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Fault diagnosis of analog circuit based on wavelet transform and neural network

HUI WANG

Nanyang Institute of Technology
China
e-mail: wh_huiwang@yeah.net

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Abstract: Analog circuits need more effective fault diagnosis methods. In this study, the fault diagnosis method of analog circuits was studied. The fault feature vectors were extracted by a wavelet transform and then classified by a generalized regression neural network (GRNN). In order to improve the classification performance, a wolf pack algorithm (WPA) was used to optimize the GRNN, and a WPA-GRNN diagnosis algorithm was obtained. Then a simulation experiment was carried out taking a Sallen–Key bandpass filter as an example. It was found from the experimental results that the WPA could achieve the preset accuracy in the eighth iteration and had a good optimization effect. In the comparison between the GRNN, genetic algorithm (GA)-GRNN and WPA-GRNN, the WPA-GRNN had the highest diagnostic accuracy, and moreover it had high accuracy in diagnosing a single fault than multiple faults, short training time, smaller error, and an average accuracy rate of 91%. The experimental results prove the effectiveness of the WPA-GRNN in fault diagnosis of analog circuits, which can make some contributions to the further development of the fault diagnosis of analog circuits.

Key words: analog circuit, fault diagnosis, neural network, wavelet transform

1. Introduction

A circuit fault is a very important problem. More than 80% of electronic equipment faults occur in analog circuits, so it is very important to improve the level of fault diagnosis. However, due to the complexity of analog circuits, it is very difficult [1]. At present, the main problems are difficulty in establishing fault models caused by continuous parameters [2], complex calculation caused by many non-linear problems [3], high difficulty in fault distinguishing caused by component tolerance [4], difficult location caused by limited test points, high sensitivity to the environment such as temperature and noise, and existence of feedback loop. Restricted by these problems, the accuracy of fault diagnosis is greatly affected. With the development of science and technology, the fault diagnosis of analog circuits has been studied more and more deeply. Ma *et al.* [5] proposed a diagnosis method based on a binary support vector machine (BSVM), tested the method through two simulation circuits, and found that the method had better accuracy. Deng *et al.* [6] designed a method of Wigner–Ville distribution (WVD) based on a subband Volterra model. The feature vectors were extracted by the WVD and then classified by a hidden Markov model (HMM). The simulation results showed that the method was effective. Zhang *et al.* [7] diagnosed faults by matrix perturbation analysis which could diagnose complex circuits directly without training samples and proved the feasibility of the method by experiments. Luo *et al.* [8] proposed an improved Gauss mixture HMM classifier with three random sequences as feature samples. An analog circuit fault diagnosis is a key and difficult problem in the field of an electronic system. Improving the analog circuit fault diagnosis technology has important significance to the automatic fault diagnosis of an electronic circuit and the overall development of the electronic system. In the perspective of the current research, the existing methods are mostly aimed at a single soft fault in the circuit, but in practice, there are not only single soft faults but also multiple soft faults in the circuit. This study combined a wavelet transform with a neural network to diagnose single and multiple faults in analog circuits and proved the advantages of the wavelet transform in the extraction of fault characteristics through experiments. This work makes some contributions to the development of the analog circuit fault diagnosis field and offers some theoretical bases for improving the diagnosis level of analog circuit faults and realizing the safe and reliable development of an electronic system.

2. Wavelet transform feature extraction

A wavelet transform can perform signal analysis in a time-frequency domain [9], which has good application prospects in feature extraction [10] and also has an extensive application in fault diagnosis [11, 12]. Its principle is as follows.

It is supposed that $\psi(t)$ is a square integrable function

$$\int_{-\infty}^{\infty} \frac{|\psi(\varpi)|}{|\varpi|} \mathrm{d}\varpi < \infty,$$

where $\psi(\varpi)$ stands for the Fourier transform of $\psi(t)$, i.e. the stretching and translation transform of $\psi(t)$. Then

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right)$$

is obtained, where a, b are the scaling and translation factors. $\psi_{a,b}(t)$ is called the wavelet basis function. The wavelet transform means taking $\psi_{a,b}(t)$ and signal $f(t)$ which needs analysis as inter products, i.e.

$$WT_f\,(a,b) \leq f(t), \qquad \psi_{a,b}(t) \geq \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t)\psi^*\left(\frac{t-b}{a}\right) \mathrm{d}t, \quad a > 0, \tag{1}$$

where $*$ stands for the conjugate.

The specific steps of the feature extraction of a wavelet transform are as follows:

1. A simulation circuit is established, and a fault signal is collected.
2. The mother wavelet function (dbN wavelet in this study) is selected, and the wavelet decomposition is carried out.
3. High frequency coefficient $\left\{h^1,\ h^2, \cdots,\ h^N\right\}$ and low frequency coefficient d^N are obtained by the decomposition of an N-layer wavelet transform.
4. The square sum of the absolute value of the low-frequency coefficient sequence of the N-th layer is expressed as D_N. The square sum of the absolute value of the high-frequency coefficient sequence of the j-th layer is expressed as H_j.

$$D_N = \sum_{l=1}^{m} |d_N|^2, \qquad H_j = \sum_{l=1}^{n} \left|h_l^j\right|^2, \tag{2}$$

where m stands for the number of d^N and n stands for the number of h^j.

5. A fault feature vector $\left\{\overline{H}_1, \overline{H}_2, \cdots, \overline{H}_N, \overline{D}_N\right\}$ is obtained after normalization on D_N and H_j.

3. Neural network fault diagnosis

3.1. Generalized regression neural network

A generalized regression neural network (GRNN) [13] has great advantages in fault diagnosis because of its simple structure and high learning speed, and its network structure is shown in Fig. 1.

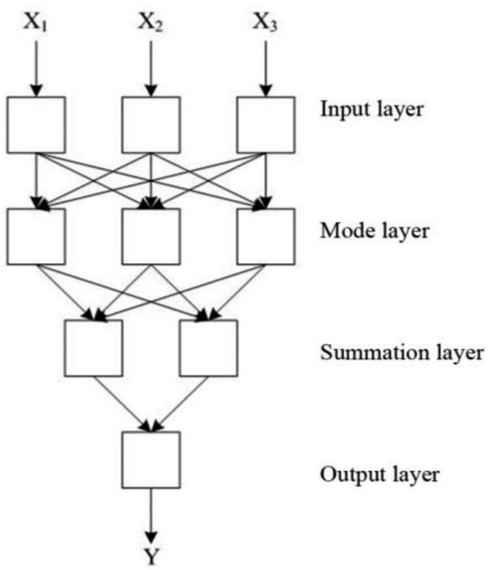

Fig. 1. The structure of GRNN

The input of the network is $X = [X_1, X_2, \cdots, X_n]^T$, and the output is Y. The transfer function of the i-th neuron of the mode layer can be expressed as:

$$P_i = e^{\left[-(X-X_i)^T (X-X_i)/2\sigma^2\right]},$$

where σ stands for the hyper-parameter. The neuron of the summation layer includes the neuron algebra sum S_D and weighted sum S_N of the mode layer. The output of the output layer is

$$Y = \frac{S_N}{S_D}.$$

3.2. WPA-GRNN algorithm

A GRNN does not need to update the weights and thresholds in training, and the output results are only related to super-parameter σ. Therefore, the determination of a hyper-parameter is the focus of the GRNN. In this study, a wolf pack algorithm (WPA) was selected to optimize the hyper-parameter.

The WPA is a simulation of wolf hunting phenomena in nature [14]. It has good global convergence and can avoid falling into local optimum. It has a good application in parameter optimization. The algorithm which searches for the hyper-parameter of the GRNN through the WPA is defined as a WPA-GRNN algorithm. The steps of the algorithm are as follows:

1. Parameters are initialized, the leader wolf is selected, and the perceived prey odor of the leader wolf is set as Y_{lead}.
2. s scouting wolves with the optimal fitness are selected from the remaining wolves for wandering around, and the perceived prey odor of the wolves is set as Y_i. When $Y_i > Y_{\text{lead}}$ or it reaches the maximum wandering times $T_{\max}$, wandering stops.
3. The fierce wolf gets close to prey. When $Y_i > Y_{\text{lead}}$, the fierce wolf replaces the leader wolf, $Y_{\text{lead}} = Y_i$; otherwise it continues to get close to prey until $d_{is} < d_{\text{near}}$, where d_{is} stands for the distance between the fierce wolf and leader wolf and d_{near} stands for the determined distance. The positions of all the wolves are updated, and then they siege.
4. The prey are classified in order from strong to weak, and weak wolves are eliminated; a new leader wolf generates. Then the wolf pack is updated.
5. The position of the leader wolf, i.e. the optimal solution (the optimal hyper-parameter σ of a GRNN) is output when the preset accuracy or the maximum iteration times is reached; otherwise, it turns to step 2.
6. A GRNN network is established using the optimal hyper-parameter σ for fault classification.

4. Example analysis

4.1. Sample collection

A typical analog circuit, a Sallen–Key bandpass filter [15], was used to verify the proposed method. The circuit diagram and the parameters of different components are shown in Fig. 2.

The circuit is simulated by the PSPICE software. The tolerance of capacitor resistance is 10% and 5%, the test point is the output point of the circuit and the output voltage is the test signal.

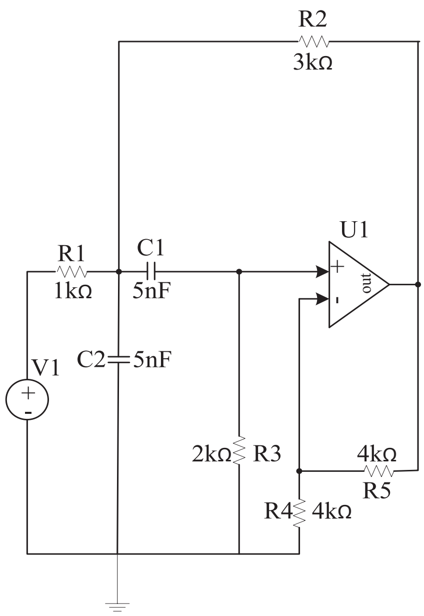

Fig. 2. Sallen–Key bandpass

Through sensitivity analysis, it can be found that C1, C2, R2 and R3 have the greatest influence on the voltage. Therefore, the four circuit faults include C1↑, C1↓, C2↑, C2↓, R2↑, R2↓, R3↑, R3↓, C3↑C4↑, C3↑C4↓, C3↓R3↓, C4↑R2↓, C4↓R3↑ and R2↓R3↑, where ↑ means that the failure value of components is larger than 50% of the standard and ↓ means that the failure value is smaller than 50% of the standard.

A Monte-Carlo analysis was carried out 50 times for each of the above faults and normal circuits. 750 eigenvalues were collected at a time, and then 40 of them were selected as original data, totally 600 groups of data. The first 500 groups were used as training samples, and the last 100 groups were used as test samples. The data was processed by three-layer db3 wavelet decomposition, and the decomposition coefficient sequence of nodes (3, 0), (3, 1), (2, 1) and (1, 1) were extracted. The extracted eigenvectors are shown in Table 1.

4.2. Fault coding

The nodes of the input layer of the GRNN was 4, that was, the 4-dimensional eigenvector in Table 1. The output of the GRNN was the fault result, and the network accuracy was 0.001. The fault coding is shown in Table 2.

4.3. Diagnostic results

To verify the advantages of a wavelet transform in the extraction of fault characteristics, extraction of fault characteristics was performed on same data using wavelet transform and wavelet packet processing. Then the faults were classified using a GRNN. The results are shown in Table 3.

Table 1. Extraction results of wavelet transform features

Fault	(3, 0)	(3, 1)	(2, 1)	(1, 1)
Normal	0.805	0.108	0.057	0.030
C1↑ (C1 failure value larger than 50% of the standard)	0.787	0.116	0.058	0.029
C1↓ (C1 failure value smaller than 50% of the standard)	0.809	0.105	0.054	0.030
C2↑ (C2 failure value larger than 50% of the standard)	0.756	0.117	0.058	0.029
C2↓ (C2 failure value smaller than 50% of the standard)	0.797	0.117	0.058	0.029
R2↑ (R2 failure value larger than 50% of the standard)	0.803	0.112	0.057	0.029
R2↓ (R2 failure value smaller than 50% of the standard)	0.796	0.108	0.066	0.031
R3↑ (R3 failure value larger than 50% of the standard)	0.786	0.118	0.060	0.028
R3↓ (R3 failure value smaller than 50% of the standard)	0.808	0.106	0.057	0.029
C3↑C4↑ (C3 failure value larger than 50% of the standard; C4 failure value larger than 50% of the standard)	0.526	0.584	0.362	0.274
C3↑C4↓ (C3 failure value larger than 50% of the standard; C4 failure value smaller than 50% of the standard)	0.426	0.852	0.123	0.521
C3↓R3↓ (C3 failure value smaller than 50% of the standard; R3 failure value smaller than 50% of the standard)	0.562	0.256	0.521	0.325
C4↑R2↓ (C4 failure value larger than 50% of the standard; R2 failure value smaller than 50% of the standard)	0.458	0.465	0.412	0.242
C4↓R3↑ (C4 failure value smaller than 50% of the standard; R3 failure value larger than 50% of the standard)	0.498	0.822	0.821	0.516
R2↓R3↑ (R2 failure value smaller than 50% of the standard; R3 failure value larger than 50% of the standard)	0.408	0.567	0.498	0.267

It was found from Table 3 that the accuracy of fault classification was significantly higher after the application of a wavelet transform, indicating that the wavelet transform could more effectively improve the accuracy of fault classification.

To verify the effectiveness of a WPA-GRNN, firstly, the performance of the GRNN optimized by a WPA was analyzed, and the optimization effects of a GA and the WPA were compared. The results are shown in Fig. 3.

It was found from Fig. 3 that the GRNN reached the preset accuracy after 30 times of iterations when it was not improved, the preset accuracy achieved at the 8th iteration when the WPA was used to optimize the GRNN and at the 28-th iteration when the GA was used to optimize the GRNN, which proved the effectiveness of the WPA optimization.

Experiments were carried out on three algorithms, the GRNN, GA-GRNN and WPA-GRN for 10 times, and the changes of the fault diagnosis accuracy are shown in Fig. 4.

Table 2. Fault coding

Fault	**Code**
Normal	0000
C1↑	0001
C1↓	0010
C2↑	0011
C2↓	0100
R2↑	0101
R2↓	0110
R3↑	0111
R3↓	1000
C3↑C4↑	1001
C3↑C4↓	1010
C3↓R3↓	1100
C4↑R2↓	1101
C4↓R3↑	1110
R2↓R3↑	1011

Table 3. Fault classification results

Method	**Accuracy**
Wavelet transform-GRNN	81.2%
Wavelet packet-GRNN	76.4%

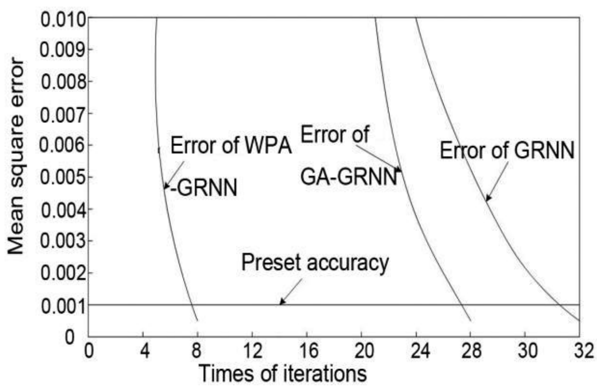

Fig. 3. Comparison of optimization effects between WPA and GA

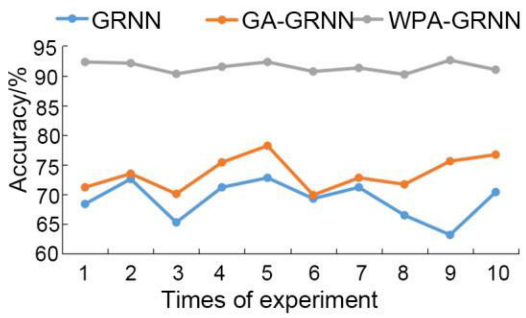

Fig. 4. Changes of accuracy of different algorithms

It was found from Fig. 4 that the accuracy rates GRNN and GA-GRNN were below 80%, and the fluctuations were large; the accuracy of the WPA-GRNN was significantly higher than that of the GRNN and GA-GRNN and stabilized above 90%. To further verify the reliability of the algorithm in the fault diagnosis, the 10-th experiment was taken as the example to compare the diagnostic accuracy of different algorithms for different faults, and the results are shown in Table 4.

Table 4. Fault diagnosis results

Fault	**Accuracy of algorithm/%**		
	GRNN	GA-GRNN	WPA-GRNN
Normal	80.1	85.5	96.6
C1↑	72.3	75.6	93.2
C1↓	71.2	78.3	95.4
C2↑	73.6	77.2	94.6
C2↓	72.9	79.4	92.6
R2↑	74.3	78.5	95.7
R2↓	75.2	79.2	96.8
R3↑	76.2	77.4	95.2
R3↓	74.6	78.6	94.7
C3↑C4↑	61.2	71.2	85.6
C3↑C4↓	65.5	73.8	86.2
C3↓R3↓	63.7	75.4	84.3
C4↑R2↓	64.5	74.2	85.1
C4↓R3↑	66.2	73.1	83.6
R2↓R3↑	64.3	73.6	84.9

It was found from Table 4 that the accuracy of the diagnosis results was not high when the GRNN was used for fault diagnosis. After the GA optimization, the accuracy of the algorithm was obviously improved. Taking the normal circuit as an example, the diagnosis rate was 85.5% when the GA-GRNN was used, while the WPA-GRNN had a higher accuracy rate than the GA-GRNN, which was 96.6%. In addition, according to the diagnosis results of different faults, the diagnosis performance of a single fault was better than that of multiple faults. As to the diagnosis results of the WPA-GRNN, the highest accuracy of a single fault was 96.8% and the lowest was 92.6%, while the highest accuracy of multiple faults was 86.2% and the lowest was 83.6%.

The performance comparison of the algorithms is shown in Table 5.

Table 5. Performance comparison of algorithms

Algorithm	**GRNN**	**GA-GRNN**	**WPA-GRNN**
Training time/s	32.1	14.6	3.2
Training error/%	3.6	1.3	0.2
Accuracy/%	70.4	76.7	91.0

It was found from Table 5 that the training time of the WPA-GRNN was shorter compared to the GRNN and GA-GRNN, it could complete training in 3.2 s, with a smaller training error, and the fault diagnosis accuracy of the WPA-GRNN was 29.26% and 18.64% higher than that of the GRNN and GA-GRNN. It was found that the WPA-GRNN had higher calculation efficiency and diagnosis accuracy in the diagnosis of faults and could accurately diagnose analog circuit faults in a short time, which had stronger practicability and better application effect in reality.

5. Discussion

With the development of technology, the scale of an electronic system is expanding, and the complexity and integration are also increasing. Traditional fault diagnosis methods cannot meet the needs of current circuits. Moreover, compared with digital circuits, the fault diagnosis of analog circuits is more difficult [16] and the current diagnosis methods are less mature. Therefore, it is very important to study the diagnosis of analog circuits, for example, it can effectively improve the reliability of an electronic system and saving energy [17].

In order to improve the classification performance of a GRNN algorithm, a WPA algorithm was used to optimize the super-parameter of the GRNN, and then the optimal super-parameter was input into the GRNN. In the simulation experiment, firstly, the advantages of a wavelet transform was analyzed, and it was compared with the wavelet packet processing. It was found that the accuracy rate of fault classification was higher in the extraction of fault characteristics with the wavelet transform, indicating that the wavelet transform was reliable. Then the optimization performance of the WPA was analyzed firstly. Compared with a GA algorithm, it was found that the WPA could reach the preset accuracy quickly and had better optimization performance. It was found from Table 4 that the diagnostic accuracy of the WPA-GRNN was the highest, followed by the GA-GRNN and the GRNN, and the diagnostic accuracy of a single fault was slightly higher than that of multiple faults. The diagnostic accuracy of this single fault was more than 90%, the highest was 96.8%, while that of the multiple faults was about 85%, the highest was 86.2%, and the lowest was 83.6%. It shows that the diagnostic difficulty of multiple faults was greater than that of a single fault. In the comparison of the performance of different algorithms, the training time of the WPA-GRNN was 3.2 s, the training error was 0.2%, and the average accuracy was 91.0%, which was better than the GRNN and GA-GRNN algorithm. Therefore the method designed in this study was reliable.

Based on the experimental results, the main achievements of this study can be summarized as follows:

1) it proves the advantages of a wavelet transform in the extraction of fault characteristics;
2) it realizes the optimization of GRNN classification performance through a WPA algorithm;
3) it proves the effectiveness of the proposed method through a simulation experiment, and an accuracy rate of 91% is obtained.

Fault diagnosis of analog circuits is a complex problem. Although some achievements have been made in this study, there are still many problems to be solved. For example, how to further improve the performance of neural networks and how to further improve the diagnostic accuracy of multi-fault types need to be discussed; the method was only validated in simulation circuits, but it still needs to be applied in practical circuits to deeply study the reliability of the algorithm.

With the development of science and technology, more and more new technologies have been applied in the fault diagnosis of analog circuit, especially artificial intelligent technologies such as a neural network and genetic algorithm, which will make breakthrough progress for the analog circuit fault diagnosis technology.

6. Conclusions

In this study, an analog circuit fault diagnosis method combining wavelet transform based fault characteristics extraction with a WPA-GRNN was designed. The eigenvector was reduced by a wavelet transform. The classification performance of a GRNN was improved by a WPA. The simulation experiment found that the wavelet transform had significant advantages in fault characteristics extraction, the WPA showed an excellent optimization effect on the GRNN, the highest diagnosis accuracy rate of a single fault reached 96.8%, and the highest diagnosis accuracy rate of multiple faults was 86.2%. The comparison of the diagnostic results of the GRNN, GA-GRNN and WPA-GRNN suggested that the training time of the WPA-GRNN algorithm was the shortest, the training error was the smallest, and the average accuracy rate was the highest, indicating that the WPA-GRNN algorithm was effective and feasible.

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