Incipient fault diagnosis of analog circuits based on wavelet transform and improved deep convolutional neural network

Yueyi Yang¹, Lide Wang¹, Xiaobo Nie¹, a) and Yin Wang¹

Abstract To enhance the reliability of analog circuits in electrical systems, this letter proposes a novel incipient fault diagnosis method by integrating wavelet transform (WT) and improved convolutional neural network. Different from traditional methods, where feature extraction and classification are separately designed and performed, this letter aims to automatically learn fault features and classify the type of faults simultaneously. An improved convolutional neural network named multi-channel compactness convolutional neural network (MC-CNN) is proposed, which can obtain complementary and rich diagnosis information from multi-scale components extracted by wavelet transform. Moreover, we adopt center loss as an auxiliary loss function to maximize the interclass separability and intraclass compactness of samples. The proposed method is fully evaluated with the Sallen-Key bandpass filter circuit and the four-opamp biquad high-pass filter circuit. The experimental results demonstrate that the proposed method is very effective in feature extraction for fault diagnosis, and has higher diagnosis accuracy than other typical fault diagnosis methods.

Keywords: analog circuits, fault diagnosis, wavelet transform, convolutional neural network, feature learning

Classification: Integrated circuits (memory, logic, analog, RF, sensor)

1. Introduction

Analog circuit is one of the most critical parts of industry electronic system, accurate and timely fault diagnosis of analog circuits is always needed [1]. Since it is difficult to obtain accurate model of most complicated analog circuits, data-driven fault diagnosis approaches are widely applied, which mainly involve feature extraction and fault classification [2]. A variety of feature extraction algorithms have been developed involving time-domain analysis methods [3], frequency-domain analysis methods [4], time-frequency-domain analysis methods [5, 6], information entropy method [7, 8]. Besides, some shallow machine learning models have been applied for fault classification, such as neural network (NN) [9, 10, 11, 12], support vector machine (SVM) [13, 14, 15, 16, 17], extreme learning machine [18], adaptive neuro-fuzzy interface system (ANFIS) [19]. Nevertheless, these methods rely heavily on engineering experience and much prior knowledge about failure symptoms and have poor generalization ability.

Due to their excellent performance, deep learning methods have gained great interests and are successfully introduced in many fields [20, 21, 22, 23, 24]. Stacked autoencoders (SAE) [25] and deep belief network (DBN) [26] are employed to learn features directly from original signals for fault diagnosis of analog circuits. However, both DBN and SAE belong to fully connected networks, which can not handle well the high-dimensional data in terms of learning performance and computational complexity. The convolutional neural network (CNN) holds the potential to be the end-to-end approach due to the good feature learning ability of the convolutional structure. Compared with the 2D-CNN, 1D-CNN is widely applied to process time-series data in one-dimensional form in many pattern recognitions [27, 28]. However, the diagnostic performance of 1D-CNN model would be deficient in the fault characteristics due to the singleness of the raw signals. Furthermore, to achieve a good performance on fault classification, the interclass separability and intraclass compactness of instances should be simultaneously maximized.

To address these problems, this study proposes an improved CNN named multichannel compactness CNN (MC-CNN) in this letter for analog circuit fault diagnosis. The structure of MC-CNN is adding a layer with multi-channel before the first layer of the original 1D-CNN. The MC-CNN not only learns fault features from different multi-scale components extracted by wavelet transform but also fuses multi-scale information of input signals, which is superior to original 1D-CNN. Besides, the center loss is used to enhance the ability of feature learning for fault diagnosis. The main contributions of this letter are summarized as follows.

1) A new MC-CNN architecture is developed by introducing a multi-channel layer into the traditional 1D-CNN. The MC-CNN can effectively learn the high-level features from different channels and perform a multi-channel signal fusion. Besides, we adopt center loss as an auxiliary loss function to obtain the deep features with inter-class dispersion and intra-class compactness as much as possible.

2) A novel end-to-end incipient fault diagnosis method is proposed based on WT and the proposed MC-CNN for analog circuits. The one-dimensional raw signals are decomposed at different scales by wavelet transform, and multi-scale signals are used as input of the network. The MC-CNN can automatically learn discriminative features from the input signals in both time and frequency domains and classify different fault modes simultaneously. Compared with traditional methods, the proposed method directly processes raw signals without expert’s experiences and manual intervention to realize...
the fault diagnosis of analog circuit.

3) The proposed method is evaluated through two familiar circuits. Compared with the original 1D-CNN and other typical methods, our method achieves significantly better feature learning ability and diagnosis performance.

2. Methodology

2.1 Wavelet transform

Wavelet transform is an effective technique for signal analysis and processing, which has an advantage for the multi-resolution problem. Wavelet transform is accomplished using translated and scaled versions of a mother wavelet function \( \psi (t) \) defined by

\[
\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi \left( \frac{t - b}{a} \right)
\]

where \( a \) and \( b \) represent the parameters of scaling and translating of a mother wavelet, respectively. Given a signal \( f(t) \) and a mother wavelet function \( \psi (t) \), the wavelet transform is given as follow:

\[
w(t,a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t) \psi \left( \frac{t - b}{a} \right) dt
\]

where \( w(t,a,b) \) denotes the wavelet coefficients of the signal \( f(t) \). A wavelet transform is the decomposition of a signal into an approximation \( A \) and \( M \)-level of details \( D \) by a set of wavelet basis. Compared with other wavelet functions, the haar function is very suitable to implement wavelet transform on impulse responses of circuits [29]. The decomposition process of level \( M \) is denoted as:

\[
f(t) = A_1 + D_1 = A_2 + D_2 + D_1 = A_M + D_M + \ldots + D_1
\]

2.2 MC-CNN architecture

The structure of the MC-CNN is graphically illustrated in Fig. 1. The proposed network architecture consists of six important parts, that is, multi-channel layer, convolution layer, pooling layer, fully connected (FC) layer, softmax layer, and center layer. The data input into the network is multi-scale signals processed by WT, and the multi-scale information is fused in the MC layer. MC-CNN produces the feature maps after a sequence of convolution and pooling operations, the feature maps are flattened by FC layer. The softmax layer is utilized to obtain the probability of different conditions, and the center layer is employed to obtain the distance between features extracted by the network and the center vector of the class corresponding to the features. We use softmax loss and center loss jointly as the supervisory signals to improve the classification performance.

The convolution operation of layer \( l \) can be expressed:

\[
x_l^j = g \left( \sum_{i=1}^{N_l} W_{l,i,j}^{l-1} * x_{l-1}^i + b_l^j \right)
\]

Where \( l \) denotes the number of the layer, \( * \) is the one-dimensional convolution operator, \( x_{l-1}^i \) is the input, \( W_{l,i,j}^{l-1} \) is the weight from the \( i \)th neuron at layer \( l-1 \) to the \( j \)th neuron at layer \( l \), \( b_l^j \) is a bias of the \( j \)th neuron at layer \( l \), \( x_l^j \) is the output of the \( j \)th neuron at layer \( l \) and \( g \) is a nonlinear activation function. In multi-channel layer, the convolution is performed on each channel independently, and the feature maps are fused before being fed to the next layer, the fused feature map is described as:

\[
x_l^j = \sum_{n=1}^{k} g^n \left( \sum_{i=1}^{N_l} W_{l,i,j}^{l-1} * x_{l-1}^i + b_l^j \right)
\]

In classification task, softmax loss is usually utilized to measure the different distribution between predicted output and label, which is expressed as:

\[
L_S = - \sum_{i=1}^{m} \log \frac{e^{y_i x_i}}{\sum_{j=1}^{C} e^{y_j x_j}}
\]

2.2.1 Multi-channel layer

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Where \( s_i \) is the feature of the \( i \)th sample, belonging to the \( y_i \)th class. \( \theta \) is the model parameter, the number of classes and the size of mini-batch are \( n \) and \( m \), respectively. To enhance the feature discrimination ability, the center loss is used as an auxiliary loss function. The center loss simultaneously learns a center for deep features of each class and minimizes the distances between the deep features and their corresponding class centers [30]. The center loss function is written as:

\[
L_C = \frac{1}{2} \sum_{i=1}^{m} \left\| s_i - c_{yi} \right\|_2^2
\]

where \( c_{yi} \) denotes the \( y_i \)th class center of deep features, which is updated based on mini-batch. The loss function of the MC-CNN is defined by combining the softmax loss and center loss as:

\[
L = L_S + \lambda L_C
\]

where \( \lambda \) is a weight parameter for balancing the two-loss terms and \( 0 < \lambda \leq 1 \). In real applications, the value of \( \lambda \) depends on the specific training effect.
2.3 Procedures of our method

The general procedures of the proposed fault diagnosis method are summarized as follows.

Step 1: For a circuit under test (CUT), the diagnosis problem is defined and the nominal parameters of components and their tolerances are determined.

Step 2: The raw signals of each fault class are obtained by the time domain transient analysis and Monte Carlo analysis method. A two-level wavelet transform is used to create an approximation and two details from each signal, the coefficients are then reconstructed to create three-channel signals. Each sample is normalized in the constructed dataset to [0, 1] by Min-Max normalization. The normalized dataset is randomly and equally divided into the training set and the testing set.

Step 3: Parameters of MC-CNN, including the number of iterations, learning rate, and training batch, are determined. The training set is used to model training. The Adam algorithm is applied here to optimize the loss function.

Step 4: The diagnosis performance of the proposed model is evaluated on the testing set.

3. Experiments and results analysis

In this section, the proposed method is evaluated using experiments on two familiar circuits. We start with the description of the experiments, and then the detailed results are shown and discussed.

3.1 Experiment setup

Sallen-Key band-pass filter circuit and four-opamp biquad high-pass filter circuit are used as experimental circuits. The schematic diagrams of the circuits are shown in Fig. 2, where the parameters of the components are marked. The tolerance ranges for resistors and capacitors of CUTs are set 5% and 10%, respectively. The component with 30% deviation from its nominal value is considered as the incipient fault, the fault classes for CUT 1 and CUT 2 are given in Table I and Table II, respectively. The excitation source is a single pulse with an amplitude of 5V, duration of 10us and period of 1ms. The circuit simulation software is PSpice in OrCAD16.6, and we employ Keras to implement the MC-CNN model.

The faulty components are intentionally introduced in both circuits to generate response signals, Monte-Carlo simulations are conducted 600 times for each fault mode under these two circuits. Thus, there are 600 fault-free signals and 4800 faulty signals for CUT 1, as well as 600 fault-free signals and 7200 faulty signals for CUT 2. The total dataset of each CUT is randomly and equally divided into training set and testing set. We utilize the corresponding Harr wavelet for preprocessing the impulse responses of CUTs. Two-level wavelet transform is employed to create approximations and details from the raw signals, the coefficients generated in the wavelet transform are then reconstructed to create three-channel signals, so the input size of MC-CNN is 400*1*3. The network parameters are listed in Table III, the pooling type is the max pooling, and the activation function is rectified linear unit (ReLU). To balance the separation of inter-class samples and the compactness of intra-class samples, the weight parameter $\lambda$ is set to 0.5. The mini-batch size is 100, and Adam with a learning rate of 0.001 is applied.

3.2 Feature extraction and visualization

To demonstrate that the proposed method can learn effective and discriminative features from raw signals, the t-SNE (t-distributed stochastic neighbor embedding) technique is applied to provide a two-dimension representation features of the original signals and the output of the FC layer. The
Table III  The network parameters of MCCNN

<table>
<thead>
<tr>
<th>Layer type</th>
<th>Kernel size/stride</th>
<th>#Filters</th>
<th>Output size</th>
</tr>
</thead>
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<tr>
<td>MC layer</td>
<td>5*1/3/2</td>
<td>24</td>
<td>(200,24)</td>
</tr>
<tr>
<td>P1 layer</td>
<td>2*1/1/2</td>
<td>/</td>
<td>(100,24)</td>
</tr>
<tr>
<td>C1 layer</td>
<td>3*1/1/1</td>
<td>16</td>
<td>(100,16)</td>
</tr>
<tr>
<td>P2 layer</td>
<td>2*1/2/1</td>
<td>/</td>
<td>(30,16)</td>
</tr>
<tr>
<td>C2 layer</td>
<td>3*1/2/1</td>
<td>12</td>
<td>(25,12)</td>
</tr>
<tr>
<td>P3 layer</td>
<td>2*1/2/1</td>
<td>/</td>
<td>(13,12)</td>
</tr>
<tr>
<td>FC layer</td>
<td>/ /</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>Softmax layer</td>
<td>/ /</td>
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</tr>
<tr>
<td>Center layer</td>
<td>/ /</td>
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<td></td>
</tr>
</tbody>
</table>

Fig. 3  Feature visualizations in CUT 1. (a) Original data. (b) Output of FC layer.

Feature visualization results in the testing set of two CUTs are shown in Fig. 3 and Fig. 4, respectively. It can be seen that the features of the original data spread in a large overlap under the different classes. In contrast, the features extracted by the MC-CNN show stronger clustering characteristics than that of these original inputs where these data points of different fault classes are separated well. It is clear that the proposed method has a stronger ability to extract fault features of complex analog circuits, and higher accuracy can be obtained by feeding these features into the classifier.

3.3  Classification performance and analysis

To evaluate the performance in fault diagnosis, the experiments are conducted, and the confusion matrices of testing results are shown in Fig. 5. In Fig. 5(a), it can be seen that most of the diagonal elements in different fault classes in CUT 1 is close to 1, the fault class S1 has the worst accuracy of 98.7%, 4 samples in S1 fault class are misclassified into S3. As shown in Fig. 5(b), some fault classes in CUT 2, including F1, F5, F7, F8 and F10, are accurately identified, and other fault classes exhibit minimal diagnosis error. The misdiagnosis rates of the C2 and R3 faults are high, which indicates that the aliasing of these component faults is more serious. The results verify that the proposed method has stable performance in diagnosis of different fault classes.

3.4  Comparison with other diagnosis methods

To verify the superiority of the proposed method, our proposed method is compared with the original CNN and other methods in the published literatures. The 1D-CNN is composed of three convolutional layers, three pooling layers and a fully connected layer. The parameters of 1D-CNN are the same as the MC-CNN, the raw signals are directly used as the input of 1D-CNN. Ten hold-out trials are conducted, the comparison results are provided in Table IV and Table V. The average classification accuracy of our approach in CUT 1 and CUT 2 is 99.71% and 97.48%, respectively. The proposed method achieves the highest accuracy over the other methods, which demonstrates the superior diagnostic performance of our proposed method over other methods. Furthermore, our proposed method outperforms 1D-CNN by 8.38% for CUT 1 and 2.14% for CUT 2. This is because multichannel fusion and discrimination ability caused by the center loss have a positive impact on classification performance.

4.  Conclusion

This work presents a novel incipient fault diagnosis method
for analog circuits based on WT and MC-CNN, the design and implementation of the proposed method are discussed in detail. Wavelet transform is utilized to decompose the raw signals into multi-scale components according to time and frequency information. The MC-CNN can perform feature extraction and identify the fault classes simultaneously, in which a multi-channel convolutional layer is used to fuse the multi-scale information of the raw signal. MC-CNN combines the center loss and softmax loss to jointly supervise the multi-scale information of the raw signal. The effectiveness of the proposed method has been demonstrated through two familiar circuits. Compared with the existing data-driven methods, the application of our approach can improve the performance in feature extraction and the possibility of classifying the patterns into their actual class.

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References


