Data Fusion Based Fault Diagnosis of Analog Circuits

Minfang Peng, Meie Shen, Jianbiao He

Abstract—**A new approach to the fault diagnosis of analog circuits is presented based on radial basis function (RBF) neural network and D-S evidence theory. The proposed technique taken from data fusion consists of two stages, namely preliminary diagnosis and fusion decision. Preliminary diagnosis is performed separately by using an independent RBF network employing one kind of fault signatures from multiform circuit responses. These diagnoses are then considered as pieces of evidence ascertaining to the condition of the circuit and are aggregated using an evidential reasoning algorithm. Fault location is accomplished according to the fusion results based on the fusion decision regulation. The experimental results show that the proposed diagnosis strategy has the capability to diagnose catastrophic and parametric faults of analog circuits, and can effectively combine the evidence to produce a more meaningful and accurate diagnosis.**

Index Terms—**analog circuit, data fusion, fault diagnosis, neural network**

I. Introduction

With the rapid development of integrated circuits, there is a growing interest in the development of automatic tools for testing analog circuits. Although large electronic systems are usually implemented by digital techniques, quite often they interface with the external world through analog devices. As an example, all control systems, even when control is implemented by digital techniques, must take inputs from sensors and provide outputs through actuators. Conditioning, multiplexing, and converting analog signals are tasks that most complex systems have to perform. However, automated fault detection and location for analog circuits is subject to many problems, such as variety of faults, the presence of noise, the unknown deviation in tolerances of nonfaulty component values, non-linearity of circuit parameters and the diagnosis of soft faults. Testing systems of analog circuits is surely less understood, yet strongly relevant for application[1][2].

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The difficulties in analog test make the application of neural networks to these problems very appealing[3]-[6]. These diagnosis techniques occupy neural network' ability to generalize and function without physical fault models or detailed tolerance information. Nevertheless, generally, such approaches have not make full use of the information from the tesed circuits so that accurate diagnosis has been hampered by deficient fault information especially in complex circuits with limited accessible nodes.

As a powerful tool in information processing, data fusion has been used successfully in automatic object identification, fault diagnosis of mechanical, electrical equipments and so on[7-9]. Similarly, analog circuit fault diagnosis based on data fusion will certainly have good application prospects and maybe break through in practicality of diagnosis methods. But it is very pity that the research has just started[10][11].

Based on data fusion technology, this paper deals with analog circuit fault diagnosis by means of neural network and D-S evidence theory. The principle fundamentals of fault diagnosis including structure of diagnosis system, diagnosis approach based on RBF neural network, data fusion algorithm and fault location regulation are discussed. A new analog fault diagnosis method is proposed based on data fusion of multiform circuit responses. The proposed technique consists of two stages: preliminary diagnosis and fusion decision diagnosis. Preliminary diagnosis is performed separately by using an independent RBF network employing one kind of fault signatures from multiform circuit responses. These diagnoses are then considered as pieces of evidence ascertaining to the condition of the circuit and are aggregated using an evidential reasoning algorithm. Fault location is accomplished according to the fusion results based on the fusion decision regulation.

II. Diagnosis Strategy

There are many kinds of test signals used for fault diagnosis in analog circuits such as accessible node voltages, terminal currents, circuit gains of output to input, impedance, admittance and so on. Besides, there are non-electric signals such as temperature of circuit components. Conventional methods perform fault diagnosis based on only one kind of test signal. Thus, diagnosis accuracy is often unsatisfactory because of the insufficiency of fault information. In this paper, we select more than one kind of suitable test signals for fault diagnosis and employ artificial neural networks (ANNs) to implement preliminary diagnosis.

The characteristic feature of an ANN is that it considers the accumulated knowledge acquired through training examples and responds to new events in the most appropriate manner, on the basis of experiences gained through training. This means that ANNs have the ability to learn the desired input-output mapping based on training examples, without looking for an exact mathematical model. Once an appropriate ANN is properly trained, it will contain a representation of the non-linearity of the desired mapping between the inputs and outputs. The ability of ANNs to learn complex nonlinear input/output relationships have motivated researchers to apply ANNs for solving model-free nonlinear problems related to various fields, including those of analog-circuit fault diagnosis. The multilayer feed-forward network with a back-propagation (BP) training algorithm is the most widely used ANN model for analog-circuit fault diagnosis. However, BP has a number of deficiencies such as slow training and local minimum, and the algorithm does not work satisfactorily when the case to be diagnosed falls in a region with no training data. The RBF based neural network is well suited for such cases[12].

RBFNs share features of the BP NNs for pattern recognition. They are being extensively used for on- line and off-line non-linear adaptive modeling, control and fault diagnosis applications. RBF NNs store information locally whereas the conventional BP NNs store the information globally. RBF NNs have certain advantages which are not found in conventional BP NNs. Using the RBF NN, the parameters can be independently controlled and hence the training is easier and faster when compared to a BP NN[13].

Moreover, as there are many kinds of transducer information and symptoms in diagnosis, the training time would be very long and the network may be difficult to converge if all the information and symptoms are inputted into the same network. Therefore, in the proposed diagnosis model, each type of fault signatures is inputted as independent samples into a separate RBF network, and then the map from symptom space to fault pattern space for each kind of characteristic parameters is constructed. The diagnosis results from every radial basis function network (RBFN) may be same or different, but since all the symptoms are collected from the same system, their relative fault patterns can be integrated with D-S evidence theory to get the correct fault pattern.

III. Diagnosis Based on RBFN

A typical RBF NN structure (Fig. 1) has three layers: an input layer, a nonlinear hidden layer and a linear output layer. The hidden nodes are the radial basis function units and the output nodes are simple summations. The number of input, output and hidden nodes are n_I, n_o and n_h, respectively.

The number of input nodes represents the dimension of characteristic parameters corresponding to the kind of test signal, and the number of output nodes represents the sorts of faults. Since every output node represents a sort of fault and the network outputs are the values ranging [0,1], the output value of any output node represents the possibility of the circuit state belonging to the sort of fault corresponding to the node.

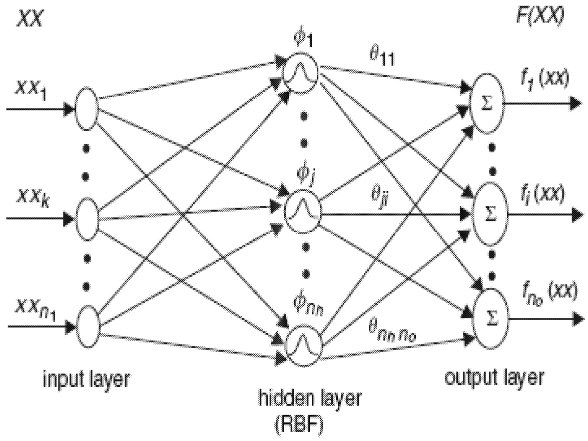

Fig. 1 Architecture of RBF NN

Any of the functions such as spline, multiquadratic and Gaussian function may be used as a transfer function for the hidden neurons. The Gaussian RBF as the most widely used one has been considered for the fault classification and location applications[12-14]. The Gaussian function was also chosen in this paper. The response ϕ_j of the j[th] hidden neuron to the input vector $\mathbf{XX}$ can be expressed as:

$$\phi_j(\mathbf{XX}) = \exp(-\frac{1}{\sigma_j^2}\left\|\mathbf{XX} - C_j\right\|^2) \qquad 1 < j \le n_h \qquad (1)$$

where, $\mathbf{XX} \in R^{nI}$ is the input vector; C_j is the RBF centers; $\|\bullet\|$ denotes the Euclidean norm; σ_j is the spread of the Gaussian function.

The output f_i of i[th] node in the output layer is given by:

$$f_i(\mathbf{XX}) = \sum_{j=1}^{n_h} \phi_j(\mathbf{XX})\theta_{ji} \qquad 1 \le i \le n_o \qquad (2)$$

where θ_{ji} is the weight from the j[th] hidden node to the i[th] output node.

The performance of an RBFN depends on the choice of the values of the centers. The task of network learning is to choose appropriate centers and determine the corresponding weights based on a given set of training inputs and outputs. In this paper, the simulation studies have been carried out by means of MATLAB, which makes use of the Orthogonal Least Squares (OLS) learning procedure for determining the RBF centers.

The OLS procedure can be implemented by considering a RBF ϕ with a spread σ and introducing an error term ε in (2), which can be described as follows

$$d_i(\mathbf{XX}) = \sum_{j=1}^{n_h} \phi_j(\mathbf{XX})\theta_{ji} + \varepsilon \qquad 1 \le i \le n_o \qquad (3)$$

where d_i is the desired output of the i[th] output node, and then maximizing the error reduction ratio by OLS principle.

Choosing the spread of the RBF depends on the pattern to be diagnosed. Many algorithms are available to find the optimal spread of the RBF. Generally, the spread should be larger than the minimum distance and smaller than the maximum distance between the input vector and the center of the RBF spread to get better generalization.

The number of RBF neurons selected are based on the patterns to be diagnosed and on the required accuracy. Normally, in the RBFN, the number of hidden neurons equals the number of patterns to be detected if the required sumsquared-error is to be zero.

IV. Decision Fusion

D–S evidence theory represents uncertainty through belief and plausibility, all derived from a basic probability assignment. It attains the goal of data fusion by means of a combination rule applied to evidence sources. Let a aggregation function m: $2^{\Theta} \rightarrow [0，1]$, which meets: ① m（ϕ）=0，② $\sum_{A\subset\Theta} m(A) = 1$, where m is called belief function assignment in recognition frame Θ (here, ϕ stands for empty sets). As for $A \subseteq \Theta$ ，m（A）is called belief function value which reflects belief magnitude of A itself. When m（A）$\neq$ 0, A is called focal element.

The belief function assignment $m_j(i)$ for the sensor S_j to the object i (i.e. the test information j to the fault set i) can be expressed as[7][8]:

$$m_j(i) = \frac{C_j(i)}{\sum_{i=1}^{N_C} C_j(i) + N_s(1-R_j)(1-W_j\alpha_j\beta_j)} \tag{4}$$

The belief function assignment $m_j(\theta)$ of the indeterminacy θ for the sensor S_j can be expressed as:

$$m_j(\theta) = \frac{N_s(1-R_j)(1-W_j\alpha_j\beta_j)}{\sum_{j=1}^{N_C} C_j(i) + N_s(1-R_j)(1-W_j\alpha_j\beta_j)} \tag{5}$$

where

$$\alpha_j = \max_{i=1}^{N_c} \{\mathbf{C}_{\mathbf{j}}(i)\} \tag{6}$$

$$\beta_j = \{[N_c W_j / \sum_{i=1}^{N_c} C_j(i)] - 1\} \Big/ (N_c - 1) \tag{7}$$

$$R_j = W_j\alpha_j\beta_j \Big/ \sum_{k=1}^{N_s} W_k\alpha_k\beta_k \tag{8}$$

$\mathbf{C}_{\mathbf{j}}(i)$ is the correlation coefficient for the sensor S_j to the object i, which is the output value of i[th] output node of the RBF NN_j accepting the test signal from S_j ; α_j is the maximal correlation coefficient for the sensor S_j ; β_j is the correlation assignment value for the sensor S_j; R_j is the reliability coefficient for the sensor S_j ; W_j ranging [0，1] is weighted coefficient dependent on the environment; Ns is the number of all sensors; Nc is the sorts of the objects, here Nc is the sorts of faults to be diagnosed.

From (4) and (5), we can obtain the fused belief function assignment by means of D-S evidential reasoning rule. Let m_1 , m_2 ,⋯, m_n stand for the belief function assignment corresponding to fault sets Θ respectively, and { A_j } stand for their focal elements correspondingly. The fused belief function $m = m_1 \oplus m_2 \oplus \cdots \oplus m_n$ is given by

$$m(A) = \sum_{\cap A_j = A} \prod_{j=1}^{N_S} m_j(A_j) \Big/ [1 - \sum_{\cap A_j = \phi} \prod_{j=1}^{N_S} m_j(A_j)] \tag{9}$$

Thus, as for test information j from sensor S_j, y_{ji} (the possibility of the circuit state belonging to fault state i) can be calculated by a relative RBF NN_j. y_{ji} is used to express the correlation coefficient $\mathbf{C}_{\mathbf{j}}(i)$. By using (4) and (5), the belief function value $m_j(i)$ and the belief function value $m_j(\theta)$ of the indeterminacy before fusion can be obtained. Then, By using (9), the fused belief function value $m(j)$ and the fused belief function value $m(\theta)$ of the indeterminacy can be obtained. Finally, fault location can be implemented according to the following regulation:

① The fault set must have the maximal belief function value.

② The belief function value of the fault set must be more than the belief function value of the indeterminacy.

③ The difference between the belief function value of the fault set and the value of others must be more than a given threshold value.

④ The belief function value m(θ) of the indeterminacy must be less than a given threshold value.

V. Simulation Example

By the above method, we have diagnosed the circuit shown in Fig. 2[15]. The precision of component parameter is 0.01. Node 1, 3, 5, 8 were chosen to be accessible nodes. Assuming that hard fault of every component and the parameter diversification ratios of faulty components $|\triangle X_j| / X_{j0}$ are 0.05, 0.5, 5, 50, 500 respectively, we obtained 105 kinds of single fault states. From these samples, chose 60 samples for NN training and 45 samples for samples to be diagnosed.

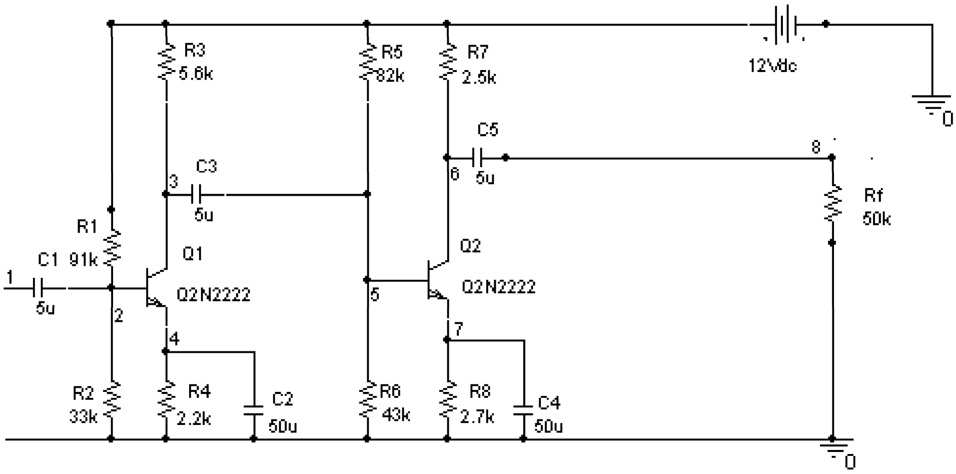

Fig. 2 The Circuit as an Example

Accessible nodal voltages and circuit gains of output to input under different test frequencies were employed for test signals. In order to select suitable testing frequencies for measuring circuit gains, we acquired the transfer function of the circuit $H(S) = V_8(S)/V_1(S)$ and the mplitude -frequency distribution under the consideration of the normal circuit. According to the amplitude -frequency distribution, we can obtain the turnover frequencies. Then, chose a frequency less than the lowest frequency and a frequency more than the highest frequency according to the turnover frequencies. Furthermore, chose a test frequency over and below the tuning point of complex critical frequency respectively. In addition, since adjusting frequencies and measuring circuit gains have some errors, we took frequencies more than the number decided by the above method. Thus, 6 test frequencies were obtained, i.e. 100 Hz、180 Hz、300 Hz、1.5KHz、10KHz、30KHz.

Based on the two kinds of test signals, Voltage of accessible nodes and circuit gains, the single fault in the circuit was diagnosed respectively by using the proposed approach. The diagnosis results are listed in Table Ⅰ to the Table Ⅲ.

Table Ⅰ Faults Location Based on Node Voltage

Category	Rate of correctness	Rate of refusal	Rate of mistake
Training sample	100%	0%	0%
Diagnosed sample	80.00%	6.67%	13.33%
Sum total	91.43%	2.86%	5.71%

Table Ⅱ Faults Location Based on Circuit Gains

Category	Rate of correctness	Rate of refusal	Rate of mistake
Training sample	100%	0%	0%
Diagnosed sample	86.67%	4.44%	8.89%
Sum total	94.29%	1.90%	3.81%

Table Ⅲ Faults Location Based on Fusion

Category	Rate of correctness	Rate of refusal	Rate of mistake
Training sample	100%	0%	0%
Diagnosed sample	93.33%	2.22%	4.44%
Sum total	97.14%	0.95%	1.90%

From the Table Ⅰ to the Table Ⅲ, we can find that the accuracy of fault location increases greatly by using fusion diagnosis. Although single fault location is given as the example, its diagnosis principle can be applied to multiple fault location.

I. Conclusion

In this paper, a fault diagnosis approach based on RBF neural network and D-S evidence theory has been developed for fault location of analog circuits. The proposed method makes full use of the fault information by means of data fusion and reduces the input dimensions of the RBFN by assigning an independent RBFN to every kind of test signal. Moreover, preliminary diagnosis based on RBFN gets over some deficiencies of BP such as slow training and local minimum, and fusion decision by using the evidential reasoning improves diagnosis accuracy. The given simulation results show that the proposed strategy has the capability to diagnose catastrophic or parametric faults of tolerance circuits with satisfactory accuracy.

References

[1]Fang Liu; Ozev, S. Statistical Test Development for Analog Circuits Under High Process Variations. IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, 2007, 26(8) , pp. 1465–1477.

[2] Tadeusiewicz M., Halgas S., Korzybski M.. An algorithm for soft-fault diagnosis of linear and nonlinear circuits[J]. IEEE Transactions on Circuits and Systems I: Fundamental Theory and Applications, 2002,49(11), pp. 1648 – 1653.

[3]D. Micˇusˇı´k, V. Stopjakova´, L'. Benˇusˇkova´. Application of Feed-forward Artificial Neural Networks to the Identification of Defective *Analog* Integrated Circuits. Neural Computing & Applications,2002,11(1), pp.71–79.

[4]Marcantonio Catelani, Ada Fort. Soft Fault Detection and Isolation in Analog Circuits:Some Results and a Comparison Between a Fuzzy Approach and Radial Basis Function Networks[J]. IEEE Transactions on Instrumentation and Measurement, 2002, 51(2), pp. 196-202.

[5] Cannas, Barbara; Fanni, Alessandra; Manetti, Stefano; et al. Neural network-based analog fault diagnosis using testability analysis. Neural Computing & Applications, 2004, 13(4), pp. 288-298.

[6] Aminian, M.; Aminian, F.. A Modular Fault-Diagnostic System for Analog Electronic Circuits Using Neural Networks With Wavelet Transform as a Preprocessor. IEEE Transactions on Instrumentation and Measurement, 2007, 56(5), pp. 1546 – 1554.

[7] Luo Zhizeng,Ye Ming. Fusion of Dependency Information Using Dempster-Shafer Evidential Reasoning[J]. Journal of Electronics and Information Technology, 2001,23(1), pp. 970-974。

[8] K. Spurgeon, W.H. Tang, Q.H. Wu, Z.J. Richardson and G. Moss. Dissolved gas analysis using evidential reasoning[J]. IEE Proc.-Sci. Meas. Technol., 2005, 152(3), pp. 110-117.

[9] Bar Shalom, Y.. On the Sequential Track Correlation Algorithm in a Multisensor Data Fusion System. IEEE Transactions on Aerospace and Electronic Systems, 2008, 44(1), pp. 396 - 396

[10] ZHU Da-qi,YU Sheng-lin. Data Fusion Algorithm Based on D-S Evidential Theory and Its Application for Circuit Fault Diagnosis[J]. ACTA ELECTRONICA SINICA, 2002, 30(2), pp.221 - 223.

[11] Peng Minfang, He Yi-Gang, Wang Yao-Nan, He Jianbiao. Synthetic Intelligence Based Fault Diagnosis of Analog Circuits. Proceedings of the CSEE,2006,26 (3), pp. 19 -24.

[12] K. G**.** Narendra, V. K. Sood, K. Khorasani, etc. Application of a Radial Basis Function (RBF) Neural Network for Fault Diagnosis in a HVDC System [J]. IEEE Transactions on Power Systems, 1998, 13(1), pp. 177-183.

[13] R.N. Mahanty, P.B. Dutta Gupta. Application of RBF neural network to fault classification and location in transmission line[J]. IEE Proc.-Gener. Transm. Distrib., 2004,151(2), pp. 201-212.

[14]Whei-Min Lin, Chin-Der Yang, Jia-Hong Lin,etc. A Fault Classification Method by RBF Neural Network With OLS Learning Procedure[J]. IEEE TRANSACTIONS ON POWER DELIVERY, 2001, 16(4), pp. 473-477.

[15] Gao Huan-Wen, Wang Hui. Computer Aided Analyse and Design for Analog Circuits—Application of PSPICE [M]. Beijing,, Tsinghua University Press, 2003.

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