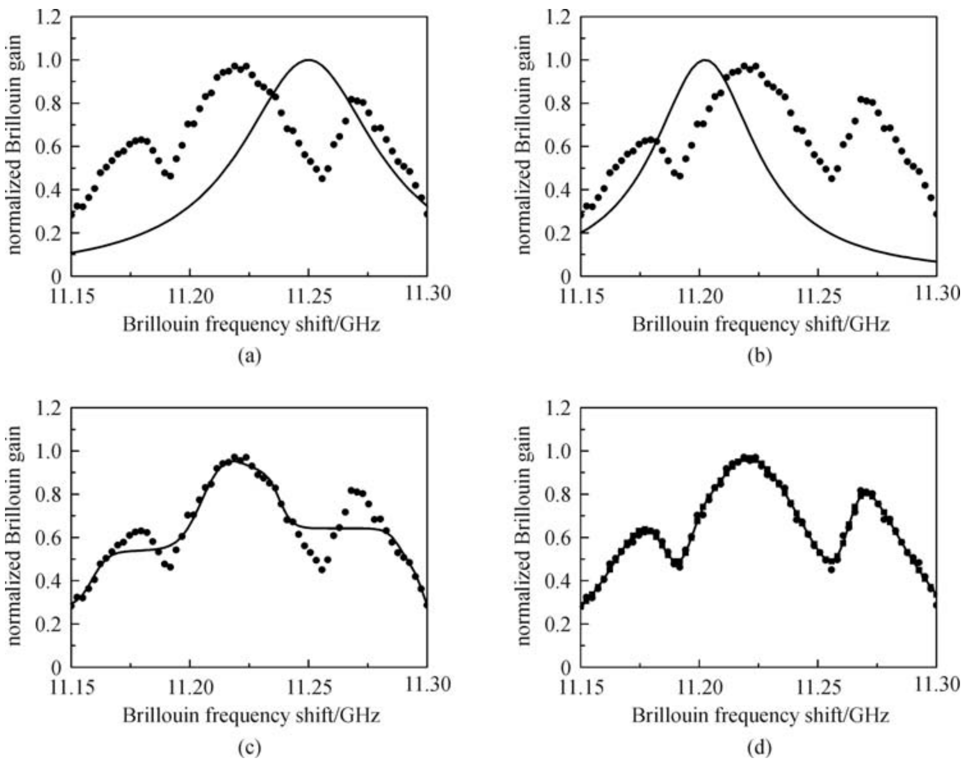

Fig. 5 Comparison of fitting results among four algorithms: (a) PSO; (b) GA-QPSO; (c) BP; and (d) GA-BP

Table 3 Comparison of MSE, R^2, and running time among four algorithms in simulation results

algorithm	R^2	MSE	running time/s
PSO	0.4261	0.3076	2.32
GA-QPSO	0.4096	0.4377	10.20
BP	0.8704	0.0664	3.27
GA-BP	0.9899	0.0186	11.53

the left and deficiently learn about the peak on the right. After combining GA with BP neural network, the GA part uses its selection, crossover, and mutation operations to correct the determination of initial value of the weights and thresholds in the BP neural network part adequately. The GA part provides the BP neural network part with in-depth learning capability and improves the global search capability and the convergent speed to the global optimal solution of BP neural network. The GA part enables the optimized BP neural network part to determine the amount and position of peaks in multi-peak Brillouin scattering spectrum accurately and plot the consecutive multi-peak fitted curve correctly. However, the running time of the GA-BP hybrid algorithm was 10.76 s, which was slower than other algorithms. The main reason is that GA needs much time to perform its selection, crossover, and mutation

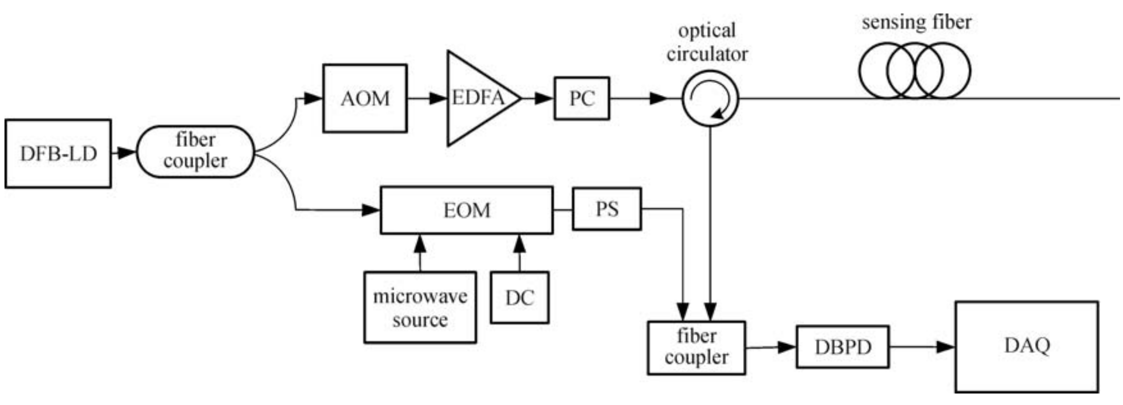

Fig. 6 Principle diagram of the experimental system. DFB-LD: distributed feedback-laser diode, AOM: acousto-optic modulator, EDFA: erbium-doped fiber amplifier, PC: polarization controller, EOM: electro-optic modulator, DC: direct current, PS: polarization scrambler, DBPD: double balance photoelectric detector, DAQ: digital acquisition

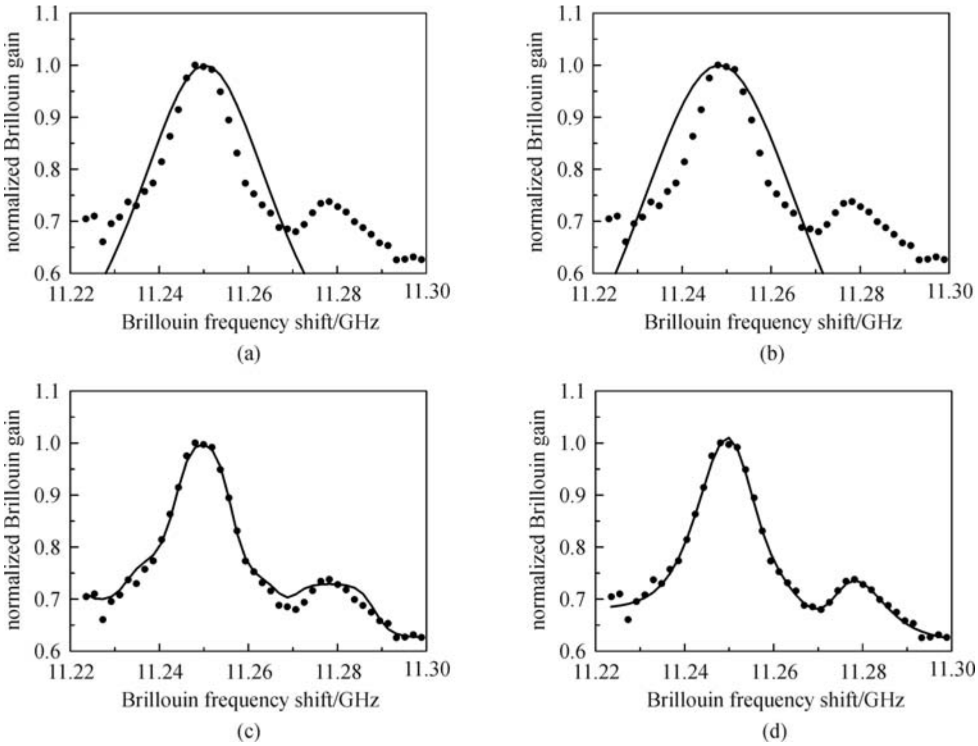

Fig. 7 Comparison of experimental results among four algorithms: (a) PSO; (b) GA-QPSO; (c) BP; and (d) GA-BP

Table 4 Comparison of MSE, R^2, and running time among four algorithms in experimental results

algorithm	R^2	MSE	running time/s
PSO	0.6401	0.1663	2.02
GA-QPSO	0.3809	0.1937	10.09
BP	0.9836	0.0137	3.91
GA-BP	0.9923	0.0094	10.76

operations to conduct a global search and provide a better initial value for the BP neural network algorithm. The frequency sweep method is performed at regular frequency intervals at a certain frequency range. The measuring time of multi-peak Brillouin scattering spectrum includes not only the time for acquiring the multi-peak Brillouin scattering spectra but also the time for improving R_{sn} and other data processing. Thus, the actual measurement process is generally more than tens of minutes. Therefore, compared with the long system acquisition time, the data processing of the GA-BP hybrid algorithm in 10 s is nearly negligible. Moreover, in analyzing the feature extraction of multi-peak Brillouin scattering spectrum, focusing on the whole continuity of the multiple peaks is more important than paying attention to the relative variation in Brillouin frequency shift in each peak. Thus, an ideal feature extraction algorithm should not only accurately identify the amount and position of peaks in multi-peak spectrum but also present a good capability for fitting multi-peak Brillouin scattering spectrum. Compared with the three other algorithms, the GA-BP hybrid algorithm obtained the maximum fitting degree of 0.9923 and the minimum MSE of 0.0094. Therefore, the GA-BP hybrid algorithm presents certain superiority in fitting multi-peak Brillouin scattering spectrum.

6 Conclusions

The simulation and experimental results show that the GA-BP hybrid algorithm can accurately determine the amount and position of peaks in multi-peak Brillouin scattering spectrum accurately and plot the consecutive multi-peak fitted curves correctly. Compared with the three other algorithms for fitting the same set of data from multi-peak Brillouin scattering spectrum, the GA-BP hybrid algorithm obtained the maximum fitting degree of 0.9923 and the minimum MSE of 0.0094. Therefore, the novel hybrid algorithm not only optimizes the learning capability of BP neural network but also presents the advantages of good fitting precision and strong applicability. The proposed algorithm can be used in the feature extraction of multi-peak Brillouin scattering spectrum in special conditions.

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References

1. Zhang Y, Li J, Meng C, Chen X, Dong W, Zhang X, Ruan S, Chen W. Hybrid optimization algorithm of Brillouin scattering spectra fitting. High Power Laser and Particle Beams, 2015, 27(9): 091013-1–091013-7
2. Zhang Y, Xu J, Fu X. Method of Brillouin scattering spectrum character extraction based on genetic algorithm and quantum-behaved particle swarm optimization hybrid algorithm. Chinese Journal of Lasers. 2016, 43(2): 0205002-1–0205002-10
3. Liang H, Zhang X, Li X, Lu Y. Design and implementation of data fitting algorithm for Brillouin back scattered-light spectrum data. Acta Photonica Sinica, 2009, 38(4): 875–879
4. Liu X, Bao X. Brillouin spectrum in LEAF and simultaneous temperature and strain measurement. Journal of Lightwave Technology, 2012, 30(8): 1053–1059
5. Zhao L, Xu Z, Li Y. An accurate and rapid method for extracting parameters from multi-peak Brillouin scattering spectra. Sensors and Actuators A, Physical, 2015, 232: 276–284
6. Yin Z, Wu C, Gong W, Gong Z, Wang Y. Voigt profile function and its maximum. Acta Physica Sinica, 2013, 62(12): 123301-1–123301-5
7. Niklès M, Thévenaz L, Robert P A. Brillouin gain spectrum characterization in single-mode optical fibers. Journal of Lightwave Technology, 1997, 15(10): 1842–1851
8. Zhang Z, Zhang P, Han S. Strain characteristic extraction of Brillouin spectrum based on general regression neural network. Chinese Journal of Lasers, 2013, 40(s1): s105008-1–s105008-6
9. Ida T, Ando M, Toraya H. Extended Pseudo-Voigt function for approximating the Voigt profile. Journal of Applied Crystallography, 2000, 33(6): 1311–1316
10. Xie Z, Li X, Li C, Feng C. Forward kinematics of 3-PPR parallel mechanism based on displacement compensation of BP neural network. Computer Integrated Manufacturing Systems, 2015, 21(7): 1804–1809
11. Wang S, Wang X, Chen D, Wei M, Wang Z. Application of GA-BP neural network in detection of trace phosphate. Chinese Journal of Lasers, 2015, 42(5): 0515001-1–0515001-6
12. Zhang J, Wan W, Zheng Z, Gan X, Zhu X. Research on X band extended cosecant squared beam synthesis of micro-strip antenna arrays using genetic algorithm. Acta Physica Sinica, 2015, 64(11): 110504-1–110504-9

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