Fault Diagnosis Method of Analog Circuit Based on Radial Base Function Neural Network

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Abstract. Neural network is competent for fault diagnosis and pattern classification such as poorly defined model system, noisy input environment and nonlinearity in analog circuit. One of the most known type of neural network used to identify and classify the method of faulty diagnosis of analog circuit is presented based on the radial basis function (RBF) neural network. The proposed method introduces the fault features and classify the fault classes of the given two circuits. The experiment and simulations of the fault diagnosis for the two circuits (Sallen-Key and four OP-AMP band-pass filter) establish the diagnosing process of our method that proposed in this paper, locating faults effectively and be successful in classifying the fault values. Its performance analysis show that the fault diagnosability learned by RBF method accomplishes a better satisfactory diagnostic accurateness for the fault diagnosis of analog circuit.

1. Introduction

Fault diagnosis of analog circuits has been one of the most unreliable and least testable issues for testing engineers and researchers since the mid-1970s [1-4]. In the study of fault diagnosis, the creation of a fault components using fault simulation strategies are extensively used for selecting the test technique. For that matter, some approaches [5] use some schematic diagram as the starting point to pick up fault lists in fault simulation study (circuit design, fault model, fault recognition criterion and test vector). As a result, analog fault diagnosis appeared as a central issue in the literature of many works and became an active area of research. In reference [6], the issue on fault diagnosis of analog circuit at the system, board, and chip level have been addressed. A survey of the study conducted in this area evidently shows that analog circuit is complicated due to the lack of component tolerances, fault diagnosis models and nonlinearity problems [2,3,4].

Neural network widely used as an ideal tool to solve problems in fault diagnosis due to their strong competency in deal with classification of fault values, and nonlinear problem in the past several years. As an example, the faults result under consideration in classes which can be separated from each other and the fault-free components by means of appropriate features to accomplish good performance. Also NNs has been applied to a different types of problems in the areas like pattern recognition, image processing, signal processing, process identification and classification. [2,3,7].

In this paper we use one of the most popular NN methods broadly used in data classification, nonlinear function approximation, systems modelling and controlling that is, the radial basis function (RBF) neural network based on fault diagnosis method for analog circuit. We can apply this tool to the fault diagnosis in analog circuits and has a powerful feature ability, such as fault diagnosing, recognize...
nonlinear mapping among fault features and fault modes in addition for locating fault classes quickly and exactly. This method is also effective for characterizing the fault diagnosis when the experimental simulations match with the measurements sufficiently [8, 9, 11].

Since RBF have high performance and the greater problem solving involved with deep neural network, scholars have tried to enrich the proposed method and use different methods for applying it to the deep learning and to improve its performance. As a result, they have found that RBF can yield better results related to other kinds of NNs such as faster learning speed, better approximation ability and stronger tolerance to input noise. Their work was depending on adjusting the parameters of hidden units’ of radial basis functions, for instance the width or centers, or even proposing the different Gaussian functions [8-13].

In this work, we compare RBF with support vector machine (SVM), back propagation (BP) neural networks and wavelet neural networks for analog circuit. For definition of the back propagation neural networks, wavelet neural networks and support vector machine the reader can refer to [14-20].

Our result shows that the experimental simulation of Sallen-key and OP-AMP band pass filter circuits based on RBF for the fault classes of the two circuits has wider feature distance and it is stronger in aggregation ability compared to the other methods. Consequently, the result clearly indicates that RBF has much more powerful performance and it can be used for categorising faulty elements of analog circuit powerfully than the other methods.

In section 2, we briefly discuss the concept of RBF neural network and its structure, section 3 describes the fault diagnosis of analog circuit based on radial base function, in section 4 we explain the experimental research of two circuits to demonstrate the effectiveness of our diagnosis technique about analogue circuit of fault diagnosis, in section 5 we interpret the analysis of experimental results and section 6 of the paper concludes our work.

2. Radial Basis Function Neural Network

Radial basis function (RBF) neural network is a multi-layer topology that can be used for function approximation ability, faster learning speed, time series prediction, controlling and stronger tolerance to input noisy pattern (data statistics) problems and classification [10, 11, 21].

This neural network is also a 3-layer feed forward neural network as shown in figure 1. Each of these layers has different tasks. The first layer is designed by the signal source node which is the input layer, the second layer is with a non-linear RBF activation function that is the hidden layer and third layer is the linear output layer [22]. The elements of an RBF neural network are obtained with the training procedure. Assume the numbers of nodes in the above layers are \( n \), \( h \) and \( k \), respectively on a multi-input multi-output RBF [11]. The second layer frequently uses the Gaussian function \( \varphi_i(x) \) as the RBF activation function. RBF neural network plots’ nonlinearly the original data to a high-dimensional feature space, moreover in a feature space it solves a linear classification problem by using RBF function [23]. The standard structure of RBF is designed and modelled by Microsoft Office Visio 2007 software.

As activation functions RBF neural network uses radial function. Different types of RBFs could be used, but the most common one used is the Gaussian function [10, 11].

\[
\varphi_i(x) = \exp \left( -\frac{\|x-c_i\|^2}{\sigma_i^2} \right), \quad i = 1, 2, ..., \mathcal{H}
\]  

where \( \varphi_i(x) \) is the activation function (Gaussian function) of radial base function, \( x = [x_1, x_2, ..., x_n]^T \) is an input vector; \( c_i = [c_{i1}, c_{i2}, ..., c_{in}]^T \) is known as the center vector of the \( i^{th} \) node in the second layer which means hidden layer; \( \sigma_i \) is the width of the \( i^{th} \) hidden node; and \( \| \cdot \| \) represents the computation of Euclidean norm of two vectors. The parameters \( c_i \) and \( \sigma_i \) are used to control the position and shape of the \( i^{th} \) RBF center, respectively. The output of \( j^{th} \) node in the third layer can be calculated by solving the following equation:

\[
y_j(x) = \sum_{i=1}^{\mathcal{H}} \omega_{ij} \varphi_i(x), \quad j = 1, 2, ..., \mathcal{K}
\]
where $\omega_{ij}$ is the weight between the $i^{th}$ center and the $j^{th}$ output node, $\phi_i$ represents the bias weight between the $i^{th}$ node in the first layer and the third layer for the simplicity.

![Figure 1. Structure of RBF neural network.](image)

The error function will be defined as:

$$E = \frac{1}{2} \sum_{i=1}^{M} (y_d - y_i)^2$$  \hspace{1cm} (3)

where $y_d$ is the target value of the $i^{th}$ output unit and $y_i$ is the network outputs.

3. Fault Diagnosis of Analog Circuits Based on RBF Neural Network

The idea of fault diagnosis is to testing and training the result of the given experimental circuits at a specific nominal time frequency. The output response will affect either in its amplitude or phase when the deviations in the circuit element caused by any fault. In order to illustrate the components of fault classes, the author must be first need to design circuits of the experimental analog circuit which satisfy the fault diagnosis requirements. After designing the experimental analog circuit, through the setting of the simulation circuit, collect the data of the CUT at each boundary of the fault tolerance at the selected critical components. In the actual simulation operation, the collected data are used for fault feature extraction. Next, the extracted fault features are used as a sample set and divided into two parts, one is used as a training sample set and the second is used as a test sample set. Then the training sample set is used to train the RBF neural network to get the fault classification and use the test sample set to access the trained RBF neural network for fault diagnosis results of the analog circuit [5, 25].

4. Experiment Research in Analogue Circuit Diagnosis

4.1. Experimental Analog Circuit

For comparisons purpose, the experimental analog circuit are the same as within the references [14, 26].

**Example 1:** Sallen-Key band-pass filter is the first circuit commonly used in the study of analog circuit of fault diagnosis. As shown in figure 2, the circuit contains 5 resistors, 2 capacitors, and a single amplifier. The nominal value of the components is labelled in the circuit diagram. The capacitance and resistance assumed to have a tolerance of the circuit used in each experiment is set to 10% and 5% respectively; The CUT is normal even if we assume that the CUT’s fault classes have different tolerance values. If the given components are lower or higher than its nominal value by 50%, fault circuit happens. According to this, nine fault models are found, including the fault free state. We fixed faulty classes in the circuit but other fault values are varied within their tolerances to obtain training data for different fault classes.

**Example 2:** FOUR OP-AMP band pass filter circuit is shown in figure 3, the nominal value of the components is indicated in the circuit diagram. This circuit is the second model circuit and which is more complicated, because it contains 2 capacitors, 10 resistors and 4 operational amplifiers. For the resistors and capacitors, the tolerance of the circuit is fixed to 5% and 10% respectively. If any of the
components is higher or lower than its nominal value by 50%, and assuming the CUT’s components varying within their tolerance values and the CUT is normal, then circuit fault happens. Hence, thirteen fault models are found, including a fault-free state (normal fault).

4.2. Specific Experimental Procedures

The two experimental circuits include the following parameters.

a) For the experimental circuit Add pulse excitation signal, the specific parameters are: V1=0, V2=5V, TD=1μs, TR=1μs, TF=10μs, PW=10μs, PER=0.5ms and 1ms respectively (for circuit 1 and circuit 2);

b) Collect the voltage response waveform at the “out” node, the number of samples is 128, and the period is set to 0-1.2ms.

4.2.1. Experimental circuit 1. Sallen-Key band pass filter: According to the component sensitivity analysis, because of their greater impact on the center frequency R2, R3, C1 and C2 are assumed to be the main components. Therefore, we select R2, R3, C1 and C2 as experimental components. The faulty impulse results are generated as to form 9 fault classes, which are R2⇑, R2⇓, R3⇑, R3⇓, C1⇑, C1⇓, C2⇑, C2⇓ and fault free (NF), where⇑ and⇓ represents to values higher and lower than the nominal value of the given circuit, respectively.

![Figure 2. The simulation circuit diagram of Sallen-Key band-pass filter.](image)

| Fault code fN | Fault class | Nominal | Tolerance range | Fault value |
|---------------|-------------|---------|----------------|-------------|
| f1            | NF          | –       | –              | –           |
| f2            | C1⇑         | 5nF     | 10%            | 2.5nF       |
| f3            | C1⇓         | 5nF     | 10%            | 10nF        |
| f4            | C2⇑         | 5nF     | 10%            | 2.5nF       |
| f5            | C2⇓         | 5nF     | 10%            | 10nF        |
| f6            | R2⇑         | 3k      | 5%             | 1.5k        |
| f7            | R2⇓         | 3k      | 5%             | 6k          |
| f8            | R03⇑        | 2k      | 5%             | 1k          |
| f9            | R3⇓         | 2k      | 5%             | 4k          |
The relevant parameter settings under different fault mode categories of the circuit are shown in table 1, 240 types of data are sampled for each type of failure mode. As training sample 150 sets of data are used and 90 sets of data are used as test samples.

4.2.2. Experimental circuit 2. FOUR-OP-AMP bi-quad band pass filter circuit: R1, R2, R3, R4, C1 and C2 have been chosen as the experimental components. The faulty impulse results are processed as to form 13 fault classes, namely R1⇑, R1⇓, R2⇑, R2⇓, R3⇑, R3⇓, R4⇑, R4⇓, C1⇑, C1⇓, C2⇑, C2⇓ and fault free.

![Circuit Diagram](image_url)

Figure 3. The simulation results circuit diagram of FOUR OP-AMP band-pass filter.

| Fault mode | Fault class | Nominal | Tolerance range | Fault value |
|------------|-------------|---------|-----------------|-------------|
| \( f_1 \)  | NF          | –       | –               | –           |
| \( f_2 \)  | C1⇑        | 5nF     | 10%             | 10nF        |
| \( f_3 \)  | C1⇓        | 5nF     | 10%             | 2.5nF       |
| \( f_4 \)  | C2⇑        | 5nF     | 10%             | 15nF        |
| \( f_5 \)  | C2⇓        | 5nF     | 10%             | 2.5nF       |
| \( f_6 \)  | R1⇑        | 6200    | 5%              | 15000       |
| \( f_7 \)  | R1⇓        | 6200    | 5%              | 3000        |
| \( f_8 \)  | R2⇑        | 6200    | 5%              | 18000       |
| \( f_9 \)  | R2⇓        | 6200    | 5%              | 2000        |
| \( f_{10} \) | R3⇑       | 6200    | 5%              | 12000       |
| \( f_{11} \) | R3⇓       | 6200    | 5%              | 2700        |
| \( f_{12} \) | R4⇑       | 1600    | 5%              | 2500        |
| \( f_{13} \) | R4⇓       | 1600    | 5%              | 500         |
For every sort of failure mode, 80 sets of data are repeatedly collected for each type of failure mode, from those 50 sets of data are taken as a training data samples, and 30 samples are taken as test data samples. The fault mode related parameters are shown in table 2.

The original data samples of the experimental circuits one and two are processed according to the method flow of FIG. The fault mode coding of the circuit is in the form of table 3. Since the number of bits of the failure mode code is 9, number of RBF classification is set to 9 layer neurons, the learning rate and the convergence criterion. When the loss reaches 0.01, the global fine adjustment of the network is completed. Experimental circuit 2 uses the same fault mode coding method.

**Table 3.** The truth table of all fault modes of Sallen-key filter circuit.

| Fault mode | Code value |
|------------|------------|
| $f_1$      | 1 0 0 0 0 0 0 0 0 |
| $f_2$      | 0 1 0 0 0 0 0 0 0 |
| $f_3$      | 0 0 1 0 0 0 0 0 0 |
| $f_4$      | 0 0 0 1 0 0 0 0 0 |
| $f_5$      | 0 0 0 0 1 0 0 0 0 |
| $f_6$      | 0 0 0 0 0 1 0 0 0 |
| $f_7$      | 0 0 0 0 0 0 1 0 0 |
| $f_8$      | 0 0 0 0 0 0 0 1 0 |
| $f_9$      | 0 0 0 0 0 0 0 0 1 |

4.3. Description of Experimental Circuits

Table 1 and table 2 show that the values of the fault codes, fault classes, nominal and fault value components of Sallen-Key and Four OP-AMP band pass filter circuit with their tolerance value of the simulation parameters respectively. This is affected by the instrument interpretations having finite precision and the elements’ values changing in the original circuit, but we could correctly complete the fault diagnosis based on the actual input data. From the two tables we see that different fault classes fall into different fault values based on the given circuits of the extracted data, that is, we can identify these faults uniquely.

5. Experimental Results and Performance Analysis

5.1. Fault Diagnosis of Performance Analysis

To determine the effectiveness of the method we proposed in this paper, this section will complete the determination of different fault types based on an experimental data according to the fault type determination rules. The fault type of each circuit in this article is assumed to be $M$, then the prior probability, $P(\omega_i)$ is defined as:

$$P(\omega_i) = \frac{1}{M}, \quad i = 1, 2, ..., M$$  \hspace{1cm} (4)

where $\omega_i$ denotes the modulation category and the selective accuracy method is used to estimate the diagnostic accuracy. $N$ samples were taken from the total of all fault types, one sample was taken from each fault $N_i$, and one sample was used $\sum_{i=1}^{M} N_i = N$ as the test set. Let $k_i$ the number of samples in the test set that is correctly classified in the $\omega_i$ category, because $k_i$ they are independent of each other, so the joint probability density $P(k_i)$ is:

$$P(k_i) = P(k_1, k_2, ..., k_M) = P(k_1) ... P(k_M) = \prod_{i=1}^{M} \epsilon_i^{k_i} (1 - \epsilon_i)^{N_i - k_i}$$  \hspace{1cm} (5)
where $\varepsilon_i$ is the true correct recognition rate of the $\omega_i$ category. Using the same method, we can get the maximum relief estimate of $\varepsilon_i$, $\hat{\varepsilon}_i = \frac{K_i}{N_i}, i = 1,2,\ldots,M$. Overall recognition rate is shown in equation (6).

$$\hat{\varepsilon}_i' = P(\omega_1)\hat{\varepsilon}_1 + \cdots + P(\omega_M)\hat{\varepsilon}_M = \sum_{i=1}^{M} P(\omega_i)\hat{\varepsilon}_i.$$  \hfill (6)

Thus, the expectation of $\hat{\varepsilon}_i'$ is

$$E(\hat{\varepsilon}_i') = \sum_{i=1}^{M} P(\omega_i)\hat{\varepsilon}_i = \varepsilon.$$  \hfill (7)

The variance of $\hat{\varepsilon}_i'$ is

$$\text{var}[\hat{\varepsilon}_i'] = \frac{1}{N} \sum_{i=1}^{M} P(\omega_i)\varepsilon_i (1 - \varepsilon_i).$$  \hfill (8)

From the definition of the expectation and unbiased estimation of equation (7) $\hat{\varepsilon}_i, \hat{\varepsilon}_i'$ is the unbiased estimator of $\varepsilon$. The correct recognition rate is obtained from the above theoretical analysis:

$$P_{cc} = P(\omega_1)\hat{\varepsilon}_1 + \cdots + P(\omega_M)\hat{\varepsilon}_M = \sum_{i=1}^{M} P(\omega_i)\hat{\varepsilon}_i.$$  \hfill (9)

According to the above calculation, it can be shown in table 4 the comparison of RBF with the other methods for fault diagnosis of analog circuit.

**Table 4. The comparison of feature evaluation indicators based on different methods.**

| Methods       | BPNN  | Wavelet NN | SVM   | RBFNN |
|---------------|-------|------------|-------|-------|
| Sallen-Key    | 87.4% | 84.6%      | 93.7% | 97.5% |
| Four OP-AMP   | 79.1% | 76.4%      | 82.9% | 94.8% |

In general, for the extracted two-dimensional fault features, table 4 gives the prediction rate of feature evaluation indicators of the Sallen-Key and Four OP-AMP circuits based on different methods of the paper, and lists the value of correct prediction rate of the quantitative indicators of circuit fault characteristic separately of the four methods. The comparison in the evaluation index of the two circuits of fault features extracted by RBF method is much higher than other methods. In addition, we can see that RBF has high accuracy and has high level of performance for Sallen-Key band pass filter circuit and its prediction rate is 97.5%.

5.2. Result and analysis

In this part we compare the feature extraction on fault diagnosis of analog circuit based on RBF neural network with back propagation (BP) neural network as in [25], wavelet neural network as in [27], and the support vector machine (SVM) as in [20]. The experiments were performed on the fault features of the circuits in figure 2 and figure 3 and the results are shown in figure 4 and figure 5. Figure 4 and figure 5 shows the two-dimensional fault feature distribution of the Sallen-key and the FOUR OP-AMP band-pass filter circuit based on the above four methods, respectively.
Figure 4. The Sallen-key band-pass circuit 2-D feature of the two CUTs based on different method.

Generally, in the comparison of the four experimental simulations the obtained results as drawn in figure 4 and figure 5. Those shows that two-dimensional fault characteristic distribution diagrams of Sallen key and bi-quad four OP-AMP band-pass circuits based on different method, but their position of the fault classes are different as follows respectively. The proposed method can give all the fault features of the circuits and can attain the purpose of fault diagnosis. However, when we compared with the other method in this paper, the three methods do not have wider feature distances between different fault, which indicates that the proposed method in this paper has the best diagnostic effect.
For comparison purpose we use the same data of the experiments for the four methods in this paper, which are BP, wavelet neural networks, SVM and RBF, and the results are shown in figure 4 and figure 5. From this, we conclude that the two-dimensional features extracted by these methods have the following characteristics:

I. The fault class in figures 4(d) and 5(d) are more separable than in figures 4(a), 4(b), 4(c), 5(a), 5(b) and 5(c). That is, the fault class drawn by RBF are wider in distance than in the other methods. So that, the classification capabilities of BP, wavelet neural network and support vector machine are limited.

II. The feature distribution within the class is denser in figures 4(a), 4(b), 4(c), 5(a), 5(b) and 5(c) than 4(d) and 5(d), which indicating that the class aggregation ability is stronger in 4(d) and 5(d).

Figure 5. The FOUR OP-AMP band-pass circuit 2-D feature of the two CUTs based on different method (Where PC1 denotes first most significant principal components.)
6. Conclusion
In this work, we have been proposed RBF method has better performance for analog circuit of fault diagnosis. As shown in our result, we compare RBF method with the other techniques that are listed in this paper, and through comparing the feature distribution of fault classes categorized by 2-dimensional feature distributions, we see that RBF method is the best for characteristics of fault feature extraction. Moreover, from the experimental and simulation results we noted that the proposed method has advanced diagnosis accuracy. Therefore, the finding of the study suggests that RBF neural network as a competitive method of the rest method for future works.

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