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A novel approach for analog circuit fault diagnosis based on Deep Belief Network

Guangquan Zhao[a], Xiaoyong Liu[a], Bin Zhang[b,*], Yuefeng Liu[a], Guangxing Niu[b], Cong Hu[c]

[a] Department of Automatic Test and Control, Harbin Institute of Technology, Harbin 150080, China
[b] Department of Electrical Engineering, University of South Carolina, Columbia, SC 29208, USA
[c] Guangxi Key Laboratory of Automatic Detecting Technology and Instruments, Guilin University of Electronic Technology, Guilin 541004, China

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ABSTRACT

Traditional fault diagnosis of analog circuits relies heavily on feature extraction and selection, which is ad-hoc and often needs complex signal processing and domain knowledge. This has severely limited the applications of fault diagnosis. To address this issue, this paper proposes an analog circuit fault diagnosis method based on Deep Belief Network (DBN). Our contributions include development of an intelligent diagnosis solution that does not rely on manual feature extraction and selection, and providing comprehensive comparison studies on two representative experimental circuits with different levels of complexities under soft fault modes. One significant advantage of the proposed method is that it extracts features adaptively from the raw time series signals and automatically classifies the fault mode, which significantly simplifies the design of diagnosis and increases the flexibility so that it can be applied to different diagnosis problems. The experimental comparison studies show that the proposed method has higher performance, lower requirements on data (small number of sampling points in learning instance), and more reliable performance (consistent diagnosis accuracy for different fault modes) than existing methods. Performance regarding the number of instances and the number of sampling points in instances are studied. The results demonstrate the effectiveness of the proposed method in analog circuit diagnosis.

1. Introduction

Analog circuits play important roles in electronic systems. Although only around 20% of an electronic system is analog, it leads to about 80% of faults in the system [1]. Compared with diagnosis of digital circuits, diagnosis of analog circuits is far more challenging mainly because of the following factors [2]: (1) Parameters of analog components are usually continuous. It is difficult to define a general fault model for analog components and circuits; (2) The number of test nodes in practical circuits under tests (CUTs) is often limited; and (3) Tolerance effect of analog components is difficult to eliminate.

Faults of analog circuits can generally be divided into hard faults and soft faults. Soft faults are mainly deviations of component values from nominal ones and degradation of performance. These soft faults, although do not change the circuit topology, will eventually move the circuits out-of-specification. As the deviation of component values and performance degradation are not as clear as hard fault, diagnosis of soft faults is more challenging than that of hard faults. As more circuits are used in safety critical systems in areas of aerospace, aircraft, satellite, military, accurate diagnosis of soft faults has important influence in the safe and reliable operation of these systems. It is therefore important to develop novel and efficient analog circuit soft fault diagnostic approaches to avoid catastrophic events and reduce maintenance costs.

Since accurate model of most complicated analog circuits is difficult to obtain, data-driven fault diagnosis methods are widely used [2–13]. Existing data-driven methods generally include two main steps, i.e. fault feature extraction and selection using signal processing techniques, and fault classification using classifiers. Commonly used calssifiers include Artificial Neural Network (ANN), Support Vector Machine (SVM), and so on. For example, Aminian et al. [3,8] utilized wavelet theory, Principal Component Analysis (PCA), and data normalization to extract features, which are used as inputs of ANN to diagnose faults. Yuan et al. [11] used kurtosis and entropy as a preprocessor to extract features, which are fed to a neural network for fault classification. Song et al. [12] extracted multiple statistical features by fractional Fourier transform (FRFT), used Kernel Principal Component Analysis (KPCA) for data dimension reduction, employed SVM for fault diagnosis. In these traditional methods, feature extraction plays a critical role in diagnosis performance. A variety of feature extraction methods for analog circuit faults were developed including time-domain features,

* Corresponding author.
E-mail address: zhangbin@cec.sc.edu (B. Zhang).

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frequency-domain features, wavelet features, and statistical features (range, mean, standard deviation, kurtosis, and entropy) [6–13]. However, due to tolerance and nonlinearity of analog components and circuits, as well as the diversity and complexity of faults, existing methods show some limitations: (1) most features are manually extracted and selected, which requires complex signal processing and extensive expert involvement; (2) feature extraction and selection for a fault model is ad-hoc and cannot be extended to other fault models; and (3) ANNs adopted in traditional methods have shallow architectures, which limits the capacity to learn the complex non-linear relationships in fault diagnosis issues [12].

To address these limitations of traditional methods, this paper develops an intelligent analog circuit diagnosis approach based on deep learning technologies. In recent years, deep learning has made great achievements in image processing, speech recognition, and others [14]. It also attracted much attention in the field of fault diagnosis because of its excellent performance in adaptively extracting features from raw data [15] and describing nonlinear fault dynamics [16]. Deep Belief Network (DBN) [17], as the first proposed deep learning algorithm, was initially applied to an aircraft engine fault diagnosis in 2013 [18]. After that, researches on diagnosis of rolling bearings, gearboxes, and reciprocating compressor valves grew rapidly [19–23]. To our knowledge, study on deep learning in analog circuit diagnosis is very limited [24] and it remains an open problem yet to be studied. DBN has great potentials in analog circuit diagnosis mainly because of three major characteristics. First, its multi-layer structure and its way of training enable to adaptively extract features. As a result, raw time series signals can be directly used in training and practical diagnosis, which minimizes the needs and requirements of signal processing and domain knowledge. Second, DBN has unique advantages in handling high-dimensional and nonlinear data, which enables DBN to characterize complex mapping relationships between measured signals and fault modes. This makes DBN a very powerful tool for diagnosis of larger-scale and complicated analog circuits. Third, DBN does not have special requirement on circuits and their stimulus signals, which makes DBN an intelligent solution for feature extraction and analog circuit diagnosis. The proposed method based on DBN is different from existing works in three aspects: (1) In ANN-based methods, ANNs are only used as classifiers and handcrafed fault feature extraction and selection is still needed. DBN integrates adaptive feature extraction and fault classification, which minimize the human involvement. (2) Different from ANNs that take manually extracted features as input, DBN uses raw time domain signals as inputs, which significantly simplifies the design and application of diagnosis.

Compared with existing data-driven methods, our main contributions are twofold: (1). Inspired by deep learning, a new method for analog circuit diagnosis is developed, which integrates feature extraction and diagnosis. In this method, features are adaptively extracted from raw time series signals using a DBN trained by a general-purpose learning procedure. A classifier is used to automatically classify the fault mode based on the extracted features. The proposed method makes the design of diagnosis much easier as it does not need human involvement in feature extraction, (2). Thorough analysis and comparison studies on representative analog circuits are conducted to verify the proposed method. Performance of the proposed method in terms of number of instances and number of sampling points in an instance in DBN training is discussed with experimental analysis. The results show that, compared with existing data-driven methods, the proposed method has higher accuracy, lower requirements on data, and more stable performance for analog circuit diagnosis. It is worth mentioning that the proposed method is suitable for fault modes whose effects are reflected in time series output signals. Our work has proved that this method could cover diagnosis of analog circuits, vibration signals, and biomedical signals.

The rest of this paper is organized as follows: Section 2 introduces the principle of DBN. Section 3 defines the problem and describes the proposed fault diagnosis method for analog circuits. Section 4 presents diagnosis of two experimental circuits, a Sallen-Key band-pass filter and a four-opamp biquad high-pass filter, to verify the effectiveness of the proposed method. Section 5 provides concluding remarks.

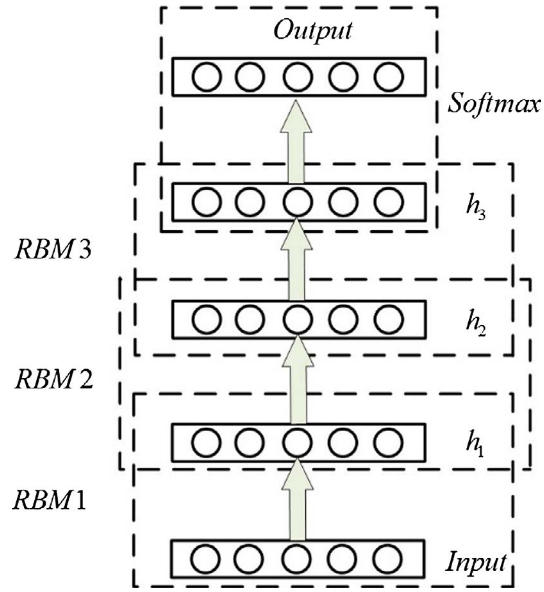

Fig. 1. A five-layer structure of DBN.

2. Principle of DBN

DBN is a generative model composed of stacked Restricted Boltzmann Machines (RBMs) and a classifier [17]. Stacked RBMs extract multiple fault features adaptively layer-by-layer, and the classifier identifies the fault mode. Fig. 1 shows an example of five-layer DBN structure, which consists of input, three stacked RBMs, and output layers. In this structure, layer 1 (input layer) and layer 2 (h1) forms RBM1, layer 2 (h1) and layer 3 (h2) forms RBM2, layer 3 (h2) and layer 4 (h3) forms RBM3. In Fig. 1, input layer takes vector sampled from time series signals of analog circuits. The three hidden layers extract features from lower layer to higher layer automatically, while the output layer uses softmax as the classifier to determine the fault mode.

2.1. RBM

RBM, as a special case of energy-based generative models, is able to provide a learning model for unknown data distributions [25]. Each RBM contains a visible layer and a hidden layer, as shown in Fig. 2. The units in the same layer are not connected. The units in two adjoining layers have directed symmetrical connections [19,26].

Fig. 2 shows the basic structure of RBM. Suppose this is RBM1 in Fig. 1 in our application, then the visible layer input vector v is the normalized time domain response signal of the analog circuit under

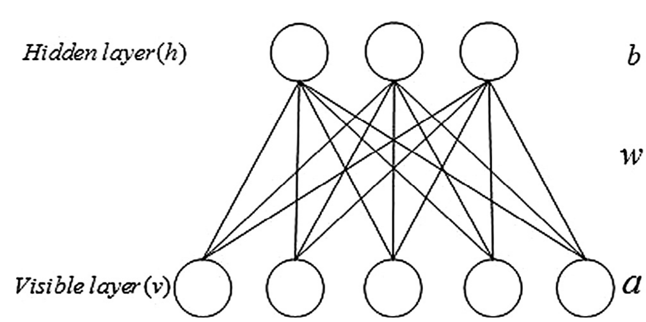

Fig. 2. Basic structure of RBM.