Fault Diagnosis of Analog Circuits Based on Wavelet Packet Energy Entropy and DBN

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Abstract. To solve the problem of low classification and recognition rate caused by small number of fault samples and inaccurate feature extraction in analog circuit fault diagnosis, a fault diagnosis algorithm for analog circuit system based on the combination of wavelet packet energy entropy and Deep Belief Network (DBN) is proposed. Firstly, the original output voltage signal of the circuit is decomposed by a multi-layer wavelet packet, then the feature vector is constructed in the form of energy entropy, and then the principal component analysis (PCA) is used for feature selection. The reduced dimension feature vector is taken as the input vector of DBN, and the fault diagnosis is completed after training and learning of the DBN network model. The experimental results show that compared with other algorithms, the proposed method can be more accurate and effective in diagnosing fault types in analog circuits, especially for Sallen-Key band-pass filter circuits, the fault recognition rate reaches 100%.

Keywords: Fault Diagnosis, Feature Extraction, Deep Belief Network

1. Introduction
With the rapid development of computer technology, the proportion of the circuit system is increasing. About 80% of faults in digital-to-analog hybrid circuits originate from analog circuits. Once the fault occurs, it may lead to environmental pollution, economic losses, and even casualties [1]. Therefore, the research on analog circuit fault diagnosis technology has become the current hot spot. Component faults in analog circuits have certain tolerance capability, most of which are soft faults caused by changes in component performance parameters, and the identification of fault samples is poor, which brings great difficulty to fault diagnosis.

At present, a large number of methods have been applied to fault diagnosis of analog circuits. Xiao et al. Used wavelet fractal to detect analog circuit faults [2]. Catelan et al. proposed to apply the RBF neural network to analog circuit fault diagnosis [3]. In reference [4], an improved Mahalanobis distance method was proposed for fault diagnosis of analog circuits. In reference [5], a neural network fault classification and recognition strategy based on S transformation was proposed, and sallen-Key low-pass filter was used for simulation experiment. In reference [6], feature vectors were constructed based on different signal processing methods, and then used as input data of the classifier to realize fault classification. The above-mentioned documents have achieved certain results in experiments, and some technologies have
been applied to industrial production. However, the above methods have some problems, such as easy to generate local extreme points, low accuracy of fault identification, or poor feature extraction. Therefore, the effective extraction of fault features is the key factor to realize analog circuit fault diagnosis. Wavelet packet transform can decompose signals at multiple scales in the range of pass frequency, and is suitable for feature extraction of non-stationary signals. Entropy can be regarded as a measure of the degree of system disorder and can represent the degree of uncertainty in the system. The combination of wavelet analysis and entropy theory is the current research hotspot.

In recent years, deep belief networks have been developed rapidly and widely used in various fields, including handwritten numeral recognition [7], computer vision [8], speech recognition [9] and fault recognition [10]. Compared with other methods, the DBN algorithm allows adaptive adjustment of weights in both supervised and unsupervised phases, and this method has excellent feature extraction and processing capabilities for high-dimensional nonlinear data. Therefore, the wavelet entropy theory and the advantages of the DBN network are combined to test the fault identification of analog circuits. At the same time, the proposed algorithm is compared with some other algorithms, and the experimental results verify that the proposed method performs better in analog circuit fault diagnosis.

2. Wavelet Packet Energy Entropy Feature Extraction

Wavelet transform has the ability to characterize the local features of signal in the time-frequency domain, but it only decomposes the low-frequency part of the signal in the next step and does not process the high-frequency signal. Wavelet packet transform decomposes low-frequency signals and high-frequency signals, providing more complete information. The steps of wavelet packet energy entropy feature extraction are as follows:

1) J - layer wavelet packet decomposition is performed for some fault data S. Take 3 layers as an example, the decomposition tree is shown in Figure 1 below. The first number in brackets represents the number of layers, and the second number represents the location of the layer. Where (3,0), (3,1)…(3,7) respectively represents the characteristic quantity of all frequency components of the third layer from low frequency to high frequency.

![Figure 1. 3-level wavelet decomposition tree](image)

2) 8 wavelet packet reconstructed signals are obtained by reconstructing the eight frequency band sequences of the last layer obtained from the above decomposition.

3) The energy entropy $H_{jk}$ of wavelet packet is calculated by the formula (1), where the letters N and J respectively represent the signal length and the number of layers of wavelet packet decomposition for
the signal, getting the decomposition sequence $X_{jk}(k=0 \sim 2^{j-1})$. The component $S_{jk}$ is obtained through a single reconstruction of the decomposition coefficient, and $E_{jk}$ is set as the power of the reconstructed signal, $E_{jk} = |S_{jk}(i)|^2$, and $\varepsilon_s(i) = E_s / E$, then $\sum E_{jk} = 1$.

$$H_s = -\sum_{i=1}^{N} \varepsilon_s(i) \log \varepsilon_s(i) \quad (1)$$

4) The energy entropy of 8 wavelet packets is obtained from Formula 1 to form feature vectors: [H30, H31, ..., H37].

3. DBN theoretical framework

Generally speaking, in a deep network with multiple hidden layers, it is difficult to learn a large number of parameters in the network due to the possibility of gradient disappearance. In order to solve this problem, an effective algorithm is proposed. Only one layer is learned at a time, and every two layers are regarded as a Restricted Boltzmann Machine (RBM) structure model, and RBM is used as the basic unit to form a DBN multi-layer network [11].

3.1. Training RBM

RBM is a common statistical module in probability science type. RBM model structure includes a visible layer and hidden layer, which are used for data input and feature extraction respectively. An energy function is proposed to describe the structure between them. The equation is:

$$E(v, h) = -\sum_{i} a_i v_i - \sum_{j} b_j h_j - \sum_{i,j} v_i h_j w_{ij} \quad (2)$$

$V_i$ and $h_j$ in equation 2 above represent the $i$-th node in the visible layer and the $j$-th node in the hidden layer respectively. $a_i$ and $b_j$ are their offsets respectively, where $w_{ij}$ is the weight between two connected nodes. The energy function can be used to derive the formula for the joint probability distribution of $(v, h)$, where the sign $\theta$ of the equation is the set of parameters $a$, $b$, and $w$.

$$p(v, h) = \frac{1}{z(\theta)} \exp(-E(v, h)) \quad (3)$$

$$z(\theta) = \sum_{v, h} \exp(-E(v, h)) \quad (4)$$

Since RBM satisfies conditional independence, that is, the state of one layer node is given, the state of another layer node can be expressed, and its equations are 5 and 6. In order to obtain the conditional probability function of the hidden layer or the visible layer, it can be assumed that the state of each node of the visible layer or the hidden layer is known, and its conditional probability can be written into equations 7 and 8.

$$p(h \mid v) = \prod_{j} p(h_j \mid v) \quad (5)$$

$$p(v \mid h) = \prod_{j} p(v_i \mid h) \quad (6)$$

$$p(h = 1 \mid v) = \sigma(b + \sum_{i} v w_i) \quad (7)$$
The $\sigma$ in equations 7 and 8 refers to the sigmoid function (activation function), usually

$$\sigma(x) = \frac{1}{1 + \exp(-x)} \quad (9)$$

In order to set up model parameters, RBM needs to be constructed with training data. In the training process, the gradient descent method is used for learning. The logarithm likelihood function probability of the training data is calculated, and the derivative of the weight value is taken as a gradient value. As shown in Equation 10, the purpose of updating the network parameters is to obtain a convergence model.

$$\frac{\partial \log p(v)}{\partial w_{ij}} = <v_i h_j>_data - <v_i h_j>_model \quad (10)$$

Gibbs sampling method is used to approximate the gradient. Then, a fast learning algorithm of contrast divergence (CD-K) is proposed, which can improve the calculation speed on the premise of ensuring the calculation accuracy. Usually, when k=1, good results can be obtained. Starting from the nodes in the visible layer, the hidden layer nodes are calculated by using equation (7), then the visible layer nodes are updated by "reconstruction" using equation (8), and then the hidden layer cell nodes are updated again. The parameter update result of the model is shown in the following equation 11:

$$\Delta w_{ij} = \epsilon ( <v_i h_j>_data - <v_i h_j>_rec ) \quad (11)$$

### 3.2. DBN framework

DBN model is a probability generation model, and its structure is a deep-level network formed by stacking multiple RBM. In the DBN model, it learns from the input data and extracts the hierarchical representation of each hidden layer.

For deep neural networks, it is not realistic to use traditional supervised training methods to learn so many parameters, because the error will be very weak when transmitted to the lower layer through multiple hidden layers, and the traditional backpropagation theory is also weak in adjusting parameters, making it very difficult for the network to generate global optimal parameters. Therefore, a layer-by-layer unsupervised greedy algorithm is used to train the DBN. Firstly, the input unit (V) and the first hidden layer (H1) are trained by RBM rules. Then, h1 and second hidden layer (h2) are trained, where the output of h1 serves as the input of h2. Training layer by layer in turn and stops when the set number of layers is met. This method is a forward unsupervised training process from a low level to a high level, which is helpful to converge to the global optimum.

For the task of classification, the parameters of this deep-level structure need to be fine-tuned after the layers are trained. This is a backward supervised fine-tuning stage from a high level to a low level, which reduces training errors by using labels, thus effectively improving classification accuracy. The fault diagnosis model is shown in fig.2
4. Analog Circuit Fault Diagnosis

Combined with the characteristics of analog circuit fault data, the original output voltage signal of the circuit is decomposed by multi-layer wavelet packet firstly, then the feature vector is constructed in the form of energy entropy, and then the principal component analysis method is used for feature selection. The reduced dimension feature vector is taken as the input vector of the DBN, and DBN's powerful feature extraction and classification capability are applied to analog circuit fault identification. The diagnostic flow is shown in Figure 3 below.

**Figure 2. DBN Diagnostic Model**

**Figure 3. Diagnostic flow chart**
4.1. Data Injection for Fault of Sallen-Key Bandpass Filter

The experimental circuit uses a Sallen-Key bandpass filter, and the circuit diagram is shown in fig. 4. The parameter values of each element are nominal values of the element, and the tolerance values of capacitance C and resistance R are 10% and 5% respectively. If the parameter value of the component in the circuit deviates from ±50% of the nominal value, it is considered as a soft fault. In this experiment, C1, C2, R2 and R3 are selected as fault components, and the fault conditions of the circuit are divided into nine states NF (normal state), C1+, C1-, C2+, C2-, R2+, R2-, R3+, R3- as shown in Table I below. The symbol- indicates that the component failure is relatively small and the symbol+ indicates that the failure is relatively large.

| code | Fault code | status | nominal value | The fault value |
|------|------------|--------|---------------|-----------------|
| F1   | (1,0,0,0,0,0,0,0,0) | NF     | -             | -               |
| F2   | (0,1,0,0,0,0,0,0,0) | C1+    | 5NF           | 7.5NF           |
| F3   | (0,0,1,0,0,0,0,0,0) | C1-    | 5NF           | 2.5NF           |
| F4   | (0,0,0,1,0,0,0,0,0) | C2+    | 5NF           | 7.5NF           |
| F5   | (0,0,0,0,1,0,0,0,0) | C2-    | 5NF           | 2.5NF           |
| F6   | (0,0,0,0,0,1,0,0,0) | R2+    | 3kΩ           | 4.5kΩ           |
| F7   | (0,0,0,0,0,0,1,0,0) | R2-    | 3kΩ           | 1.5kΩ           |
| F8   | (0,0,0,0,0,0,0,1,0) | R3+    | 2kΩ           | 3kΩ             |
| F9   | (0,0,0,0,0,0,0,0,1) | R3-    | 2kΩ           | 1kΩ             |

The circuit is simulated by using software Matlab. The applied excitation signal parameters are shown in fig. 4. A Monte Carlo analysis is carried out 100 times for various fault types in table 1, respectively, and the output data of the circuit within 120us are collected. The dimension of the obtained data is 136, and each of the 9 fault states in Table 1 is 100 data samples, resulting in a total of 900 sample data. 500 samples are randomly selected as training sets, and the remaining 400 are used for test sets.

Figure 4. Sallen-Key bandpass filter circuit

4.2. Feature Extraction

The purpose of feature extraction is to select and retain relevant information from the original signal. The signal is used for feature extraction. Firstly, a 5-layer wavelet packet transformation was performed for each sample data set, and each sample vector was reduced from 136 to 32 sequences of high and low frequencies. Then, the wavelet energy entropy was calculated to construct a 32-dimensional feature vector set. The 32-dimensional vector may still have some redundancy, which leads to poor fault
diagnosis effect. Therefore, principal component analysis (PCA) is used for feature selection, 85% of which is selected as the feature threshold. Finally, the length of the feature vector of each fault is 7.

5. test verification

The difference number of neurons in each hidden layer in the DBN model will greatly affect the fault classification performance. When the number of nodes in each layer of the network layer is small, it is easy to cause poor feature extraction. On the contrary, overfitting may occur when there are too many nodes in the hidden layer, which reduces the generalization ability.

The DBN model parameters in the experiment are as follows: the learning rate is 0.1, the iteration number is 50, the input layer size is 7, and the output layer unit number is 9. There is no fixed method to calculate the number of neurons in the hidden layer. Generally, it can be approximately obtained by rounding 2/3 of the size of the input layer and 2/3 of the size of the output layer. On this basis, the corresponding adjustment is made through experiments. In the experiments, the optimal number of neurons in each layer of the hidden layer is 11, the number of samples selected for one training (batch_size) is 5, the activation function is the sigmoid function, and the learning rate is 0.1.

5.1. Influence of Different Iterations

In the training of the DBN model, it is necessary to continuously update the parameters to reduce the error value during training and to research the loss and recognition rate under different iterations, as shown in fig. 5.

![Figure 5. Relationship between iteration number, error and recognition rate](image)

As shown in fig. 5, as the number of iterations increases, the error decreases and the fault identification rate increases. In the initial stage, as the number of iterations increases, the error decreases faster and the identification rate increases faster. When the number of iterations of DBN reached 30, the error reached a relatively low position and the accuracy rate reached 100%. Therefore, in order to reduce the training time and the fault identification rate has reached 100%, the number of iterations of the DBN network is 30.

5.2. Experimental Comparison with Other Methods

In order to verify the advantages of the DBN algorithm in analog circuit fault diagnosis, this method is compared with some other algorithms respectively. The same data set is selected for experiments with different algorithms to calculate the fault identification rate, as shown in Table II.

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### Table 2. Performance Comparison of Different Algorithms

| Algorithm                                                | Recognition Rate |
|----------------------------------------------------------|------------------|
| BP                                                       | 91.63%           |
| SVM [12]                                                 | 97.85%           |
| Global SVM [12]                                          | 100%             |
| RBF [13]                                                 | 88.00%           |
| Bagging RBF NN [13]                                      | 93.75%           |
| Bagging RBF NN with Cross-Validation [13]                | 94.80%           |
| MAX multi-wavelet [14]                                   | 98.22%           |
| Db2 wavelet [14]                                         | 92.53%           |
| PCA-ELM [15]                                             | 98.00%           |
| Proposed algorithm                                       | 100%             |

From the data in Table II above, it can be seen that the algorithm combining wavelet packet energy entropy and DBN can achieve an accurate fault identification rate of 100% in the test set, which is higher than other algorithms. Among them, the Global SVM algorithm used in reference 12 has a recognition rate of 100%, but it only diagnoses 4 fault states, while the proposed algorithm can recognize 9 states. Although algorithms proposed in reference 13, 14 and 15 can identify 9 kinds of faults, the recognition accuracy is lower than the algorithm proposed in this paper. BP algorithm may fall into local optimum when training parameters and the DBN model can effectively avoid this problem.

### 6. Detection of Quadruple operational amplifier double-order high-pass filter circuit

In order to detect the generality of the algorithm combining wavelet packet energy entropy and DBN, a more complex quadruple operational amplifier double-order high-pass filter circuit is used for verification. The nominal value of the experimental components and the excitation signal are set as shown in fig. 6.

![Figure 6. Quadruple operational amplifier double-order high-pass filter circuit](image)

Monte Carlo analysis is carried out 200 times for each fault type in the circuit. The types of faults are shown in table III. 200 data samples are extracted for each fault type. 65% of the 2600 samples of 13 types are divided into training sets and the other 35% are used as test sets.
Table 3. Fault Types and Codes of Quadruple operational amplifier double-order high-pass filter circuit

| code | Fault code | status | nominal value | The fault value |
|------|------------|--------|---------------|-----------------|
| F1   | (1,0,0,0,0,0,0,0,0,0,0,0,0) | NF     | -             | -               |
| F2   | (0,1,0,0,0,0,0,0,0,0,0,0,0) | C1+    | 5NF           | 7.5NF           |
| F3   | (0,0,1,0,0,0,0,0,0,0,0,0,0) | C1-    | 5NF           | 2.5NF           |
| F4   | (0,0,0,1,0,0,0,0,0,0,0,0,0) | C2+    | 5NF           | 7.5NF           |
| F5   | (0,0,0,0,1,0,0,0,0,0,0,0,0) | C2-    | 5NF           | 2.5NF           |
| F6   | (0,0,0,0,0,1,0,0,0,0,0,0,0) | R1+    | 6.2KΩ         | 9.3KΩ           |
| F7   | (0,0,0,0,0,0,1,0,0,0,0,0,0) | R1-    | 6.2KΩ         | 3.1KΩ           |
| F8   | (0,0,0,0,0,0,0,1,0,0,0,0,0) | R2+    | 6.2KΩ         | 9.3KΩ           |
| F9   | (0,0,0,0,0,0,0,0,1,0,0,0,0) | R2-    | 6.2KΩ         | 3.1KΩ           |
| F10  | (0,0,0,0,0,0,0,0,0,1,0,0,0) | R3+    | 6.2KΩ         | 9.3KΩ           |
| F11  | (0,0,0,0,0,0,0,0,0,0,1,0,0) | R3-    | 6.2KΩ         | 3.1KΩ           |
| F12  | (0,0,0,0,0,0,0,0,0,0,0,1,0) | R4+    | 1.6KΩ         | 2.4KΩ           |
| F13  | (0,0,0,0,0,0,0,0,0,0,0,0,1) | R4-    | 1.6KΩ         | 0.8KΩ           |

Using the experimental method mentioned above, the energy entropy of the original data is calculated after 5-layer wavelet packet transform, and then PCA feature selection is carried out. Finally, the vector length of the input layer is reduced to 5. The DBN network model is 4-layer network structure (5-11-8-13), and the number of iterations and the loss relationship are shown in Figure 7 below.

Figure 7. Relationship between iteration number and loss

The proposed algorithm is compared with BPNN and SCA-SVM algorithms respectively. The same data set is selected for 10 experiments with different algorithms, and the results are shown in Table IV.

Table 4. Fault Diagnosis Accuracy of Training Sets for Different Algorithms

| algorithm | Proposed algorithm recognition rate | BPNN recognition rate | SCA-SVM [16] recognition rate |
|-----------|------------------------------------|-----------------------|-------------------------------|
|           | 98.82%                             | 85.07%                | 97.75%                       |

The results in Table IV show that the average fault recognition accuracy of the BPNN network and SCA-SVM algorithm are 85.07% and 97.75% respectively, while the proposed algorithm is superior to BPNN and SCA-SVM algorithm in fault diagnosis, and the average fault recognition rate of 10
experiments can reach 98.82%. During the experiment, it is found that the stability of the BPNN algorithm is poor, and the classification accuracy fluctuates greatly. The proposed algorithm not only has a higher recognition rate but also is more stable in the analog circuit fault diagnosis. The effectiveness of the proposed method on the test set is still excellent, and the fault recognition rate can reach 98.24%, as shown in fig. 8. To sum up, two experiments show that it is an effective method to diagnose analog circuit faults based on wavelet packet energy entropy and DBN.

![Figure 8. Classification results of test sets of Quadruple operational amplifier double-order high-pass filter circuit](image)

7. Conclusion
Aiming at the problem that analog circuit fault is not easy to diagnose, an algorithm based on wavelet packet energy entropy and DBN is proposed. Experiments show the feasibility and effectiveness of the proposed algorithm. The experimental results show that: the proposed method can achieve a high fault recognition rate with a small number of samples. In particular, the fault identification rate of sallen-Key bandpass filter circuit reaches 100%.

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