Analog Circuit Fault Diagnosis Based on Distributed Neural Network

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***Abstract*—In order to solve the problems caused by large dataset, such as the network scale and the training time, a new method of analog circuit fault diagnosis based on distributed neural network is presented in this paper. The model of distributed neural network is simply introduced. The arithmetic mechanism is depicted in detail and the arithmetic description is given. Simulation results show that this method can improve learning speed and carry out fault diagnosis of analog circuit accurately.**

***Index Terms*—analog circuit, fault diagnosis, distributed neural network, Hebb rule**

I. INTRODUCTION

With the development of science and technology, fault diagnosis has been paid more and more attention, and gradually become a research hotspot. For electronic circuit fault diagnosis, the research of digital circuit fault diagnosis has achieved great development. However, due to element tolerances, as well as with nonlinear circuit and other reasons, the analog circuits fault diagnosis is much more complicated than digital circuits fault diagnosis. Therefore, the research of analog circuit fault diagnosis is always a hot and challenging subject. Many researchers have carried on a large amount of researches, and have presented many diagnosis methods [1-14].

At present, the artificial neural network technology is becoming mature. This technology is a new solution for analog circuit fault diagnosis. Compared with other methods, artificial neural network has good robustness and strong learning ability. It can find laws from large data. Neural network technology has become the research hotspot in the field of analog circuit fault diagnosis. Researchers have presented some diagnosis methods based on neural network [15-33].

However, with the increase of fault modes, training samples and samples dimensions, the data quantity on training sets increase greatly. For a general neural network, the training efficiency will decrease even not convergent. In order to solve the problems caused by large dataset, a new method of analog circuit fault diagnosis based on distributed neural network is presented in this paper. First, the distributed neural network model is introduced. Then, the distributed neural network learning algorithm is presented. Last, the simulation results and the experiment analysis are given.

II. DISTRIBUTED NEURAL NETWORKS

A. Artificial Neural Networks

In recent years, ANNs have received great attention in many aspects of scientific research and have been applied successfully in various fields such as chemical processes, digital circuitry, control systems, etc. ANNs provide a

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mechanism for adaptive pattern classification. Even in unfavorable environments, they can still have robust classification. It should be stressed that choosing a suitable ANN architecture is vital for the successful application of ANNs. Ever architecture of ANNs is suitable for a special application and has different precision compare to other architectures.Fig.1 shows a two-layer network.

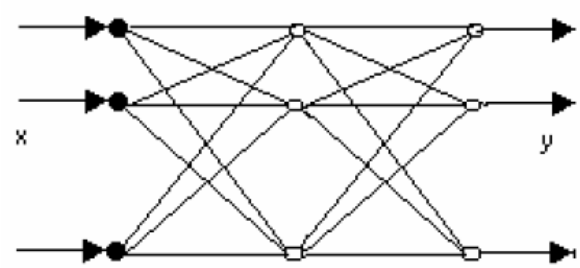

Figure 1. A two-layer network

Each input node is connected to a hidden layer node and each hidden node is connected to an output node in similar way.

B. Distributed Neural Network Model

Distributed neural network model is composed of three layers: data layer, distribution layer and concentration layer. The model is shown in Fig.2.

Data layer is composed of a whole training dataset. Distribution layer contains several disjoint sub training sets and sub neural networks whose inputs are one-to-one correspondence with the sub-training sets. The Union of these disjoint sub training sets is the whole training set. In this paper, the sub neural networks are named as distribution network. Concentration layer contains new training set which was created by distribution layer and a neural network whose input is the new training set. This neural network is named concentration network.

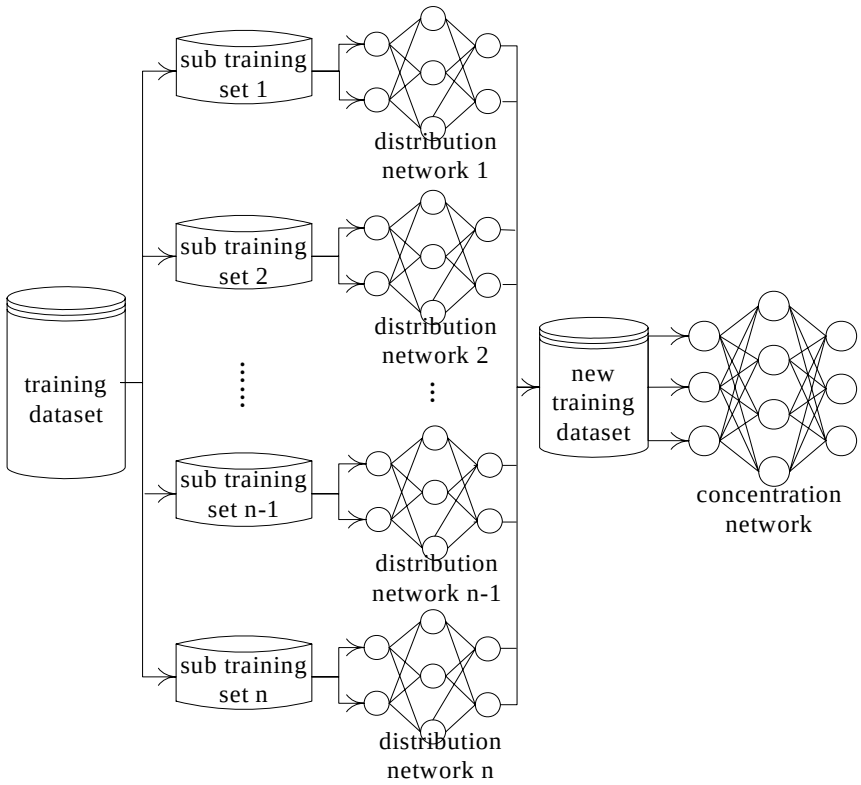

Figure 2. Distributed neural network model

III. DISTRIBUTED NEURAL NETWORK LEARNING ALGORITHM

A. Algorithm Design

In [34], a distributed neural network learning algorithm was given. With this algorithm, the space restriction problem of large dataset was solved, and the learning speed was improved. Using the algorithm can deal effectively with large data unsupervised learning problems. But analog circuit fault diagnosis is a typical supervised learning problem because the fault samples contain not only fault features but also corresponding fault modes. In this paper, supervised Hebb learning is used as learning rule of distribution layer in distributed neural network. Meanwhile, the class flag is proposed in the algorithm.

According to Hebbian hypotheses, Hebb learning rule can be expressed as:

$$\Delta w_{ij}(k) = w_{ij}(k+1) - w_{ij}(k) = \eta o_i(k) o_j(k) \quad (1)$$

Where w_{ij} is synaptic weight, o_i is activation value of neuron N_i, o_j is activation value of neuron N_j, $\eta > 0$ is learning rate factor.

Add the supervisor signal to formula(1), the supervised δ learning rule is obtained, the rule can be expressed as:

$$\begin{aligned}\Delta w_{ij}(k) &= w_{ij}(k+1) - w_{ij}(k) \\ &= \eta[d_i(k) - o_i(k)]o_j(k)\end{aligned} \tag{2}$$

Where $d_i(k)$ is anticipant output value.

Combine formula (1) and formula (2), the supervised Hebb learning rule is obtained, the rule can be expressed as:

$$\begin{aligned}\Delta w_{ij}(k) &= w_{ij}(k+1) - w_{ij}(k) \\ &= \eta[d_i(k) - o_i(k)]o_i(k)o_j(k)\end{aligned} \tag{3}$$

Namely:

$$w_{ij}(k+1) = w_{ij}(k) + \eta[d_i(k) - o_i(k)]o_i(k)o_j(k) \tag{4}$$

Where $[d_i(k) - o_i(k)]$ is supervisor signal.

The minimization functional of distributed learning algorithm base on supervised Hebb learning rule is same as the minimization functional of the algorithm in [34]. It can be expressed as:

$$\begin{aligned}R(w) &= \int (y - f(x,w))^2 dp(x,y) \\ &\quad + \int ((y - f(x,w))\Delta g(x) + \Delta g(x)^2) dp(x,y)\end{aligned} \tag{5}$$

The Formula (5) is composed of risk functional $\int (y - f(x,w))^2 dp(x,y)$ and penalty term $\int ((y - f(x,w))\Delta g(x) + \Delta g(x)^2) dp(x,y)$. It meets the minimization functional of regularization theory:

$$R(w) = R_s(w) + \lambda R_c(w) \tag{6}$$

As a result, the distributed learning algorithm based on supervised Hebb learning rule is equivalent to regularization method, the algorithm possesses integrity. In addition, because the class flag was added to the algorithm, the learning algorithm doesn't discard the partial information due to data splitting.

For the concentration layer of distributed neural network, concentration network is a BP neural network. The weight vectors of distribution networks represent knowledge Points. A new training set is formed by the synaptic weights and the class flags of hidden layer neurons in distribution network. The new training set is used as the inputs of the concentrated network. The concentration network learns by BP algorithm.

B. Algorithm Description

The distributed neural network learning algorithm is given below:

Step 1: split the training set S randomly into $S_1, S_2, S_3 \cdots S_n$, $S = S_1 \cup S_2 \cup S_3 \cup \cdots \cup S_n$ and $S_i \cap S_j = \phi$;

Step 2: according to $S_1, S_2, S_3 \cdots S_n$ initialize distribution networks $Net_1, Net_2, Net_3 \cdots Net_n$;

Step 3: Net_1 learns with S_1, Net_2 learn with S_2, Net_3 learn with $S_3 \ldots Net_n$ learn with S_n;

Step4: form the new training set S_{new} by the synaptic weights and the class flags of hidden layer neurons in $Net_1, Net_2, Net_3 \cdots Net_n$

Step5: according to S_{new} initialize concentration network Net_c;

Step6: Net_c learns with S_{new} by BP algorithm.

The detailed learning algorithm for distribution networks at Step3 is given below:

1. initialize learning rate factor η and dissimilarity threshold υ;
2. $i = 1, u = size(S_1)$;
3. take out the first sample (X_1, Y_1) from S_1, put $X_1 = (x_{11}, x_{12}, x_{13} \cdots x_{1n})$ into the inputs layer of Net_1
4. add a neuron N_1 to hidden layer, set N_1's synaptic weights $W_1 = (w_{11}, w_{12} \cdots w_{1n}) = X_1$, and set N_1's class flag $F_1 = Y_1$;
5. if $i = u$, then exit, else $i = i + 1$;
6. take out the sample (X_i, Y_i) form S_1, calculate the dissimilarity p_j between X_i and the synaptic weights of hidden layer neurons $W_j (j = 1, 2, 3 \cdots m)$;
7. get the neuron N_k whose dissimilarity is the minimum by competition function, if $p_k > \upsilon$ or $F_k <> Y_i$, then add new neurons N_{m+1} to hidden layer, set N_{m+1}'s synaptic weights $W_{m+1} = X_i$, and set N_{m+1}'s class flag $F_{m+1} = Y_i$, $m = m + 1$, go to step 5, else continue;
8. according to Formula (4) modify N_k's synaptic weightsW_k, go to 5.

IV. SIMULATION RESULTS AND ANALYSIS

The simulation circuit is shown in Fig.3. This circuit is active band-stop filter circuit. The center frequency of this active band-stop filter circuit is 1kHz, R1=R2=15kΩ, R3=R7=R9=R10=R11=10kΩ, R4=6.56kΩ, R5=R6=31kΩ, R8=5.65kΩ, R12=1kΩ, C1=C2=C3=C4=10nF.The tolerance of resistances is 5%, and the tolerance of capacitances is 5% also. The unique test point is Vout.

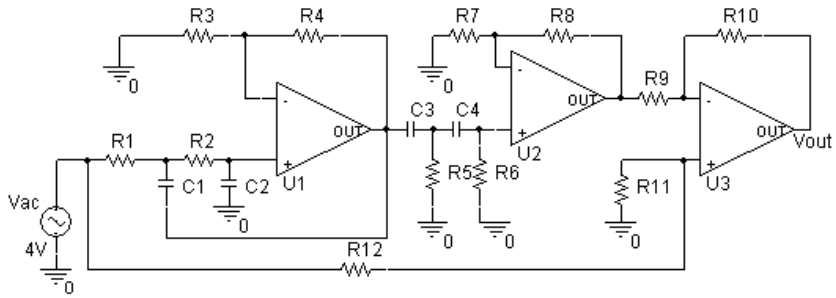

Figure 3. Active band-stop filter

The soft faults due to single resistance or single capacitance are considered. According to sensitivity analysis, the fault modes are established. The fault modes are represented by "0-1" representation, fault states are represented by "0", and normal states are represented by "1". The detailed information of fault modes is shown in table.1.

TABLE I.
DETAILED INFORMATION OF FAULT MODES

Fault code	Fault mode	Mode flag	presentation
f1	C2-50%	C2↓	01111111
f2	C2+50%	C2↑	10111111
f3	R2-50%	R2↓	11011111
f4	R2+50%	R2↑	11101111
f5	R3-50%	R3↓	11110111
f6	R6-50%	R6↓	11111011
f7	R7-50%	R7↓	11111101
f8	R9-50%	R9↓	11111110
f0	Non-fault	NORM	11111111

Take 1100 times Monte Carlo analysis for every fault mode, get the fault features. The 1000 fault features are training samples, and other 100 fault features are test samples. The training set and the test set are formed.

The training set is trained by the distributed neural network which is presented in this paper. The training set is splitf to four disjoint sub-training sets, dissimilarity threshold $v = 0.05$. The concentrated network has one hidden layer, and the hidden layer contains ten neurons. Because the process of splitting is random, 20 times trainings are taken. The average results are the training results. The training results are shown in table.2. The training times are the sum of the maximum training times of distributed networks and the training times of concentrated network. The training time is the sum of the longest training time of distributed networks and the training time of concentrated network.

TABLE II.
TRAINING RESULTS

NO.	Training times	Training time	The number of neurons in hidden layer			
			Net1	Net2	Net3	Net4
1	4228	81	89	91	82	92
2	3666	72	97	97	90	80
3	3993	77	91	88	86	95
4	3191	62	79	88	93	92
5	3577	69	80	97	88	92
6	3578	70	88	101	102	84
7	3487	66	97	96	98	89
8	3508	67	95	76	82	93
9	3836	75	77	97	89	94
10	3449	65	93	93	85	87
11	4201	80	89	88	102	93
12	3605	71	80	97	93	92
13	3636	70	95	97	98	80
14	3221	64	77	101	86	95
15	3953	74	93	96	89	84
16	3489	68	97	91	90	92
17	3597	70	97	88	82	89
18	3467	65	79	97	82	94
19	3538	69	88	93	85	92
20	3806	73	91	76	88	87
AVG	3651	70.4	87	92	90	90

The training results show that the distributed neural network which is presented in this paper can train the fault samples efficiently. The training result with the most training times and the longest training time is compared to the general BP neural network. In certain extent, the training time of general BP neural network decreases as the number of neurons in hidden layer increases. As a result, the number of neurons in hidden layer of general BP neural network is the sum of the maximum number of neurons in hidden layer of distributed networks in table.1 and the number of neurons in hidden layer of concentrated network. It is 102+10=112. The relationship between training precision and training time is shown in Fig.4. The relationship between training time difference and training time is shown in Fig.5.

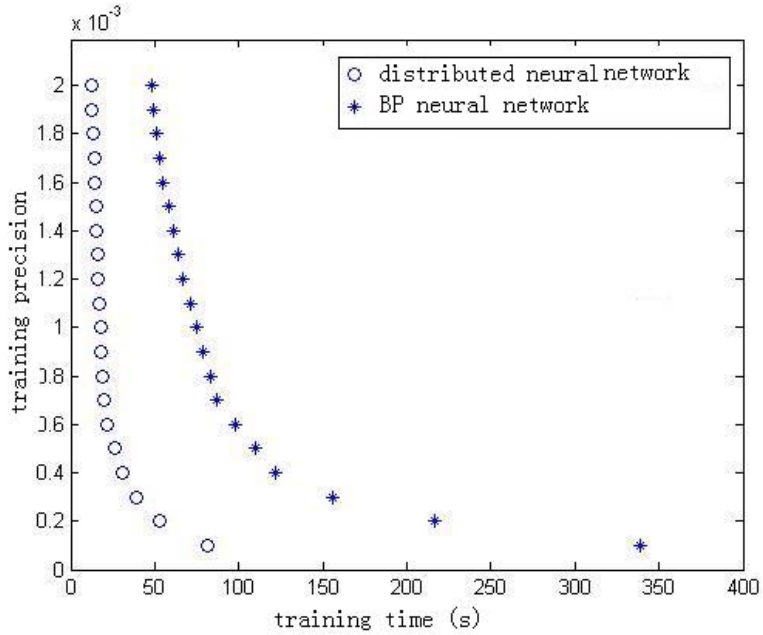

Figure 4. Relationship between training precision and training time

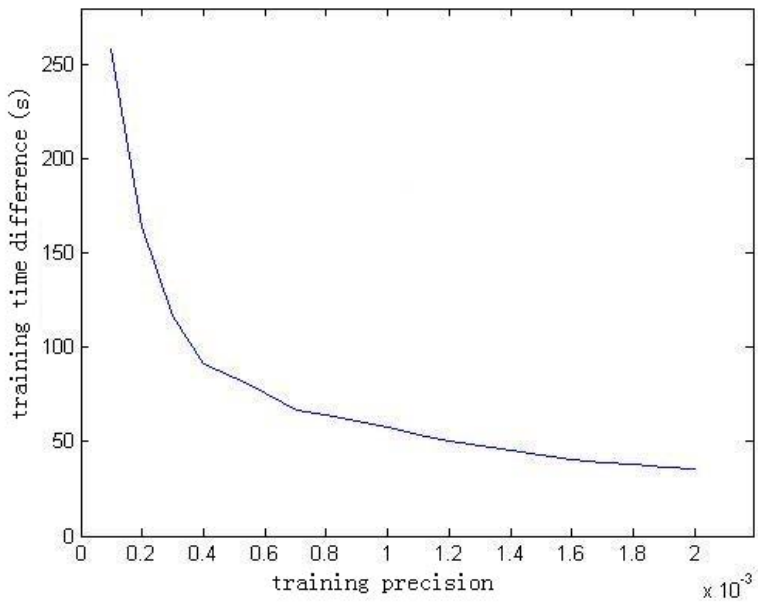

Figure 5. Relationship between training time difference and training time

It is shown in Fig.4 that under the same training precision, the training time of distributed neural network which is presented in this paper is always less than the training time of general BP neural network. And it is shown in Fig.5 that the time superiority of distributed neural network is increases as the training precision increases.

The accuracy of fault diagnosis is shown in table.3.

TABLE III.
ACCURACY OF FAULT DIAGNOSIS (%)

No.	C2↓	C2↑	R2↓	R2↑	R3↓	R6↓	R7↓	R9↓	NORM	FULL
1	100	100	96	99	99	98	99	99	99	98.8
2	100	100	98	99	100	97	99	100	100	99.2
3	100	97	96	97	98	98	98	100	96	97.8
4	100	100	100	100	99	98	100	98	98	99.2
5	99	100	100	99	97	100	98	97	100	98.9
6	100	100	97	100	98	96	98	99	98	98.4
7	98	98	96	97	98	97	96	97	98	97.2
8	100	100	99	98	99	100	100	96	99	99.0
9	100	96	97	96	97	98	100	100	99	98.1
10	99	96	98	99	98	97	96	99	98	97.8
11	100	100	98	97	99	98	97	98	100	98.6
12	99	100	100	98	97	100	96	100	99	98.8
13	98	99	99	99	99	97	100	97	98	98.4
14	100	100	98	97	99	100	99	97	98	98.7
15	97	99	100	100	100	98	97	99	100	98.9
16	98	98	97	100	99	96	98	99	99	98.2
17	99	98	100	99	96	97	99	98	100	98.4
18	98	100	100	98	99	99	99	97	98	98.7
19	99	100	99	99	99	98	97	99	100	98.9
20	100	97	98	98	97	99	100	100	99	98.7
AVG	99.2	98.9	98.3	98.5	98.4	98.0	98.3	98.5	98.8	98.5
BP	100	98	100	99	97	100	98	97	98	98.6

It is shown in table.3 that the accuracy of fault diagnosis based on distributed neural network is always beyond 96%, the average accuracy is 98.5%. It shows that the method which is presented in this paper not only speeds up learning rate but also has the satisfactory diagnosis effect. It is effective for analog circuit fault diagnosis.

V. SUMMARY

According to the characteristics and the problems of analog circuit fault diagnosis, a new method of analog circuit fault diagnosis based on distributed neural network is presented in this paper. Simulation results show that the method can solve the problems caused by large dataset effectively, such as the network scale and the

training time, etc. The training rate of distributed neural network is more rapid than general BP neural network, and the method is well able to carry out the fault diagnosis of analog circuit.

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