Analog-Circuit Fault Diagnosis Using Probabilistic Neural Network

Meie Shen, Hao Yuan, Min-Fang Peng

Abstract—**Analog circuit diagnosis using BP neural network has mainly been used to hardware fault recognition in the past. Soft faults and tolerance effort make the number of training samples for a diagnosis neural network increase greatly and the training rate of the network reduce greatly. Against the shortcomings caused by Back-propagation Neural Networks for fault diagnosis, which include slow learning speed for convergence and easily falling into local minimum value, Probabilistic Neural Network is introduced to fault diagnosis in analog circuits with tolerance in this paper. Fault samples including soft faults and hard faults in tolerance circuits are generated by Monte Carlo analysis. Fault features are extracted by using the largest deviation path so as to obtain appropriate training samples. Simulation results show that the proposed diagnosis method has high speed and accurate recognition even for soft faults in circuits with tolerance.**

***Index Terms*—Analog circuit, Fault diagnosis, Probabilistic Neural Network, Tolerance.**

I. Introduction

Since 90's last century, analog circuit fault diagnose using artificial neural networks has achieved delightful progress. These diagnosis methods based on the classical Artificial Neural Network(ANN) model mostly occupy multilayer perceptron model structure (BPNN) by means of the error back-propagation (BP) learning algorithm. Compared with the traditional method based on statistics, BPNN has the advantages of parallel computing and makes a variety of data integrated. It doesn't need original data with Gaussian normal distribution and so its classification are superior to those based on the conventional statistical method[1]. However, BP learning algorithm based on Gradient Descent Algorithm is slow to converge and easy to fall into local minimum. Moreover, it is a difficult task to identify the network structure. The mentioned shortages have greatly affected the learning efficiency and classification accuracy of the network[1,2]. Although many literatures developed some improved learning algorithm, slow learning speed for convergence and easy falling into a local minimum have not been fundamentally resolved yet. In order to increase the diagnostic accuracy, we need to find a new learning algorithm. Probabilistic Neural Networks (PNN) is a neural network based on a statistics model[3]. It has the same classification function with optimal Bayesian classifier, and it is unlike the traditional multi-layer network requiring BP algorithm to conduct reverse error spread. Compared to the traditional BP network, it has the advantages including short training time and rarely converging to the local minimum.

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II. Fault diagnosis network

A. Probabilistic Neural Network

Probabilistic Neural Network, in essence, is a parallel algorithm developed based on Bayesian minimum risk criteria. It was proposed By Specht [4] according to Bayesian Classification Rule and the probability density function of Parzen's. While training the network, it stores training samples directly as the sample vector of the network without any changes. It only needs to estimate the Smoothing Factor of the transfer function with empirical statistics, and so the process is relatively simple. Its basic structure is shown in Fig. 1.

In Fig.1, $I_{1.1}$ is the weight matrix which connects the input and the first layer (layer RBF). $I_{1.1}$=QR, Q is the number of input goals, namely, number of neurons of the first layer. R is number of predefined categories of the model, that is,the number of neurons of the second layer. P is eigenvector to be detected (R × 1). b_1 is the threshold of RBF layer (layer 1), a threshold vector (Q × 1); a_1 is the output vector of Radial Basis Transfer Functions in the first layer.$L_{2.1}$ is the weight matrix which links layer1 and layer2 (competition layer); C is a Competition Transfer Function. Suppose that there are Q couples of twin training vectors, I_1 ／O_1，I_2／O_2 ，…，I_Q ／O_Q ,in which the letter I is input vector (R×1) and the letter O is target vector.K is number of predefined categories of the model. O_i (i=1，2，…，Q)^T is the K-dimensional vector in which K subscales correspond to K model categories. And only one component is 1, the rest are 0.

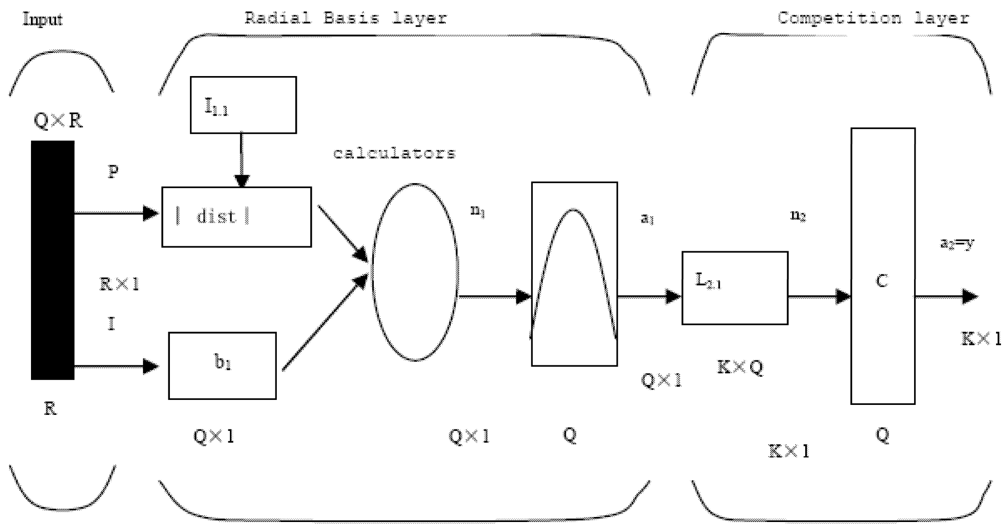

Fig.1 Probabilistic Neural Network Structure

During training, input forms input matrix Pm in a state of column vectors, the training input vector matrix (R×Q). Target vectors can be composed of a matrix vector T, the training target vector matrix (K×Q)

$$T=(O_1^T, O_2^T, \ldots, O_Q^T) \quad (1)$$

When vector $P=(P_1, P_2, \ldots, P_R)^T$ is sent to network that is well trained, the Radial Basis layer calculates distance between the input vector and sample vector.

$$D=(d_1, d_2, \ldots, d_Q)^T$$

$$D=(\| P—I_1 \|, \| P—I_2 \| \ldots \| P—I_Q \|)^T \quad (2)$$

The born vector D and b_1 multiply each other,then the result is presented by n_l,that is to say, n_1 is the the input vector of Radial Basis

Transfer Function

$$n_l=(b_1 \| P—I_1 \|, b_1 \| P—I_2 \| \ldots b_1 \| P—I_Q \|)^T \quad (3)$$

RBF output can be obtained by using n_l as RBF neuronal input,

$$a_1=\mathrm{Radbas}(n_l)=(a_{1,1},a_{1,2}\ldots\ldots a_{1,Q})^T \quad 0\leq a_{1,i}\leq i(i=l,2\ldots Q) \quad (4)$$

The second layer of network acheives summation of components of a_1 in accordance with the category of model,then gets the probability vector,

$$n_2=(n_{2,1},n_{2,2}\ldots\ldots n_{2,K})^T, \; n_2=T\times a_1 \quad (5)$$

N2 dimension K, each componet corresponds to a category of a model and the numerical size of each component shows the probability that seizure Vector P can be classified in the category of the corresponding model. Finally, the largest numerical component of probability vector is chosen after a competition transfer function C,then the corresponding component of a_2 is set to 1,others 0.It suggests that P is classfied to this category of mode[5].

B Input / output of diagnosis network

Probabilistic Neural Network training requires identified input / output mode. The input nodes in network is the dimension of mode. The output nodes is the number of categories of fault.

We assume that there are N nodes that can be detected in the circuit. the voltage value of every nodes can be achieved in fault state and will be turned into a N-dimensional vector as input samples of a neural network. The number of fault suggests the number of groups of training samples and at the same time corresponds to the output nodes of network.

C Training sample

Actual tolerance of circuit makes the existence of a soft fault possible. Soft fault parameters can be be obtained through Monte Carlo transient analysis in PSPICE. Through looking up the .OUT document of Monte Carlo analysis, the value under tolerance state that is the farthest from the normal training samples was selected as training samples of Soft Fault.

III DIAGNOSIS STRATEGY

A. Circuit as a Diagnosis Example

In order to expound the proposed the method, we occupy a circuit shown in Fig.2.

This circuit is pure resistor circuit. It is made up of the 4.5v DC voltage source and 20 resistors, 19 of which (R1 - R18) are nominal resistors with 1k resistance and 1 of which (R20)is the resistor of tolerance with grant tolerance (lot) 5% and separate tolerance (dev) 50%. Circuit nodes that can be detected are node4, node5, node8, node9 and node10. That is to say, the fault information is extracted from the above four nodes.

B Fault diagnosis process

Hard Faults are set up as follows, open circuit R1, short circuit R1, open circuit R2, short circuit R2, open circuit R3, open circuit R4 or short circuit R4. The node voltage is extracted for training samples. Soft Fault parameters caused by tolerance component can be obtained through Monte Carlo transient analysis in PSPICE. Node3 was analyzed and the node voltage was set for analysis parameters. The number of simulation is set to 10. After simulation, .OUT document is achieved, which is shown as Fig. 3.

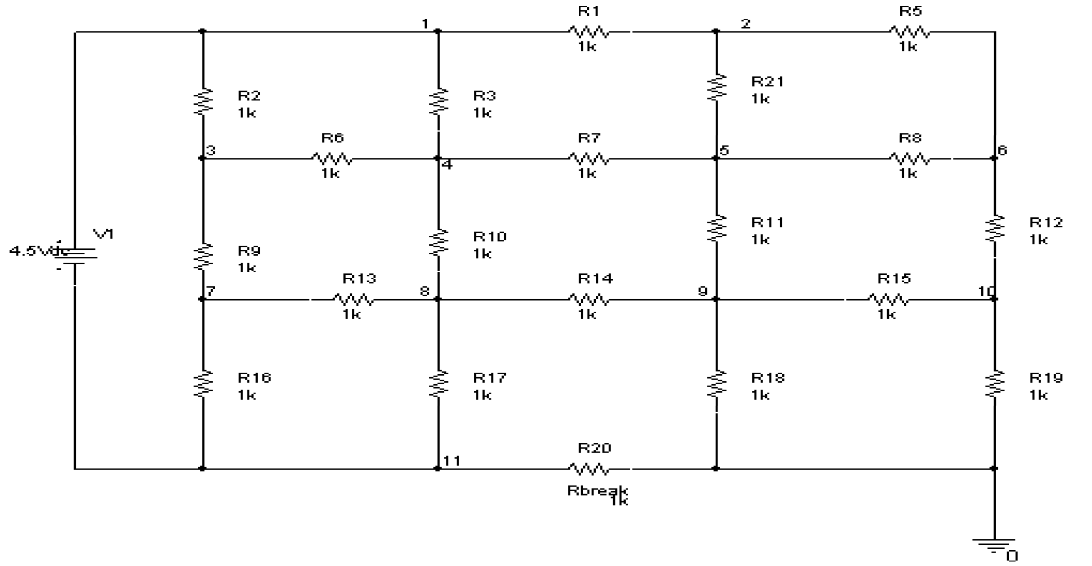

Fig.2 Circuit as diagnosis example

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Mean Deviation =  344.8500E-06
Sigma          =      .1023

 RUN                    MAX DEVIATION FROM NOMINAL

Pass    4                .2475  (2.42 sigma)  higher  at T =    1.0000E-06
                        ( 114.27% of Nominal)

Pass    5                .1179  (1.15 sigma)  lower  at T =    1.0000E-06
                        (  93.203% of Nominal)

Pass    3                .0648  ( .63 sigma)  lower  at T =    1.0000E-06
                        (  96.267% of Nominal)

Pass    8                .0632  ( .62 sigma)  lower  at T =    1.0000E-06
                        (  96.358% of Nominal)

Pass    9                .0618  ( .60 sigma)  lower  at T =    1.0000E-06
                        (  96.439% of Nominal)

Pass    7                .0535  ( .52 sigma)  higher  at T =    1.0000E-06
                        ( 103.08% of Nominal)

Pass   10                .0483  ( .47 sigma)  lower  at T =    1.0000E-06
                        (  97.215% of Nominal)

Pass    2                .0392  ( .38 sigma)  higher  at T =    1.0000E-06
                        ( 102.26% of Nominal)

Pass    6                .0189  ( .18 sigma)  higher  at T =    1.0000E-06
                        ( 101.09% of Nominal)
```

Fig.3 .OUT Document

Fig. 3 shows that node voltage of node3 deviates from the normal farthest in Pass4 and Pass5. The Pass4 positively deviates farthest while Pass5 negatively farthest.

The voltage values of node4, node5, node8 and node9 node10 is obtained in Pass4 and Pass5 as two kinds of typical training samples of Soft Faults, which are showns in Table Ⅰ.

While using Probabilistic Neural Network to analyze circuit fault, we regard node voltage as input vector and fault type as the target vector, as shown in TableⅡ. In this table, "1" represents the corresponding fault occurred, and "0" represents no fault of correspondence. There are 5 input-layer neurons which correspond to five nodes voltage value in PNN network model. 10 model layer neurons correspond to 10 training sample sets; 10 summation layer and output layer neurons correspond to 10 fault modes.

Newpnn () function in neural networks toolbox of Matlab is used to design PNN, code: net = newpnn (p, t, spread), in which p is the input vector, t target vector and spread which is set to 0.1 is density distribution function of Radial Basis.After

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setting up PNN network, the network can be used to do fault diagnosis and analysis. Sim () function is used to test which category of fault the sample sets belongs to.The output needs to be transformed to vector forms using vec2ind () function. Sample sets in Table Ⅰ are used to train network, then fault samples in Table Ⅲ are tested and output is shown as follows.

yctest =

7 6 5 10

The results of diagnosis are that R4 open circuit, R3 open circuit, R2 short circuit and negative Soft Fault, which coincide with the actual situation.

Table Ⅰ Fault Samples

Inputs of neural network (Node voltage)					
node4	node5	node8	node9	node10	Fault samples
1.681	1.410	0.325	0.596	0.650	Normal
1.766	0.944	0.478	0.453	0.392	R1 open circuit
1.613	1.779	0.204	0.709	0.855	R1 short circuit
1.367	1.291	0.163	0.514	0.603	R2 open circuit
2.067	1.555	0.523	0.697	0.709	R2 short circuit
0.949	1.144	0.154	0.464	0.560	R3 open circuit
1.645	1.195	0.323	0.541	0.645	R4 open circuit
1.718	1.636	0.327	0.655	0.655	R4 short circuit
1.621	1.363	0.268	0.564	0.626	Positive Soft Fault
1.908	1.587	0.541	0.718	0.743	Negative Soft Fault

Table Ⅱ Output of fault samples

Output nodes										Fault samples
1	2	3	4	5	6	7	8	9	10	
1	0	0	0	0	0	0	0	0	0	Normal
0	1	0	0	0	0	0	0	0	0	R1 open circuit
0	0	1	0	0	0	0	0	0	0	R1 short circuit
0	0	0	1	0	0	0	0	0	0	R2 open circuit
0	0	0	0	1	0	0	0	0	0	R2 short circuit
0	0	0	0	0	1	0	0	0	0	R3 open circuit
0	0	0	0	0	0	1	0	0	0	R4 open circuit
0	0	0	0	0	0	0	1	0	0	R4 short circuit
0	0	0	0	0	0	0	0	1	0	Positive Soft Fault
0	0	0	0	0	0	0	0	0	1	Negative Soft Fault

Table Ⅲ Test Samples

node4	node5	node8	node9	node10	Actual fault
1.666	1.192	0.333	0.541	0.665	R4 open circuit
0.900	1.143	0.166	0.452	0.577	R3 open circuit
2.050	1.530	0.520	0.700	0.712	R2 short circuit
1.907	1.593	0.544	0.723	0.744	Negative Soft Fault

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The results of diagnosis are that R4 open circuit, R3 open circuit, R2 short circuit and negative Soft Fault, which coincide with the actual situation.

Ⅳ Conclusion

PNN network has a fast training speed and rarely converges to the local minimum. It is easy to be applied to engineering practice. Simulation shows that the proposed approach based on PNN network can diagnose faults in analog circuits with tolerance effectively and have high diagnostic accuracy. Future studies will attempt to use the network to perform multiply fault diagnosis.

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