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Strategy for Identifying Analog Circuit Faults Using Improved Neural Network Algorithms

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Abstract. Analog circuit faults are the main cause of performance degradation or paralysis in integrated circuit systems. However, due to the complex causes and diverse manifestations of circuit faults themselves, traditional methods have high difficulty in identifying typical faults in analog circuits and low recognition accuracy. This article constructs an improved ResNet deep feature recognition network model and establishes one-dimensional and two-dimensional fault information sources. Finally, particle swarm optimization algorithm is used to search for the optimal parameters solved by the model, ultimately achieving improvements in the accuracy and recognition speed of analog circuit fault diagnosis. Finally, through experimental verification, the recognition accuracy of typical fault C_2 reached 99.6%, proving the effectiveness of the method proposed in this paper.

Keywords: analog circuit failure, artificial intelligence, particle swarm optimization

1 Introduction

With the increasing integration and complexity of electronic circuits, the complexity of electronic systems is increasing exponentially, and the reliability requirements for electronic devices are constantly increasing. Currently, widely used circuit systems are based on mixed digital and analog circuits.

Analog circuits are an important component of many electronic products. In integrated circuits, analog circuits account for about 5-10% of the entire chip area, and the fault rate of analog circuits is as high as 80%. The instability of analog circuits determines the performance of chip operation, so analog circuit fault diagnosis is constantly receiving attention.

Currently, there are mainly the following issues in fault diagnosis of analog circuits:

(1) The early fault and non fault states of analog circuits are close, so the recognition of early fault features is not accurate enough;

(2) The rise of artificial intelligence has enabled feature recognition networks to automatically identify fault features, but the unreasonable network structure has low accuracy in identifying features and insufficient recognition speed.

Therefore, this article has done the following work to improve the accuracy and speed of feature recognition:

(1) A new model was constructed based on the classic ResNet network. After improvement, the model can recognize one-dimensional time-domain signals and two-dimensional time-frequency signals, increasing the richness of feature information sources;

(2) The use of particle swarm optimization algorithm to recognize feature information has increased recognition speed and accuracy, and the recognition process has been described;

(3) Taking a typical bandpass filtering circuit fault as an example, the method proposed in this paper was used for fault identification, and the identification results were compared and analyzed to verify the feasibility and recognition accuracy of the algorithm.

In order to complete the description of the work done in this article, it is divided into the following structure.

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Chapter 2 mainly searches for the current development status of intelligent diagnosis for analog circuits. Chapter 3 mainly discusses the process of establishing recognition models. Chapter 4 describes the recognition process and principles. Chapter 5 uses bandpass filter circuit faults as recognition objects to verify the feasibility of the method. Chapter 6 is the conclusion section.

2 Related Work

Hannes Leipold proposed an annealing algorithm for circuit faults, which can improve search efficiency in large-scale circuits [1]. Aizenberg proposed a multi valued neural network classifier for analog circuit fault diagnosis, which combines machine learning techniques for classification and approximation, as well as testability analysis programs for analog circuits. It can improve the fault identification accuracy of the algorithm, but the overall time consumption is high [2]. Meron Gebregiorgis proposed a radial basis function based method for identifying and classifying analog circuit faults, which can accurately classify faults and significantly improve recognition accuracy [3]. Shuai Shan proposed a method for extracting fault features in analog circuits based on the combination of wavelet packet energy spectrum and independent component analysis, which can effectively extract feature parameters that can characterize circuit faults, and the diagnostic accuracy can reach 95.7% [4]. Wei Gao proposed a fault diagnosis method for analog circuits based on one-dimensional convolutional neural networks, which can directly extract fault features from the original time series signals. The method can more accurately extract deep fault features [5]. Guoxiang Chang used the improved Whale algorithm for circuit fault diagnosis, which solved the problems of slow convergence speed of traditional algorithms and first entering local minimum solutions. However, the accuracy of the algorithm needs to be improved [6].

3 Improving ResNet Deep Feature Recognition Network

Feature extraction is crucial for fault diagnosis. In order to extract more rich and comprehensive effective information from the original data, this article improves ResNet to achieve the ability to extract deep features from one-dimensional time-domain data and two-dimensional time-frequency image data, thus enabling better fault classification.

3.1 Establishment of Feature Extraction Network

In order to better extract deep features from analog circuit fault data, this paper incorporates a one-dimensional convolutional neural network into the classic ResNet [7]. The improved network structure is shown in Fig. 1, which uses cross wavelet transform to transform one-dimensional raw data into two-dimensional time-frequency information. After improvement, the recognition network can accurately extract rich one-dimensional and two-dimensional information.

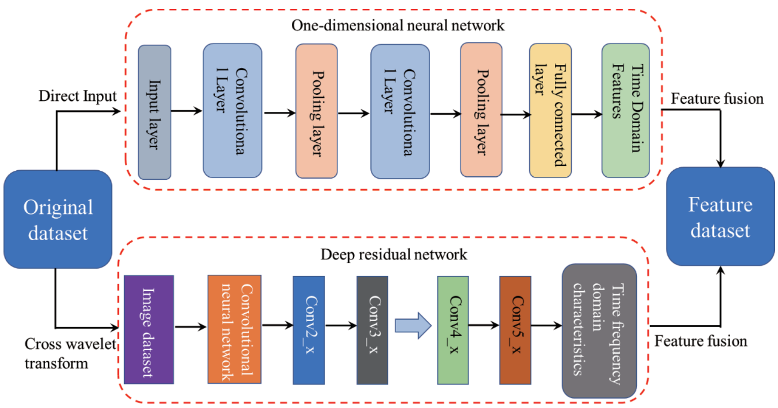


Fig. 1. Neural network structure

3.2 Extraction of One-dimensional Time-domain Feature Information

This article uses a one-dimensional convolutional neural network to extract one-dimensional time-domain features of analog circuits. After the original fault data is input into the one-dimensional convolutional neural network, multiple convolutional checks are performed on the local area of the input signal for convolution calculation to extract the features. Each convolutional kernel detects specific features at all positions on the input feature map to achieve weight sharing on the same input feature map. Assuming the layer is a convolutional layer, the convolutional layer formula is expressed as:

$$x_j^l = f\left(\sum_{i=1}^{M} x_i^{l-1} * k_{ij}^l + b_j^i\right). \tag{1}$$

Where, k is the convolution kernel, j is the number of convolution kernels, M is the number of channels input to x_i^{l-1}, b is the deviation of the corresponding convolution kernel, $f(\cdot)$ is the activation function, and $*$ is the convolution operation.

After the convolution calculation, the pooling layer is used to extract the secondary features of the fault and reduce the dimensions of the data. The pooling layer can effectively avoid overfitting caused by too many parameters and complex core structure, and the maximum pooling method is used for pooling operation. After passing through several convolutional and pooling layers, the one-dimensional features learned from each convolutional kernel are input into the fully connected layer. The fully connected layer maps features to different classes and completes classification operations in the output layer. If the input of the fully connected layer is layer $l+1$, the calculation formula is as follows:

$$h(x) = f(w^{l+1} \cdot x^{l+1} + b^{l+1}). \tag{2}$$

Where, w is the weight, b is the deviation, and $f(\cdot)$ is the activation function. The one-dimensional convolutional neural network used in this article consists of two convolutional layers, two maximum pooling layers, and one fully connected layer. The parameter designs of each layer are shown in Table 1.

Table 1. Parameter design of one-dimensional convolutional neural networks

Serial number	Network layer type	Convolutional kernel size	Step	Number
1	Conv1	7×1	1×1	16
2	Pool1	2×1	2×1	16
3	Conv2	3×1	1×1	32
4	Pool1	2×1	2×1	32
5	Fc	15	/	1

In order to obtain more comprehensive feature information, the first convolutional layer is set as the convolutional kernel, while the one-dimensional convolutional neural network is only used for feature extraction and does not perform feature classification.

3.3 Transforming One-dimensional Data into Two-dimensional Features

Wavelet transform performs localized orthogonal decomposition in both time and frequency domains by dynamically adjusting scale and translation parameters [8]. Assuming $x(t)$ is a signal with finite energy and satisfies the following formula:

$$x(t) \in L^2(R) \Leftrightarrow \int_R |x(t)|^2 \, dt < +\infty. \tag{3}$$

The wavelet transformation of $x(t)$ can be expressed as:

$$WT_x(a,\tau)=\frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty}x(t)\psi_{a,\tau}(t)dt, a>0. \tag{4}$$

In the formula, $\psi_{a,\tau}(t)$ is the wavelet function cluster obtained based on the wavelet function $\psi(t)$ through the scaling kernel translation transformation, and the expression is:

$$\psi_{a,\tau}(t)=\frac{1}{\sqrt{a}}\psi(\frac{t-\tau}{a}), a>0, \tau\in R. \tag{5}$$

In the equation, a and τ are scale parameters and translation parameters, respectively. Different wavelet functions $\psi_{a,\tau}(t)$ are used to scan and translate the signal to obtain feature information. In order to increase the decomposition and extraction of high-frequency information in fault signals, wavelet packet decomposition is used on the basis of wavelet transform. In addition to decomposing the low-frequency part of the signal, wavelet packet decomposition can further decompose the high-frequency part, adaptively selecting the optimal basis function that matches the signal. The schematic diagram of wavelet packet decomposition is shown in Fig. 2.

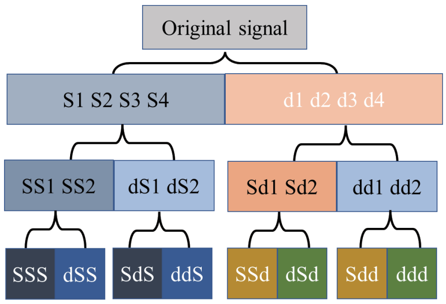


Fig. 2. Schematic diagram of wavelet decomposition

In fault feature extraction, wave packet decomposition is first used to solve the original fault data and extract features from different frequency bands. Then calculate the energy values of different frequency bands using the following formula:

$$E_{i,j}=\sum\left|m_i^j(k)\right|^2. \tag{6}$$

In the formula, $m_i^j(k)$ is the wavelet coefficient of node j in layer i, $E_{i,j}$ is the energy value of that frequency band, and the energy characteristics of each fault sample after small packet decomposition can be expressed as:

$$E=\left[E_{i,0},E_{i,1},\cdots,E_{i,j}\right]. \tag{7}$$

Based on wavelet transform and combined with cross spectral analysis, the correlation between two signals can be analyzed in the time domain [9]. The cross wavelet transform is represented as:

$$CWT(a,\tau)=WT_x(a,\tau)WT_y^*(a,\tau). \tag{8}$$

Where, $WT_x(a, \tau)$ and $WT_y(a, \tau)$ are continuous wavelet transforms of $x(t)$ and $y(t)$, $x(t)$ and $y(t)$ are two time series, and $*$ is complex conjugate.

3.4 Establishment of A Deep Residual Network Model

Deep residual networks are used to identify two-dimensional data information. The more layers the network has, the richer the extracted feature levels. In order to eliminate the possible phenomena of gradient disappearance, gradient explosion, and network degradation, a residual module is used on the basis of the original network. The residual module consists of two branches, namely the front layer branch and the identity mapping branch. The structure of the residual module is shown in Fig. 3.

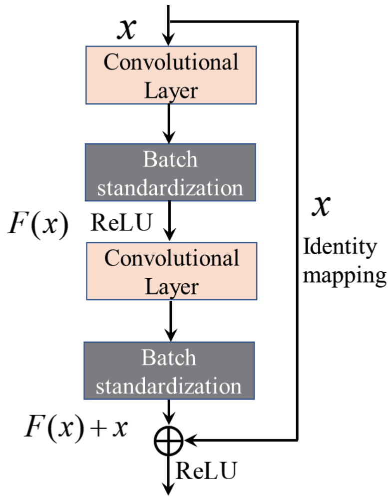


Fig. 3. Schematic diagram of residual module

This article uses the ResNet18 network to extract features from time-frequency image datasets. Table 2 shows the parameter settings of the ResNet18 network. The overall module consists of five parts, namely a normal shallow convolutional neural network and four different types of residual blocks.

Table 2. Parameter design of one-dimensional convolutional neural networks

Serial number	Network layer type	Convolutional kernel size	18-layer
1	Conv1	112 × 112	7 × 7 , 64, stride2, 3×3 max pool, stride2
2	Conv2_x	56 × 56	$\begin{bmatrix} 3\times3 & 64 \\ 3\times3 & 64 \end{bmatrix}\times 2$
3	Conv3_x	28 × 28	$\begin{bmatrix} 3\times3 & 128 \\ 3\times3 & 128 \end{bmatrix}\times 2$
4	Conv4_x	14 × 14	$\begin{bmatrix} 3\times3 & 256 \\ 3\times3 & 256 \end{bmatrix}\times 2$
5	Conv5_x	7 × 7	Fc, Softmax
6	/	1 × 1	$\begin{bmatrix} 3\times3 & 512 \\ 3\times3 & 512 \end{bmatrix}\times 2$

4 Description of Diagnostic Algorithms

4.1 Description of Diagnostic Algorithms

This article uses an improved particle swarm optimization algorithm to search for the optimal solution in the vector proposed in Chapter 3 [10]. In d -latitude space, the example updates its own speed and position by tracking two extreme values. The speed and position of Example i are represented as:

$$v_{id}(k+1) = wv_{id}(k) + c_1 r_1 \left[p_{id}(k) - x_{ki}(k) \right] + c_2 r_2 \left[g_{id}(k) - x_{id}(k) \right]. \tag{9}$$

$$x_{id}(k+1) = x_{id}(k) + v_{id}(k+1). \tag{10}$$

In the formula, d is the current latitude, $v_{id}(k)$ is the velocity component of the particle during the k -th iteration, $x_{id}(k)$ is the position component of the example during the k -th iteration, c_1 and c_2 are learning factors, $p_{id}(k)$ is the individual extreme value of independent particles in the particle swarm after the k -th iteration, $g_{id}(k)$ is the global extreme value of the population after the k -th iteration, r_1 and r_2 are random numbers that follow a Gaussian distribution, w is the inertia weight, and the iteration formula is as follows:

$$w = w_{\max} - \frac{(w_{\max} - w_{\min})}{k_{\max}}. \tag{11}$$

In the equation, $k_{\max}$ is the maximum number of evolutionary iterations, and w decreases linearly with time, reflecting the convergence ability of the particle. Let the particle set be:

$$\left\{ z_k^i \right\}, i = 1, 2, \cdots, Q. \tag{12}$$

Taking the training error as a fitness function, the smaller the error is, the closer the model is to the real state. The function is expressed as:

$$fitness(z_k^i) = \frac{\sum_{i=1}^{0} (z_{nk}^i - z_{pk}^i)^2}{Q^2}. \tag{13}$$

In the formula, z_{nk}^i is the latest observed value of the particle set, and z_{pk}^i is the predicted value. Through the above improvement process, it can be achieved to improve the particle dilution problem during the search for the optimal solution, reduce the huge computational burden caused by resampling, and also improve the convergence speed.

4.2 Optimization

Supervised learning realizes classification by constructing the optimal classification hyperplane, and the classification form is:

$$\begin{cases} \min\limits_{\delta, s, \xi_i} \left(\frac{1}{2} \|\delta\|^2 + c \sum_{i=1}^{m} \zeta_i \right) \\ y_i(\delta, x_i - s) \geq 1 - \zeta_i \\ \zeta_i \geq 0, i = 1, 2, \cdots, m \end{cases}. \tag{14}$$

Where, δ is the hyperplane normal vector, c is the penalty factor, ζ_i is the relaxation variable, s is the displacement term, and x_i and y_i are sample data. In the process of solving, it is necessary to optimize and assign parameters in the early stage. The key to improving the performance of parameter optimization is to design a kernel function suitable for the given problem, select a radial basis kernel function, and the expression is:

$$K(x, x_i) = \exp(-g\|x - x_i\|^2). \tag{15}$$

Among them, g is the kernel parameter and also the optimization object of the improved particle algorithm. Therefore, the diagnostic process of the improved algorithm is as follows:

Step 1: Extract fault features from the output signal of the faulty circuit, and divide the extracted dataset into training and testing sample sets.

Step 2: Initialize the parameter model, set the learning factors c_1 and c_2 to 1.8 and 1.7 respectively, and set the particle swarm size to 60

Step 3: Randomly initialize the individual mechanism and global extremum of the population.

Step 4: Calculate the particle weight and inertia weight of the initial state, and update the particle's velocity and position.

Step 5: calculate the fitness function value in this state, and update the individual extreme value and global extreme value.

Step 6: Determine whether the current optimal combination of parameter (c, g) has been achieved. If it is the optimal combination of parameters, proceed to the next step. Otherwise, repeat steps 4 to 6.

Step 7: Bring the optimal combination of (c, g) parameters into the optimization model, and train to obtain test samples and verify the diagnostic rate.

5 Simulation Results and Analysis

The experimental circuit of this article is shown in Fig. 4. Set the tolerance of circuit components, Res tolerance: $\pm 5\%$, Cap tolerance: $\pm 10\%$, and locate components C_1, C_2, R_1, and R_2 as faulty components. For the convenience of research, it is assumed that only a single component has failed.

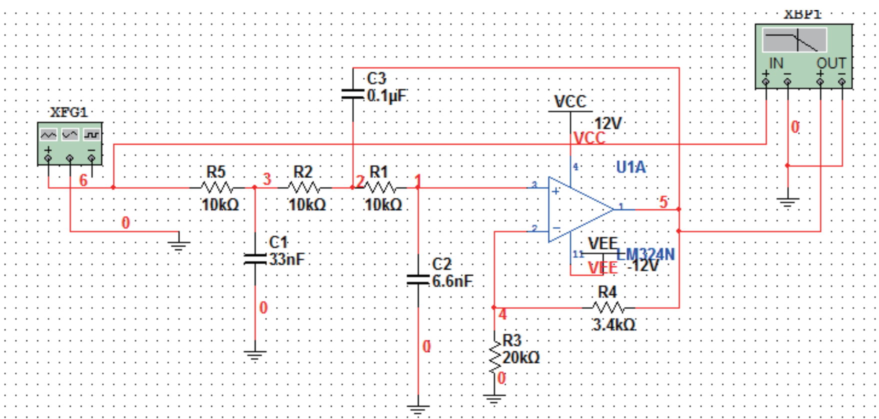
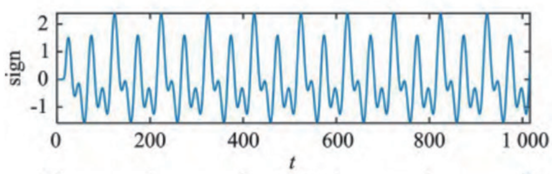
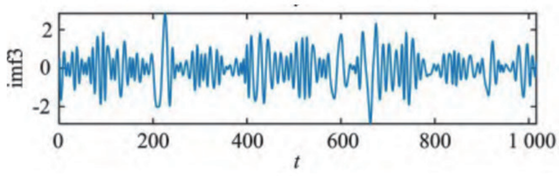


Fig. 4. Band-pass filter

Taking C_2 fault as an example, C_2 has a nominal value of $5n$ and a fault value of $7.5n$. 100 analyses were conducted using the fault circuit shown in Fig. 4, and 900 original fault samples were obtained through sampling. The waveform of the fault state is shown in Fig. 5(a). Use the improved ResNet algorithm model described in Chapter 3 to extract features from the above fault waveforms, and the extraction results are shown in Fig. 5(b).



(a) Fault waveform



(b) Extract results

Fig. 5. Feature extraction results

The fault features are composed of 900 fault samples. Due to the small amount of data, in order to ensure the number of test samples, 600 of the fault samples are divided into a sample set, and the remaining 300 samples are used as a test set. The test set is then applied to the improved recognition algorithm described in Chapter 4. The iterative process of the algorithm is shown in Fig. 6, and the fault classification results are obtained as shown in Fig. 7.

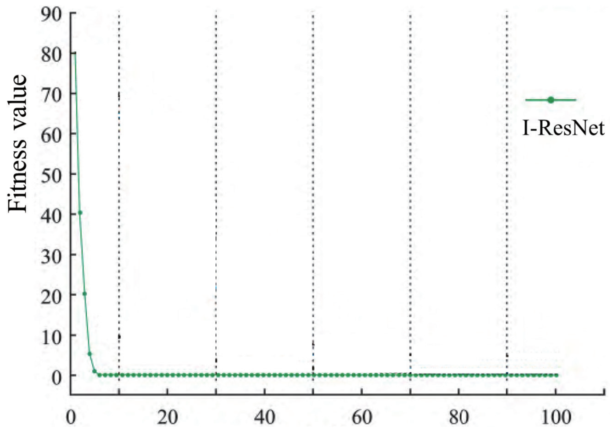


Fig. 6. Iterative process curve

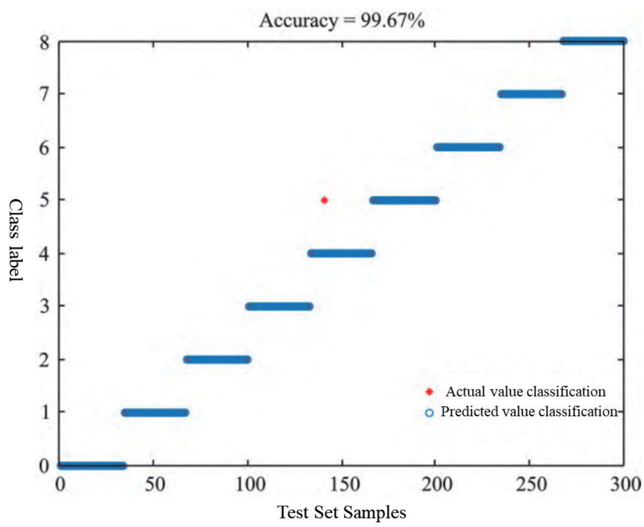


Fig. 7. Fault classification results

Through experiments, it can be seen that the improved algorithm can achieve a recognition accuracy of 99.67% for C_2 fault, which can meet the requirements of fault diagnosis. At the same time, the algorithm converges quickly, thus verifying its performance.

6 Conclusion

This article proposes an artificial intelligence recognition method based on an improved neural network algorithm to address the current situation of low efficiency and accuracy in traditional identification methods for analog circuit faults. This method can improve the accuracy of analog circuit fault recognition to 99.67%, greatly improving the recognition effect. Therefore, the improved neural network structure proposed in this article is effective. At the same time, it has also verified the feasibility of the particle swarm optimization algorithm used in this article in terms of result search. However, upon reviewing the entire text, there are still the following shortcomings, which are also future research directions.

(1) The algorithm structure continues to be streamlined, making the simplified structure occupy less space;

(2) In order to facilitate the verification of the results, the fault setting has been simplified. The fault is set as a single fault, while in reality, faults may be diverse. Therefore, how to identify the overlapping features of multiple faults is the focus of the next research step.

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