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Fault Diagnosis of Analog Circuit Based on Multi-Input Convolution

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Abstract: Due to the low ability of fault feature extraction in analog circuits, it is impossible to classify components in analog circuits. A multi-input convolutional neural network (MIL-CNN) model based on attention mechanism is proposed. In the fault diagnosis experiment, the circuit of the two-stage four-op amplifier double-second order low-pass filter of the model has better comprehensive performance and can effectively realize the efficient classification and location of all faults.

1. Introduction

Analog circuits are increasingly widely used in integrated circuits and other fields [1-3], so accurate and efficient diagnosis of analog circuit faults has become a research hotspot in the field of circuit testing.

In early analog circuit fault diagnosis, there are mainly adjoint network method, network tearing method and fault diagnosis theorem [4], but due to limited application and complex calculation, it is not suitable for nonlinear analog circuit fault diagnosis. Although wavelet transform and other signal processing methods have been widely used in fault feature extraction and diagnosis of nonlinear systems [5-7], signal processing methods tend to ignore essential features during feature extraction, resulting in low efficiency and accuracy of fault diagnosis of nonlinear analog circuits [8-10]. In order to solve this problem, BP neural network, support vector machine (SVM), Extreme Learning Machine (ELM) and other data-driven artificial intelligence methods have widely entered the research field. Su et al. [11] proposed to use DBN to extract features, which used the Grey Wolf optimization (GWO) algorithm to optimize SVM for classification. Zhang et al. [12] used differential Evolution (DE) algorithm to optimize model parameters and proposed DE-ELM model, which improved the accuracy of fault diagnosis.

In recent years, deep science has been widely used in the field of fault diagnosis due to its strong ability of data feature extraction and excellent ability of describing nonlinear fault dynamics [13-15].

As can be seen from the above literature, the authors only conduct fault diagnosis from a single perspective of time domain or frequency domain. Therefore, this paper constructed a multi-input convolutional neural network model (MIL-CNN). The fault diagnosis of double-order low-pass filter of two-stage four-op amplifier is taken as an example, and the comprehensive performance of mil-CNN model is verified

2. Materials and methods

The multiple-convolutional neural networks (MIL-CNN) model is adopted in this paper, and its structure is shown in Figure 1. The multi-input layer of MIL-CNN can combine the time domain information graph and frequency domain information graph of fault data.

The order of Net1 and Net2 layers is convolution layer + ReLU, BN layer and pooling layer respectively. Convolutional layer is used to extract the feature of input information. BN layer can reduce the risk of overfitting. Pooling layer can reduce computation. The Net2 and Net1 processes are the same. Net3 connects the time domain feature information of Net1 with the frequency domain feature information of Net2, and finally sends the output value to the classifier for classification.

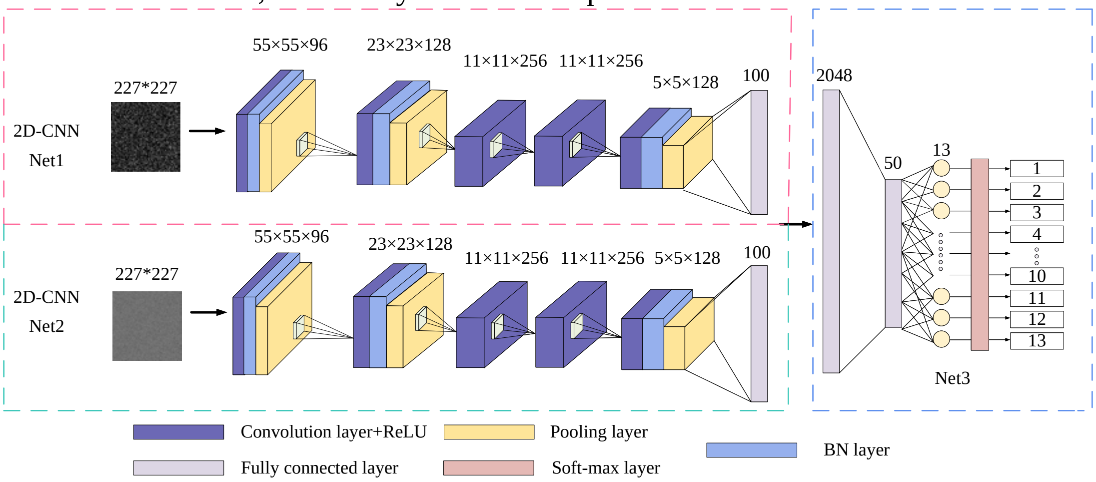

Figure 1: MIL-CNN model

Taking two-stage four-op amplifier double-order low-pass filter (figure 2) as the object, the capacitance and resistance deviate from the normal tolerance range under the interference of the components in the circuit in the external environment. The performance verification of the MIL-CNN diagnostic model was verified by simulation in terms of large size, small size and no fault.

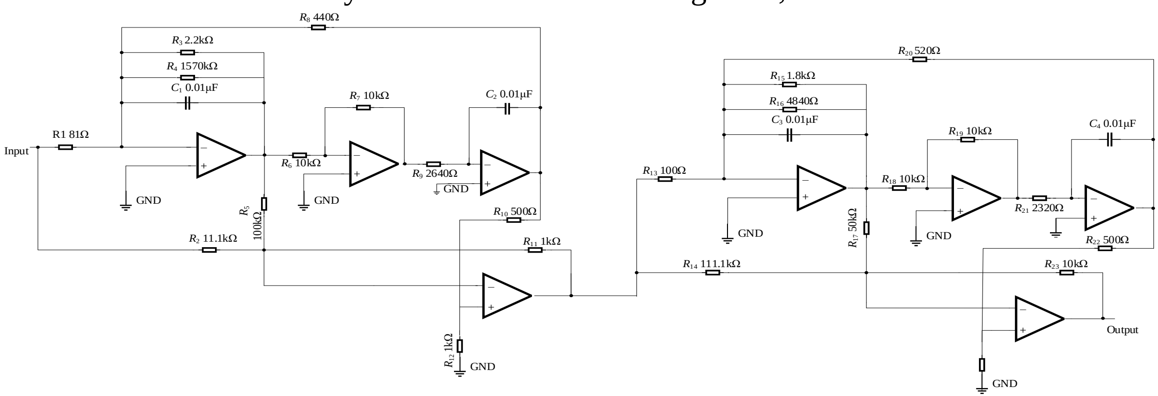

Figure 2: Two-stage four-op amplifier double-order low-pass filter

The circuit is built in Multisim environment, and the pulse signal with voltage of 10V and frequency of 1000Hz is added at both ends of the circuit to collect fault data, and 160000 data are collected for each type of fault. To solve the problem of insufficient data, overlapping sampling is used to enhance data. Label each type of fault and use it as the first input data from Net1; The frequency domain information graph obtained by image Fourier transform is used as the input data of the second subnetwork Net2 network.

The specific steps of the experimental process in this paper are as follows:

1) Add pulse signals at both ends of the circuit under test to take fault data.

2) Classify fault data and add category codes.

3) Using image processing technology to expand the data set, get the time domain image set, and use the image Fourier transform to get the frequency domain data set.

4) Divide the picture set into training set, test set and verification set.

5) Set up MIL-CNN model, use training set to train model, verify set to adjust network model to achieve the optimal model.

6) The actual coding of the test set is compared with the predictive coding generated by the model.

Table 1: Classification of severity of drought-affected areas

Grade	Scope of influence	Station proportion of drought frequency
1	Global Drought	$P_j \geq 50\%$
2	Regional Drought	$50\% > P_j \geq 33\%$
3	Partial Regional Drought	$33\% > P_j \geq 25\%$
4	Local Drought	$25\% > P_j \geq 10\%$
5	No Obvious Drought	$P_j < 10\%$

3. Results and analysis

In order to verify the effectiveness and superiority of the proposed MIL-CNN network in fault diagnosis of complex circuits, a two-stage four-op amplifier double-second-order low-pass filter was used for simulation verification. R_3, R_4, R_6, R_7, R_9 and capacitors C_2 and C_4 were selected as research objects. The failure modes are shown in table 2.

Table 2: Fault mode of two-stage four-op amplifier double-order low-pass filter

Fault code	Fault type	Tolerance range/%	Nominal value	The fault value
f1	Normal	—	—	—
f2	R_3 increase	5	3kΩ	4.5kΩ
f3	R_3 decrease	5	3kΩ	1.5kΩ
f4	R_4 increase	5	1570kΩ	2355kΩ
f5	R_4 decrease	5	1570kΩ	785kΩ
f6	R_6 increase	5	10kΩ	15kΩ
f7	R_6 decrease	5	10kΩ	5kΩ
f8	R_9 increase	5	2640Ω	3960Ω
f9	R_9 decrease	5	2640Ω	1320Ω
f10	C_2 increase	5	0.01nF	0.005nF
f11	C_2 decrease	5	0.01nF	0.015nF
f12	C_4 increase	5	0.01nF	0.005nF
f13	C_4 decrease	5	0.01nF	0.015nF

Table 3: Average accuracy of fault diagnosis for two-stage four-op amplifier double-order low-pass filter

Method	Average accuracy/%
WTF+PCA+ELM	50.93
WTF+PCA+BP	73.24
WTF+PCA+SVM	85.72
CNN	88.93
MIL-CNN	93.82

As can be seen from table 3, the average accuracy of MIL-CNN is 98.52%. MIL-CNN has better performance than traditional CNN, and in complex circuits, data is preprocessed first, so shallow learning cannot effectively classify faults.

According to the above, MIL-CNN does not require complex data preprocessing, splicing information in time domain and frequency domain, and acquiring more comprehensive features. Compared with other methods, the proposed method has obvious advantages in complex circuits.

4. Conclusions and Discussion

A fault diagnosis model for MIL-CNN analog circuit is proposed in this paper. The main conclusions are as follows:

According to the diagnostic experiment results of double-second order low-pass filter of two-stage four-op amplifier, the fault diagnosis ability of MIL-CNN network is better than that of traditional CNN. MIL-CNN greatly improved their feature extraction ability and learning ability. Compared with shallow learning, MIL-CNN network is more suitable for analog circuit fault diagnosis, providing a new solution for analog circuit fault diagnosis and other fields

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