An analog circuit fault diagnosis approach using DBN as a preprocessor

Chaolong Zhang, Yigang He, Renxiong Liu, Lanfang Zhang, and Shanhe Jiang

Abstract**—**In order to diagnose analog circuit faults effectively, an analog circuit fault diagnosis approach using deep belief network (DBN) as a preprocessor is proposed in the paper. Time responses are measured by sampling outputs of the circuits under test. Features are extracted by using the DBN method based on the time responses. A fault diagnosis model using least squares support vector machine is set up based on the extracted features. Sallen–Key bandpass filter and four-opamp biquad highpass filter fault diagnosis simulations demonstrate the diagnose procedure of the proposed approach, and a comparison simulation also validates that the proposed features extraction method can produce better extract performance than the conventional methods.

Keywords**—**analog circuits, fault diagnosis, features extraction, deep belief network, least squares support vector machine.

I. Introduction

Analog circuits are widely used in many electronic systems such as home electronics, automotive electronics, industrial electronics, military electronics, etc. Meanwhile, analog circuit fault diagnosis has been an active research area in recent years [1-12]. However, compared to the well investigated fault diagnosis of digital electronic circuits [13, 14], the diagnosis of analog circuits is far fall behind for the reason of component tolerance effects, insufficient information, and analog circuits' nonlinearity.

Features extraction is the first important problem in analog circuit fault diagnosis, which produces a strong effect on the successive classifier's efficiency [1-12]. The work in [1] directly applies impulse responses of circuits under test (CUT) to the fault diagnosis, which leads to a tremendous computing workload. As a result, signal analysis methods are researched to preprocess the measured signals of CUT as features. Wavelet transform [2-4], kurtosis and entropy [5], and wavelet-based fractal analysis [6, 7] are conventional signal-based features extraction methods in analog circuit fault diagnosis. However, it is unavoidable to extract insufficient discriminative information because the collected signals are not fully represented by features. Moreover, redundant information are generated and included in the features. Therefore, a selection criterion needs to be designed for the purpose of choosing the optimal features, which further increases the computational complexity.

Deep belief network (DBN) is a neural network with deep learning character [15]. Meanwhile, the DBN is also used as an unsupervised features extraction method for it can learn deep and inherent features from the collected signals by a series of restricted Boltzmann machines (RBMs). Compared to the conventional signal-based features extraction methods, DBN extracts features from the signals directly. Recently, DBN is successfully used to extract features for visual recognition, phone recognition and spectral–spatial classification [16-18].

Classifier selection is another critical problem in analog circuit fault diagnosis [1-12]. Artificial neural network (ANN) is commonly used for it can perform analog circuit fault diagnosis by using the extracted performance data [1-6, 8]. However, low convergence rate, falling local optimal solution, and poor generalization are disadvantages of the ANN algorithm. Support vector machine (SVM) is a machine learning tool [19] that accounts for the trade-off between learning ability and generalizing ability by minimizing structure risk, and it has been utilized to analog circuit fault diagnosis [9, 10]. Least squares support vector machine (LSSVM) improves SVM formulation by adopting least-squares linear system as the loss function [20], and LSSVM is employed to construct classification model in many recent works [7, 11, 12].

In this paper, a novel approach for analog circuit fault diagnosis by using DBN as a preprocessor is presented. Time responses are measured by sampling outputs of the CUT, and then DBN method is employed to extract features based on the time responses. LSSVM is applied to set up a fault diagnosis model to classify different fault classes. The proposed approach is demonstrated by fault diagnosis simulations of Sallen-Key bandpass filter and four-opamp biquad highpass filter.

This paper is organized in the following order: Section II introduces fault diagnosis methods used in the work. Section III gives the simulation results and discussions. Finally, conclusions are drawn in Section IV.

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II. Fault diagnosis methods

In the work, DBN is used to extract features based on the measured time responses firstly, and then LSSVM is applied to construct a fault diagnosis model based on the extracted features.

A. DBN

The goal of deep learning is to learn more abstract representations of input data in a layer-wise fashion using unsupervised learning. DBN is a typical deep learning method, and it is a neural network constructed by RBMs.

RBM is constructed by two layers of neurons: a visible layer $\boldsymbol{v}=\{0,1\}^D$ and a hidden layer $\boldsymbol{h}=\{0,1\}^K$. The hidden unit $\boldsymbol{h}$ tries to reconstruct a visible unit $\boldsymbol{v}^*$ which is little difference with the visible unit $\boldsymbol{v}$. Each neuron is fully connected to the neurons of another layer, and there is no connection between neurons of the same layer. RBM's structure is shown in Fig. 1. The energy of the units' joint configuration is defined as:

$$E(\boldsymbol{v},\boldsymbol{h})=-\sum_{i=1}^{D}\sum_{j=1}^{K}v_i w_{ij} h_j-\sum_{j=1}^{K}b_j h_j-\sum_{i=1}^{D}a_i v_i \quad (1)$$

where w_{ij} is weight of visible unit i and hidden unit j; b_i is visible unit i's bias; a_j is hidden unit j's bias.

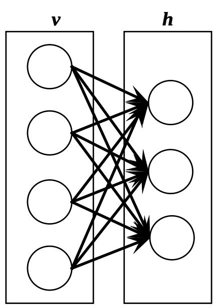


Fig. 1. RBM's structure

The conditional distributions of $\boldsymbol{v}$ and $\boldsymbol{h}$ are as follows:

$$p(h_j=1\,|\,\boldsymbol{v})=\sigma\Big(\sum_i W_{ij}v_i+b_j\Big) \quad (2)$$

$$p(v_i=1\,|\,\boldsymbol{h})=\sigma\Big(\sum_j W_{ij}h_j+a_i\Big) \quad (3)$$

where σ is sigmoid function.

w_{ij}, b_i and a_j are updated through contrastive divergence method:

$$\Delta w_{ij}=\varepsilon(v_i h_{jdata}-v_i h_{jreconstrction}) \quad (4)$$

$$\Delta b_i=\varepsilon(h_{jdata}-h_{jreconstrction}) \quad (5)$$

$$\Delta a_j=\varepsilon(v_{i\,data}-v_{i\,reconstrction}) \quad (6)$$

where ε is learning rate.

DBN is constructed by a series of RBMs and a Softmax classifier. A DBN network for features extraction is formed by two steps: pretraining and fine-tuning. In the pretraining, the measured signals are used as the input to the first RBM, and then the output of the first layer is used as the input to the next RBM. Constant executing in this way, the output of the last RBM is the learnt features of the pretraining. In the fine-tuning, a Softmax classifier is applied to fine-tune the whole pretrained network to integrate the layers of neural networks and perform classification based on the learnt features. After fine-tuning, the DBN network for features extraction is established, and the output of the last RBM is used as the extracted features.

B. LSSVM

LSSVM is an enhancement of the standard SVM. It uses a linear set of equations instead of a quadratic programming problem to obtain support vectors and adopts least-squares linear system as loss function. Consider a model in the primal weight space of the following form:

$$y(\mathrm{x})=w^{\mathrm{T}}\varphi(\mathrm{x})+b \quad (7)$$

where $\mathrm{x}_i\in R^N$ is the input and $y_i\in R$ is the output; $\varphi(\cdot)$ maps the input data to a high dimensional feature space; w is an element of R^N. Combining fitting error and functional complexity, the optimization problem of LSSVM is substituted as:

$$\min_{w,b,\xi}\frac{1}{2}w^{\mathrm{T}}w+\frac{1}{2}c\sum_{i=1}^{l}\xi_i^2 \quad (8)$$
$$\text{s.t.}: \xi_i=y_i-[w^{\mathrm{T}}\phi(\mathrm{x}_i)+b] \quad \forall i=1,2,\ldots,l$$

where c is penalty parameter and ξ_i is random error.

The Lagrangian of problem (8) is given by:

$$\begin{aligned}L(w,b,\xi,a)=&\frac{1}{2}w^{\mathrm{T}}w+\frac{1}{2}c\sum_{i=1}^{l}\xi_i^2\\&-\sum_{i=1}^{l}a_i\{y_i-[w^{\mathrm{T}}\phi(\mathrm{x}_i)+b]-\xi_i\}\end{aligned} \quad (9)$$

where α_i are Lagrange multipliers. The equation is solved by partially differentiating with respect to each variable:

$$\begin{cases}\dfrac{\partial L}{\partial w}=0\Rightarrow w=\sum_{i=1}^{l}a_i\phi(\mathrm{x}_i)\\ \dfrac{\partial L}{\partial b}=0\Rightarrow \sum_{i=1}^{l}a_i=0\\ \dfrac{\partial L}{\partial \xi_i}=0\Rightarrow a_i=c\xi_i \quad \forall i=1,2,\ldots l\\ \dfrac{\partial L}{\partial a_i}=0\Rightarrow \xi_i=y_i-[w^{\mathrm{T}}\phi(\mathrm{x}_i)+b] \quad \forall i=1,2,\ldots l.\end{cases} \quad (10)$$

After elimination of the variables w and ξ, the equation can be rewritten as a linear function group:

$$\begin{pmatrix}K+c^{-1}I & \vec{1}^{\mathrm{T}}\\ \vec{1} & 0\end{pmatrix}\begin{pmatrix}a\\ b\end{pmatrix}=\begin{pmatrix}Y\\ 0\end{pmatrix} \quad (11)$$

where $K_{ij}=k(\mathrm{x}_i,\mathrm{x}_j)$, and $k(\mathrm{x}_i,\mathrm{x}_j)$ is a kernel function; $Y=[y_1,\ldots,y_l]^{\mathrm{T}}$ and $\alpha=[\alpha_1,\ldots,\alpha_l]^{\mathrm{T}}$.

The LSSVM model can be obtained as:

$$y(\mathrm{x})=\sum_{i=1}^{l}a_i k(\mathrm{x}_i,\mathrm{x}_j)+b \quad (12)$$

where a_i, b are solutions of the linear system.

III. Simulations and results

A. Simulation procedures and settings

In the simulation, Sallen-Key bandpass filter circuit and four-op-amp biquad highpass filter circuit are used as example circuits. The circuits' input is a single pulse of height 10v with 10us duration. Tolerances of the resistors and capacitors are both set to 5%. Time impulse responses of different fault classes are measured by sampling the outputs of CUTs firstly, and then DBN is employed to extract features. 120 time impulse response data for each fault class are collected in simulations. 60 time impulse response data are randomly selected as training data, and the rest 60 time impulse response data are applied as testing data. The measured time impulse response data are 100-dimensional, and they are directly fed to the bottom visible layer of the DBN. The structure of DBN with two hidden layers is used in the simulations. The numbers of units of the first and second hidden layer are set to 50 and 25, respectively. The visible layer and the first hidden layer constitute the first RBM, and the first and second hidden layers form the second RBM. The simulation procedure is shown in Fig. 2, and a brief of detailed diagnosis steps are described as follows:

1) Acquire the time impulse responses of different fault classes.

2) Divide the measured time impulse response data into training data and testing data.

3) Input the training data to the DBN, and then a DBN network for features extraction is established.

4) Extract the features by using the DBN.

5) Set up a LSSVM diagnosis model based on the extracted features.

6) Test the DBN network and the LSSVM diagnosis model by using the testing data.

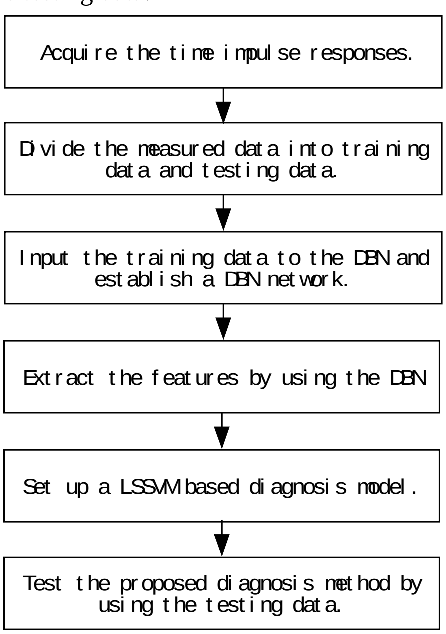


Fig. 2. Simulation procedure

B. Example 1—Sallen–Key Bandpass Filter

The circuit shown in Fig. 3 is a commonly used example circuit in analog circuit fault diagnosis [1-12]. Each component value is labeled in the figure. R2, R3, C1 and C2 are selected as experiment components. The faulty impulse responses are measured in order to form 9 fault classes including no fault (NF), R2↑, R2↓, R3↑, R3↓, C1↑, C1↓, C2↑, and C2↓, where ↑ and ↓ refer to higher and lower than the nominal value, respectively. Fault codes, fault classes, the nominal and faulty component values are shown in Table 1.

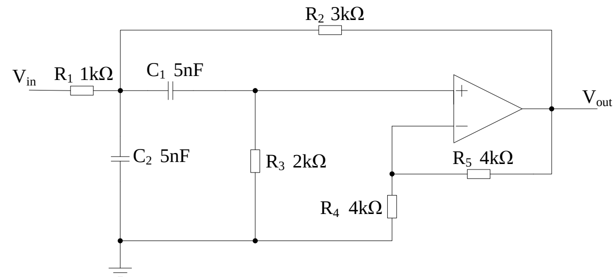
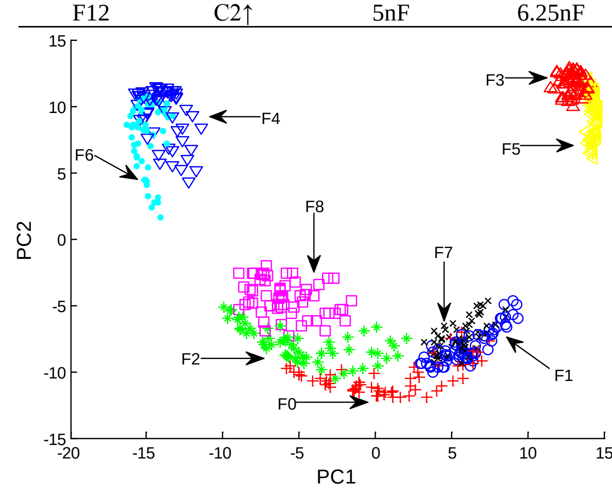


Fig. 3. Schematic of Sallen–Key bandpass filter circuit

Table. 1. Fault codes, fault classes, the nominal and faulty component values of example 1

Fault code	Fault class	Nominal value	Fault value
F0	NF	-	-
F1	R1↓	6.2kΩ	4.65kΩ
F2	R1↑	6.2kΩ	7.75kΩ
F3	R2↓	6.2kΩ	4.65kΩ
F4	R2↑	6.2kΩ	7.75kΩ
F5	R3↓	6.2kΩ	4.65kΩ
F6	R3↑	6.2kΩ	7.75kΩ
F7	R4↓	1.6kΩ	1.2kΩ
F8	R4↑	1.6kΩ	2kΩ
F9	C1↓	5nF	3.75nF
F10	C1↑	5nF	6.25nF
F11	C2↓	5nF	3.75nF
F12	C2↑	5nF	6.25nF



(a)

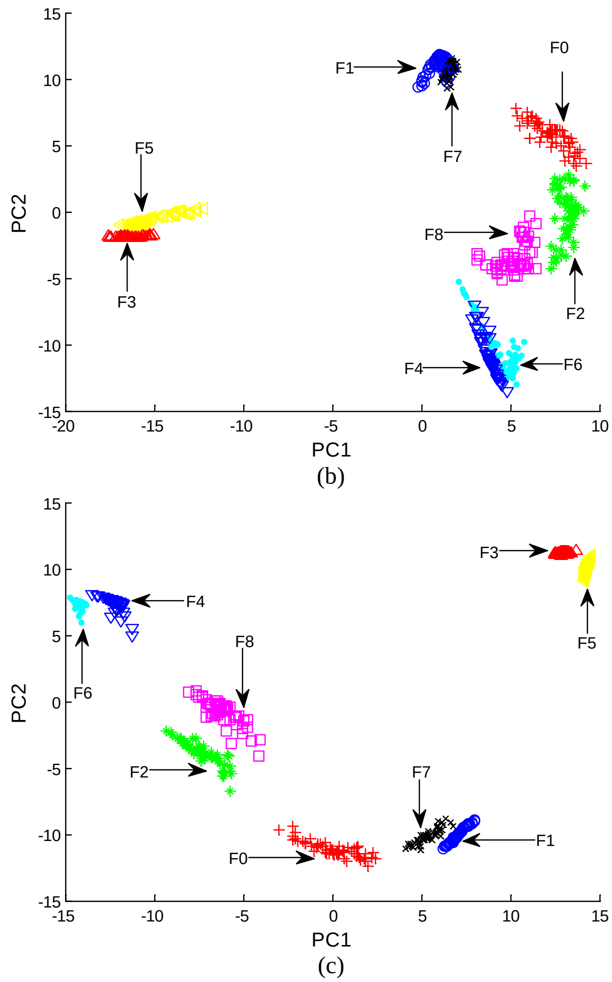


Fig. 4. Two dimensional scatter plots using KPCA of (a) input data, (b) the first RBM's output, (c) features of example 1

The collected data are 100-dimensional time impose responses, and they are used as input to the DBN. The output of the first RBM and second RBM respectively are 50-dimensional and 25-dimensional, where the output of second RBM is the features extracted by the DBN. For the purpose revealing the features extraction procedure, kernel principal component analysis (KPCA) is used to reduce the dimension of the input data, the first RBM's output and the features to two.

The first two principal components (PCs) of the input data, the first RBM's output, and the features are produced by KPCA and shown in Fig. 4(a), Fig. 4(b), and Fig. 4(c), respectively. As can be seen in Fig. 4(a), F0, F1, F2 and F7 fault classes, F4 and F6 fault classes, and F3 and F5 fault classes are respectively obviously overlapping, which manifests that it is difficult to correctly classify each fault class based on input data directly. Meanwhile, F1 and F7 fault classes, and F4 and F6 fault classes are respectively overlapping in Fig .4(b). Finally, all fault classes in Fig. 4(c) are distinct ambiguity groups, which reflects that all fault classed are well separated by DBN extraction.

A LSSVM based diagnosis model is set up based on the extracted features. Then, the testing data is used to test the performance of the diagnosis method. In the diagnosis, all fault classes are correctly diagnosed by using the constructed LSSVM diagnosis model. The overall diagnosis accuracy is 100%.

C. Example 2—Four-opamp biquad highpass filter:

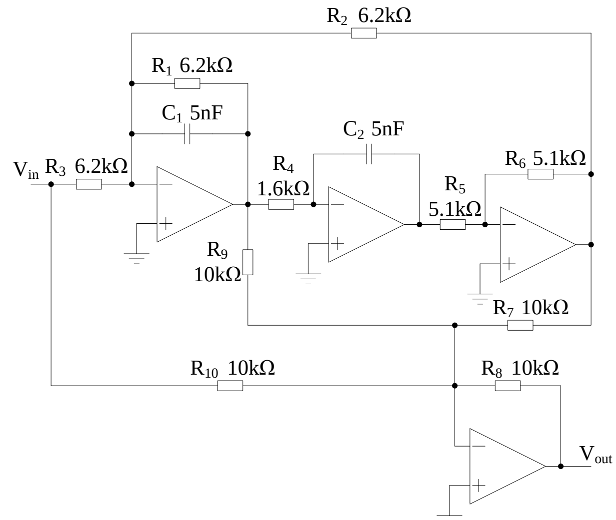
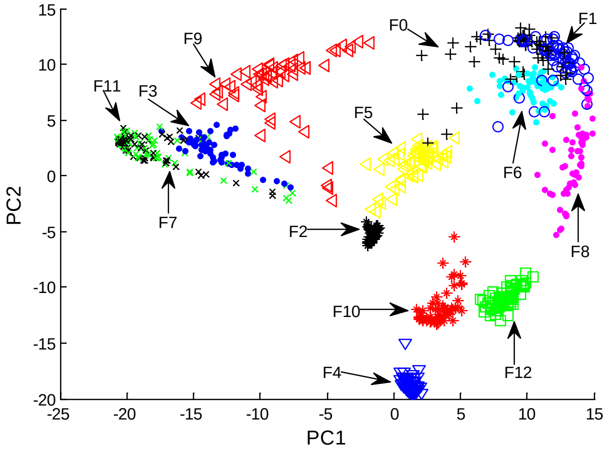


Fig.5. Schematic of four-op-amp biquad highpass filter circuit

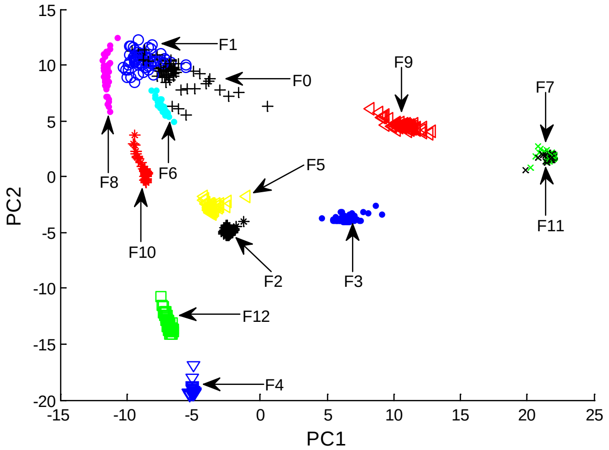
This circuit shown in Fig. 5 is more complex, and it is also a typical example circuit used in the fault diagnosis works [1-12]. R1, R2, R3, R4, C1 and C2 are considered as experiment components. The measured impulse responses are processed to form 13 fault classes including NF, R1↑, R1↓R2↑, R2↓, R3↑, R3↓, R4↑, R4↓, C1↑, C1↓, C2↑, and C2↓. Fault codes, fault classes, nominal and fault component values are shown in Table 2.

Table. 2. Fault codes, fault classes, nominal values and fault values of example 2

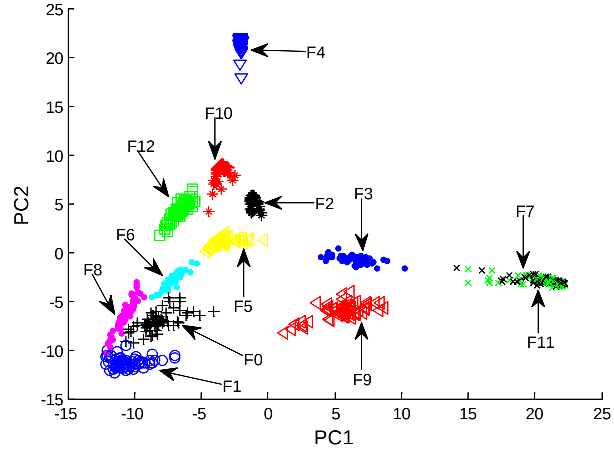
Fault code	Fault class	Nominal value	Fault value
F0	NF	-	-
F1	R1↓	6.2kΩ	4.65kΩ
F2	R1↑	6.2kΩ	7.75kΩ
F3	R2↓	6.2kΩ	4.65kΩ
F4	R2↑	6.2kΩ	7.75kΩ
F5	R3↓	6.2kΩ	4.65kΩ
F6	R3↑	6.2kΩ	7.75kΩ
F7	R4↓	1.6kΩ	1.2kΩ
F8	R4↑	1.6kΩ	2kΩ
F9	C1↓	5nF	3.75nF
F10	C1↑	5nF	6.25nF
F11	C2↓	5nF	3.75nF
F12	C2↑	5nF	6.25nF



(a)



(b)



(c)

Fig. 6. Two dimensional scatter plots using KPCA of (a) input data, (b) the first RBM's output, (c) features of example 2

The first two PCs of the input data, the first RBM's output, and features are produced by KPCA and shown in Fig. 6(a), Fig. 6(b), and Fig. 6(c), respectively. As can be seen in Fig. 6(a), there is obvious overlapping for F3, F7 and F11 fault classes, and overlapping for F0, F1, F6 and F8 fault classes. Meanwhile, F0 and F1 fault classes, and F7 and F11 fault classes are respectively overlapping in Fig .6(b). Finally, F1 and F8 fault classes are slightly overlapping, and F7 and F11 fault classes are overlapping in Fig. 6(c).

A LSSVM based diagnosis model is set up based on the extracted features. Then, the testing data is used to test the performance of the diagnosis method. The diagnosis results are shown in Table 3. In the diagnosis, 12 F7 fault classes are falsely identifies as F11 fault classes, and one F8 fault class is falsely recognized as F1 fault class, and 18 F11 fault classes are falsely identified as F7 fault classes. Meanwhile, the other fault classes are correctly diagnosed. The overall diagnosis accuracy is 96.03%.

Table. 3. Diagnosis results of example 2

	F0	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
F0	60												
F1		60											
F2			60										
F3				60									
F4					60								
F5						60							
F6							60						
F7								48				12	
F8		1							59				
F9										60			
F10											60		
F11								18				42	
F12													60

As can be concluded from Fig. 4 and Fig .6, the amount of the overlapping fault classes of features is dramatically lessened compared to that of the input data. Meanwhile, the overlapping degree of the fault classes of features is obviously reduced compared to that of the input data. It is clear that exacting features by using DBN method is easy to learn the inherent and deep characteristics of the input data.

A. Comparison simulation

For the purpose of validating the effectiveness and progressiveness of the presented features extraction method in the work, the proposed method is compared with other commonly used features extraction methods including wavelet transform method [4], kurtosis and entropy [5], and wavelet-based fractal analysis method [7] in analog circuit fault diagnosis. Measured impulse responses of example 1 and example 2 are used, and LSSVM is applied as diagnosis tool. The comparison diagnosis simulation settings and conditions are the same with that of example 1 and example 2. The diagnosis results of comparison methods and our method are shown in Table 4. From the results of the table, it can be seen that the example 1's diagnose accuracies generated by the four methods are all 100%, which indicates that LSSVM is a high-performance classification tool. Meanwhile, the example 2's diagnose accuracy generated by using wavelet-based fractal analysis is the lowest in the all methods for the reason that the advantage of the wavelet-based fractal analysis is low computation in features extraction, not high-efficiency. The example 2's diagnose accuracy generated by using DBN based features extraction method is higher than diagnose accuracies produced by using wavelet transform method, kurtosis and entropy, and wavelet-based fractal analysis method, which represents that the DBN based features extraction method can generate better extraction performance than wavelet transform method, kurtosis and entropy method, and wavelet-based fractal analysis method.

Table. 4. Diagnosis results of comparison methods and our method

Method	Example1	Example2
Wavelet transform	100%	95.26%
Kurtosis and entropy	100%	95.51%
Wavelet-based fractal analysis	100%	95.00%
Proposed DBN in the work	100%	96.03%

IV. Conclusions

In this work, DBN has been presented as a preprocessor for analog circuit fault diagnosis. Sallen-Key bandpass filter circuit and four-op-amp biquad highpass filter circuit have been used as example circuits. First, time responses have been acquired by sampling outputs of the CUTs. Afterwards, features have been extracted by using DBN method. A fault diagnosis model based on LSSVM has been constructed to identify different fault classes. Finally, satisfied results have been obtained in two fault diagnosis simulations. A comparison also has verified that the proposed extraction method can produce better extract performance than the commonly used features extraction methods.

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