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The Research on Fusion and Diagnosis Method of Multi Soft Fault of Nonlinear Analog Circuit

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Abstract

For the single source characteristics of the insufficient problem of nonlinear analog circuit soft fault diagnosis, we propose a new method that is based on dual Wiener core for fault diagnosis of intelligent information optimization fusion[1,2,3,4,5], firstly, the incentive is Gauss white noise, after sampling we obtain the Wiener core of circuit and power which is used from the discrete Wiener core, then use the improved genetic algorithm, make the feature selection and fusion combination as an optimization problem, propose intelligent optimization fusion extraction based on the improved genetic algorithm, the circuit set total Euclidean distance as the objective function optimizes, the different information in feature layer can be organic integration, then use the BP neural network for intelligent diagnosis. Experiments show that the method can effectively improve the accuracy of the diagnosis of nonlinear multiple soft faults.

Keywords: *information fusion, multi soft fault, nonlinear, dual Wiener kernel, fusion extraction*

1. Introduction

The fault diagnosis[6,7,8,9] of nonlinear analog circuit began in the 1980s, after years of development, the fault diagnosis theory and methods achieved a lot, but systematicness and practicability to be strengthened, in particular the theory of nonlinear analog circuits diagnosis still imperfect, tolerance and non-linear and other factors make nonlinear analog circuits diagnosis more difficult, and, with the integrated circuit is increasing, the accessible node of circuits becomes more and more fewer, that making measurements and troubleshooting becomes more difficult.

Since the 1990s, with the development and application of the theory of intelligent theory, nonlinear functional, fuzzy and wavelets, *etc.*, brought new vitality to nonlinear analog circuit fault diagnosis, the nonlinear analog circuit fault diagnosis theory has been major development, have proposed an analog circuit fault diagnosis methods such as neural networks, fuzzy theory, wavelet analysis, support vector machines, information fusion and the like. However, these methods are still some shortcomings, such as the automatic extraction of fuzzy rules, automatic generation and optimization of fuzzy variables; another example, support vector machine, when the order is very large, the computation time and storage capacity it needs to have a greater.

For some circuits, when the available node is few, some features of some fault are similar, with a single characteristic is difficult to distinguish. Thus, the fault diagnosis method based on multi-sensor data fusion is paid attention, scholars have done much fruitful research, however, usually wavelet transform data preprocessing, feature extraction using as the main analysis method using fuzzy sets, neural network and evidence theory information fusion, the diagnosis has improved. But still not perfect, there is no research for more soft fault nonlinear circuits; some request and multi-node; diagnostic features multi-time domain or frequency domain characteristics of the

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nonlinear characteristics of the lack of research; information fusion respect, decision-making more integration, greater reliance on the information preprocessing; even the information layer fusion, are mostly simple cross.

Therefore, this paper aim at the more soft faults of nonlinear analog circuits, use the method of information fusion to make research, extract the nonlinear analog circuits and power supply current of Wiener core characteristics as the primitive character, and use the feature extraction and integration as an optimization problem, propose genetic algorithm optimization feature fusion extraction [10-12] to achieve complementarities integration of different sources of information, and then use BP neural network to complete fault diagnosis [13,14], in order to improve the accuracy of more soft faults.

2. Intelligent Fault Diagnosis Based on Wiener Kernel Information Fusion

Intelligent fault diagnosis based on Information fusion in this article requires only circuit input, output and power supply can be accessible, generally able to meet this condition. The principle of the method is shown in Figure 1.

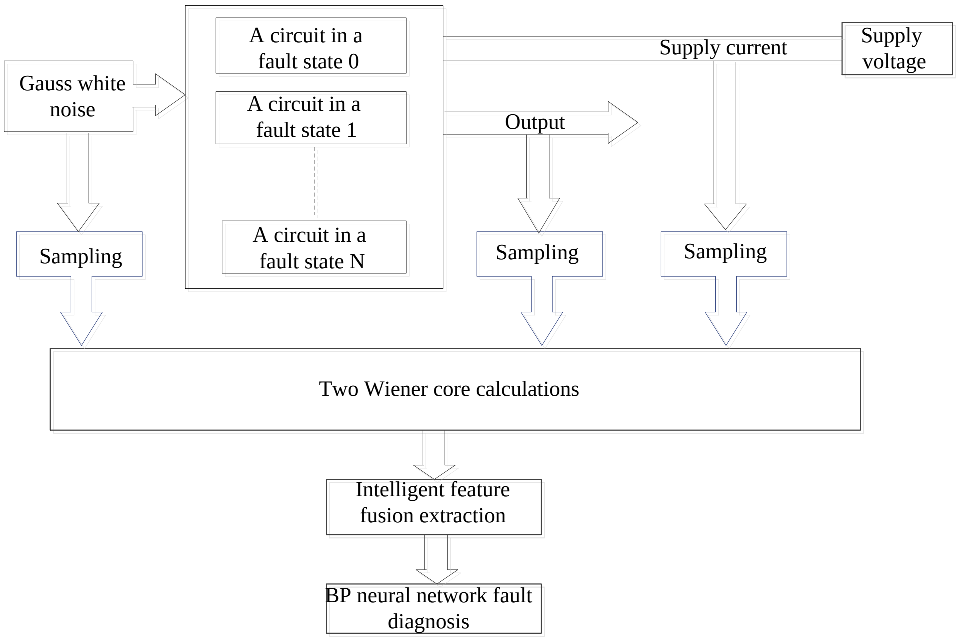

Figure 1. Intelligent Fault Diagnosis Method Based on Information Fusion

The process of intelligent fault diagnosis which is based on of information fusion of Wiener core can be divided into four stages, the first stage obtain the Weiner core; the second stage use intelligent optimization algorithm to make optimization fusion extraction for the two core, and generate a sample; the third stage design neural network and training; the fourth stage make diagnostic test for the actual circuit [15, 16].

2.1. The Acquisition of Weiner Core

The process is done into two steps:

1. Status classification

The status of tested nonlinear analog circuits is classified and numbered, including the normal state of the **circuit** and all fault conditions to be diagnosed, including soft faults and hard faults and **multi-**fault state, establish fault state set.

2. The measurements of each state of Wiener core

WGN is sequentially applied to the measured nonlinear analog circuits in each of the state as a data processing method to test excitation signal, and input, output and supply current signals are sampled simultaneously to obtain sample data sequence using discrete Wiener core acquired few bands before Wiener nucleus (For convenience, are referred to as circuit Wiener core and core power), and with a simulation of the correctness of available core test circuit and test circuit power supply system of each state. N-th order Wiener core expression is as follows:

$$k_n(\tau_1, \tau_2, \cdots \tau_n) = \frac{1}{n!A^n} E\left[y_{n-1}(t)\, x(t-\tau_1) \cdots x(t-\tau_n) \right] \tag{1}$$

$$y_{n-1}(t) = y(t) - \sum_{i=0}^{n-1} G_i(t) \tag{2}$$

The order of core appropriately selected depending on the degree of non-linear circuits, in most cases the nonlinearity is weak, can take the first few bands nucleus, in order to meet the requirements of the diagnosis demand.

2.2 The Intelligent Optimization and Fusion Selection Dual Core Feature

As mentioned above, access to the circuit Wiener core status and the Wiener core power of each circuit, fault diagnosis if only one of the core features, some states distinguish between small, or even identical, is difficult to determine in the end it is the kind of state, when there is more soft faults, more difficult to accurately diagnose. Therefore, the effective integration of the two core information and make full use of their complementary features to improve the accuracy of diagnosis. In addition, two core contains a large amount of information, much of the information for the diagnosis, it is redundant, in order to improve efficiency, should be effective feature extraction. In this paper, information fusion and feature extraction combined, as an optimization problem, the use of intelligent optimization algorithms for intelligent optimization fusion and feature selection. Where intelligent optimization algorithms have many choices, you can use the genetic algorithms, particle swarm optimization, simulated annealing algorithm and other improvements based on existing optimization algorithm. In this paper, the improved algorithm heritage research. Intelligent dual-core feature of fusion selection optimization process shown in Figure 2.

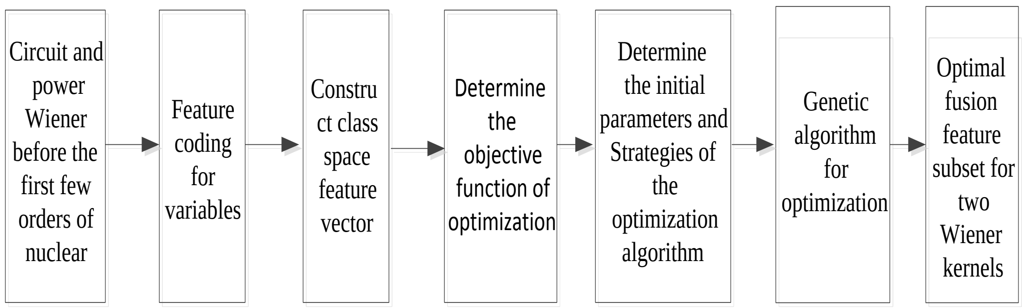

Figure 2. Intelligent Dual-core Feat Optimization Process

Double Wiener kernel feature of intelligent optimization fusion selection needs to note the following: First, the initial characteristics of previous order is a dual-core core describe data or expression; Second, you can select the values of the multidimensional "time" τ to select the core values; So, intelligent fusion selecting optimization can be carried out on the "time" τ code as an individual's signature; Thirdly, category space of the feature vector can choose dual-core core a value choice, can also according to need to choose multiple values in a certain order core; Fourthly, the objective function can choose to be in the diagnosis of the fault state eigenvector lumped distance.

After choosing intelligent fusion optimization, recording the value of the corresponding optimal feature vector of multidimensional "time" τ, than getting the fault characteristic data were normalized and generating the training sample set and test set in multiple experiments, than using for training and validation of the neural network.

2.3. Neural Network Design and Training

In this paper, BP neural network is used for diagnosis. First, design the parameters and algorithm, including the initial weights, the adaptive adjustment method of learning rate, and the learning algorithm of BP network system. Then the neural network is trained and validated. The training sample set is used to study the neural network, until the target accuracy is reached. The training effect of the neural network is verified by the test sample set. If the output is dissatisfaction, you need to improve the network and re-training. Reserve the successful neural networks for diagnosis.

2.4 Test and Diagnosis of Actual Circuit

First measure the diagnosis circuit according to the previous method of circuit Wiener kernel and power Wiener kernel. Then, use the value of "τ" of 2.2 which is in dual core characteristics of intelligent optimization fusion for the state vector, then form the diagnostic samples; finally, carry out the fault diagnosis [17, 18, 19, and 20]. The last step of the diagnosis samples input to the training successful neural network, the output of the network is the corresponding fault code and complete diagnosis.

3. Examples of Fault Diagnosis

In order to verify the improvement of multi - soft fault diagnosis which is based on the intelligent fault diagnosis method of the information fusion of Wiener kernel, and the experiment selects ITC '97 international standard circuit.

The circuit diagram is shown in Figure 3.

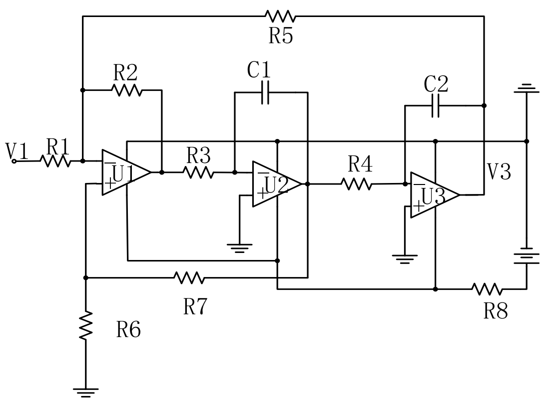

Figure 3. ITC '97 International Standard Circuit

In order to measure the supply current, a sampling resistor (R8) is connected in series with the inlet of the power supply. V1 is the voltage input; the V3 is the output of the circuit.

First, double Wiener kernel extraction

Under normal condition R1= R2= R3= R4= R5=10KΩ, R6=3KΩ, R7=7KΩ,C1=10nF,C2=20nF. The tolerance limit of component parameter values is ±10%, the soft fault is ±10%-±20%. Due to the hard fault is relatively easy to diagnose, so this paper chooses the multiple soft faults (2 or 3 element and soft fault) for diagnosis, classification of States and parameters shows in Table 1.

Table 1. State Classifications and Parameters

Fault No.	Defective elements	Fault Feature Source	Neural network fault coding
F_0	No element	K_{V1}, K_{V2}, K_{V3}, K_{I1}, K_{I2}, K_{I3}	10000000
F_1	$R_1=R_5=8.5k\Omega$	K_{V1}, K_{V2}, K_{V3}, K_{I1}, K_{I2}, K_{I3}	01000000
F_2	$R_1=R_2=8.2k\Omega$	K_{V1}, K_{V2}, K_{V3}, K_{I1}, K_{I2}, K_{I3}	00100000
F_3	$R_2=8k\Omega$ and $R_4=11k\Omega$	K_{V1}, K_{V2}, K_{V3}, K_{I1}, K_{I2}, K_{I3}	00010000
F_4	$R_2=8k\Omega$ and $C_1=8nF$	K_{V1}, K_{V2}, K_{V3}, K_{I1}, K_{I2}, K_{I3}	00001000
F_5	$C_1=8nF$ and $C_2=23nF$	K_{V1}, K_{V2}, K_{V3}, K_{I1}, K_{I2}, K_{I3}	00000100
F_6	$R_1=8k\Omega$ and $C_2=8nF$	K_{V1}, K_{V2}, K_{V3}, K_{I1}, K_{I2}, K_{I3}	00000010
F_7	$R_1=R_2=R_3=8.5k\Omega$	K_{V1}, K_{V2}, K_{V3}, K_{I1}, K_{I2}, K_{I3}	00000001

In the table, where K_{Vi}, K_{Ii},(i=1,2,3) are 1,2,3-order Wiener core of circuit and power supply.

As mentioned, the input of the circuit for each of the States is Gauss white noise, and simultaneously measures the input, output voltage and supply current. And according to the formula (1) and formula (2), the data matrix of the first 3 order Wiener kernel is calculated respectively, and the expression of the order core is obtained by curve fitting.

Second, the intelligent optimization fusion choice of the dual core.

The characteristics of intelligent optimization fusion selection process is in fact to find some variable value, consisting of a double Wiener kernel values of these points 8 circuit state in eight feature vector overall biggest difference, the overall difference between the set objective function to measure.

We extract the features from third-order Wiener core, the first order of core needs to be optimized time, represented by τ0, the second-order core need to optimize both time and with τ1 and τ2, the third-order core requires three times, represented by τ3, τ4, and τ5, these parameters are encoded, each parameter with a 16-bit binary number, six parameters use 96-bit binary number, as an individual chromosomes for subsequent optimization process. It should be noted that, where two core time parameter takes the same value, or may be respectively valued, will be more conducive selected characteristic parameters, but chromosome longer. State vector for each state by 1,2,3-order circuit Wiener core and core power six-dimensional composition to set each circuit state vector that is always Euclidean distance as the fitness function. The formula is:

$$J = \sqrt{\sum_{i=1}^{N} (K_i - \overline{K})^T (K_i - \overline{K})} \tag{3}$$

Where Ki incentives for a variety of fault conditions of core feature vectors, feature vector average. Fitness J greater, indicating the status of each fault circuit can distinguish the stronger, therefore, the higher the efficiency and accuracy of fault diagnosis.

The improved genetic algorithm used to be optimized. Studies have shown that the crossover of typical hybrid genetic algorithm operators have characteristics of forced convergence, both may converge to the global optimum; it may prematurely mature and converge to local optima. Therefore, in order to prevent genetic algorithm premature to take a method and basis for dynamically adjusting adaptive function determines accept diversity [21, 22].

The intelligent optimization of the dual core feature is based on the method such as the former.

Third, the neural network design and training

We use three layers BP neural network to diagnose circuit fault of this example. The input layer consists of 6 neurons, and output layer is composed of eight neurons, selected from the hidden layer 12 neurons. Since the BP neural network prediction error equal to the training error and the network complex error and the generalization ability of the network and learning set is a function of the mean and the desired output is in direct proportion to the difference, so the training set were root mean square error of 0.001 degree caused.

The data obtained from the above are trained as training samples and the BP neural network is trained, and the paper converges to the default error. In addition, the data of the soft fault state of the 6 groups are not trained, and the trained neural network is trained to diagnose and the diagnosis is completely correct.

Fourth, fault diagnosis

According to the method described in principle, the diagnosis of two multi fault states is completely correct.

In order to compare the diagnosis effect, the diagnostic accuracy of the circuit Wiener core and the Weiner core is separately, and the diagnostic accuracy of the multi soft fault is obviously less than that of the information fusion.

4. Experimental Results and Analysis

According to the method mentioned above, the fault diagnosis of the 8 states is carried out, and the results are all correct.

Also, set up fault states which is close to F7,F4, but the degree of fault is slightly different, respectively (R1=R2=8.5k and R3=8k) and (R2=8.5k and C1=8nF) and neural network are all correct judgment for F7, F4 fault. The results show that the diagnosis system has better functional capacity.

In order to compare the diagnostic results, the diagnostic accuracy of the Wiener core and the power Weiner core is separately, and the diagnostic accuracy of the multiple soft faults is obviously less than that of the information fusion.

The experimental results show that the fault diagnosis based on the information fusion can improve the accuracy of fault diagnosis obviously, and has good generalization ability.

5. Conclusions

From the theoretical analysis and experimental studies, it can be seen that the intelligent fault diagnosis method based on double Wiener kernel can effectively improve the diagnostic accuracy of the nonlinear analog circuit with multiple soft faults. The improved genetic algorithm based on intelligent optimization fusion extraction method is proposed in the paper, and has a remarkable effect on the improvement of the diagnosis effect.

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