Fault Diagnosis of Analog Circuits Based on Information Fusion in the Time-Frequency Domain

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Abstract. To address the low fault feature extraction capability in analog circuits for component classification in analog circuits. Convolutional Block Attention Module-multiple-convolutional neural networks (CBAM-MIL-CNN) is proposed. The model has a better comprehensive performance in fault diagnosis experiments for circuits with secondary four-operator dual second-order low-pass filters, and can effectively achieve efficient classification and localization of all faults.

Keywords: Analog circuit, convolutional neural network, attention mechanism, fault diagnosis.

1. Introduction

As an important pillar in the military, defense, and aviation fields [1], accurate and efficient fault diagnosis of analog circuits has become a research hotspot in the field of circuit testing [2], and the development of efficient and accurate diagnostic strategies has become an urgent need in the field of analog circuit fault diagnosis [3-6].

In the early days of analog circuit fault diagnosis, the accompanying network method, network tearing method and fault diagnosis theorem [7-8] were mainly used, but they were not applicable to nonlinear analog circuit fault diagnosis because of the application limitation and computational complexity. Although signal processing methods such as wavelet transform are widely used in nonlinear system fault feature extraction and diagnosis [9-10], the signal processing methods tend to ignore the essential features in the process of feature extraction, resulting in low efficiency and accuracy of nonlinear analog circuit fault diagnosis [11-13].

To solve the above problems, data-driven artificial intelligence methods such as support vector machine (SVM) [14] and extreme learning machine (ELM) [15] have widely entered the research field, providing feasible technical support for analog circuit fault diagnosis. Long et al [16] proposed a method based on a conventional time-domain feature vector based on the impulse response characteristics of the control system, and according to the last squares SVM (LSSVM) experiments showed that the classification performance of LSSVM can be improved using the improved vector. Long et al [17] used Mahalanobis distance (MD) particle swarm optimization (PSO) to optimize the classifier and reasonably select the feature vectors so as to improve the classification accuracy. Chen et al [18] proposed a double-chain quantum genetic algorithm (DCQGA) based on DCQGA and experimentally showed that the overall best fit and classification accuracy of DCQGA-SVM were improved.

In recent years, deep learning such as the Convolutional neural network (CNN) [19] and Deep belief network (DBN) [20] are widely used in the field of fault diagnosis with their powerful learning ability and feature extraction [21-22]. Su et al. [23] adopted DBN to extract the deep features of the output signal of an analog circuit and exploited the grey wolf optimization (GWO) to optimize the support vector machine (SVM) to obtain a GWO-SVM model for diagnosis classification. Experimental results show that this method has significantly improved the diagnosis rate and shortened the diagnosis time. In addition, As can be seen from the above literature, the authors only perform fault diagnosis from a single perspective in the time domain or frequency domain. In response, a multi-input convolutional neural network model (CBAM-MIL-CNN) based on the attention mechanism is constructed in this paper. The fault diagnosis of the Butterworth low-pass filter is used as an example, and the CBAM-MIL-CNN model's comprehensive performance is verified.

2. Materials and Methodology

In this paper, we use the Convolutional Block Attention Module-multiple-convolutional neural networks (CBAM-MIL-CNN) model, whose structure is shown in Fig. 1. The multi-input layer of MIL-CNN can combine the time-domain information graph of fault data with the frequency-domain information graphs.

The order of Net1 and Net2 layers are convolutional layer + ReLU, BN layer, and pooling layer, respectively. Net2 is the same process as Net1. Net3 connects the time-domain feature information of Net1 and the frequency-domain feature information of Net2, and finally, the output value is fed to the classifier for classification.

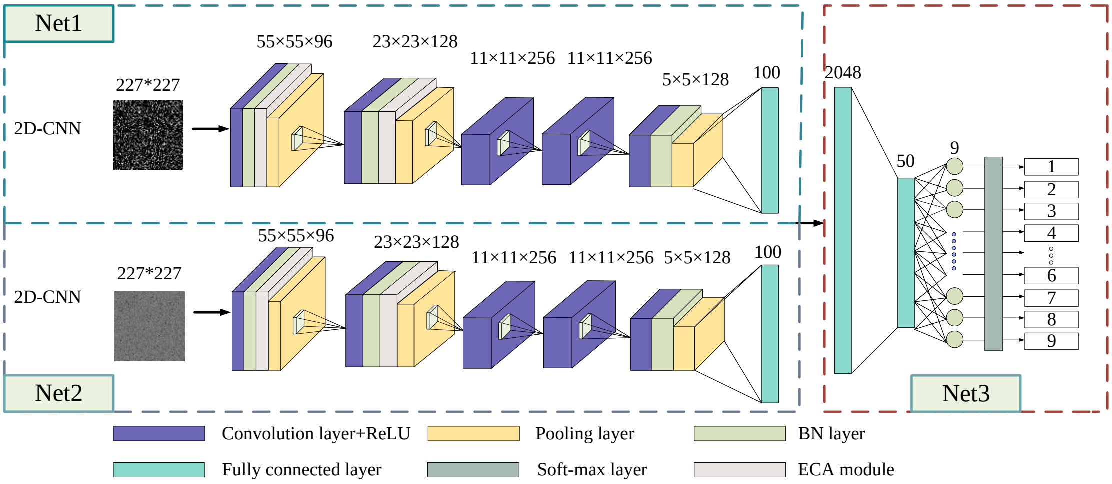

Figure 1. ECA-MIL-CNN model

The Butterworth low-pass filter (Figure 2) is used to target the components in the circuit to deviate the capacitance and resistance from the normal tolerance range under the disturbance of the external environment. Simulations are performed according to the deviation from large, small, and no fault to verify the performance validation of the MIL-CNN diagnostic model.

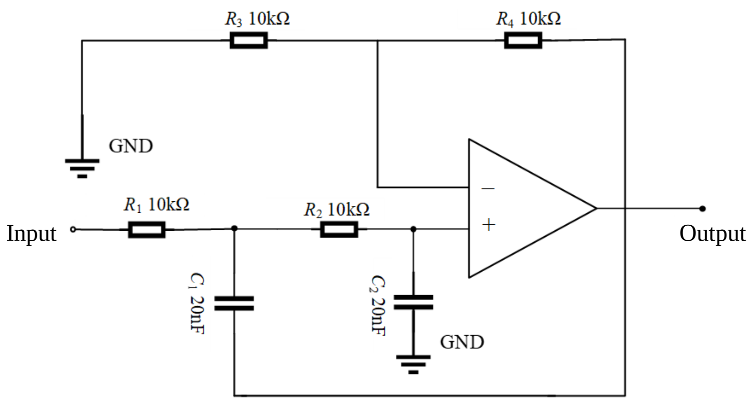

Figure 2. Butterworth low-pass filter

The circuit is built in Multisim environment, and a pulse signal with a voltage of 10V and frequency of 1000Hz is added at both ends of the circuit for fault data collection, and 160,000 data are collected for each type of fault. To solve the problem of insufficient data volume, overlapping sampling is used for data enhancement. The label is added to each type of fault and used as the input data of the first self-network Net1; the frequency domain information map obtained by the Fourier transform of the image is used as the input data of the second sub-network Net2 network.

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

1) Add pulse signals at both ends of the circuit under test and take the fault data.
2) Classify the fault data and add category codes.
3) Use image processing techniques to expand the data set to get the time domain picture set and the image Fourier transform to get the frequency domain data set.
4) Divide the image set into training, test, and validation sets according to the ratio of 6: 2: 2.
5) Build a CBAM-MIL-CNN model, train the model using the training set, and adjust the network model in the validation set to make the model optimal.
6) The actual coding of the test set is compared with the predicted coding generated by the model.

3. Results

In order to verify the effectiveness and superiority of the CBAM-MIL-CNN network based on fault diagnosis in complex circuits proposed in this paper, a Butterworth low-pass filter is used as the object for simulation verification. R2, R3, and capacitors C1, and C2 is selected as the study objects. The failure modes are shown in Table 1.

Table 1. Fault mode of Butterworth low-pass filter

Fault code	Fault type	Tolerance/%	Nominal value	Fault value
F1	Fault-free	-	-	-
F2	Large R_2	5	10 kΩ	10.5 kΩ
F3	Small R_2	5	10 kΩ	9.50 kΩ
F4	Large R_3	5	10 kΩ	10.5 kΩ
F5	Small R_3	5	10 kΩ	9.50 kΩ
F6	Large C_1	10	20 nF	22.0 nF
F7	Small C_1	10	20 nF	18.0 nF
F8	Large C_2	10	20 nF	22.0 nF
F9	Small C_2	10	20 nF	18.0 nF

4. Discussion

Table 2. The average accuracy of Butterworth low-pass filter

Method	Average accuracy/%
WTF+PCA+ELM	68.27
WTF+PCA+BP	75.92
WTF+PCA+SVM	82.77
CNN	85.93
CBAM-MIL-CNN	96.71

From Table 2, we can see that the average correct rate of CBAM-MIL-CNN proposed in this paper is 96.71%, and its main advantages are as follows: (1) it can effectively extract the essential features of data compared with shallow layer; (2) and no complicated data pre-processing operation is required.

Based on the above, it can be seen that CBAM-MIL-CNN does not require complex data preprocessing, and the features obtained by stitching the information in time and frequency domains are more comprehensive. Compared with other methods, the method proposed in this paper has obvious advantages in complex circuits.

5. Conclusion

The CBAM-MIL-CNN simulation circuit fault diagnosis model is proposed in this paper. The main findings are as follows:

According to the experimental results of Butterworth low-pass filter diagnosis, the fault diagnosis ability of the CBAM-MIL-CNN network is better than that of conventional CNN. In addition, the feature extraction ability and learning ability of the CBAM-MIL-CNN network is greatly improved, and the comparison with shallow learning shows that the CBAM-MIL-CNN network is more suitable for analog circuit fault diagnosis, which provides a new solution to the field of analog circuit fault diagnosis.

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