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Fault diagnosis method for analog circuits based on MODA optimized deep belief network

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Abstract

To address the problems of unsupervised training process of traditional DBN, such as long pre-training time and poor diagnosis accuracy, an analog circuit fault diagnosis method based on improved multi-objective dragonfly optimization deep belief network (MODA-DBN) is proposed. The traditional DBN utilizes BP algorithm in the supervised tuning process, however, BP algorithm has the problem of easily falling into local optimum, in order to improve the problem, the improved MODA algorithm is used instead of BP algorithm to improve the network classification accuracy. Finally, MODA-DBN is applied to the diagnosis experiment of a two-stage quad op-amp dual second-order low-pass filter, and the experimental results show that the proposed MODA-DBN ensures the classification accuracy based on the fast convergence speed, and MODA-DBN has a higher diagnosis rate than other methods mentioned in this paper, which can realize the classification and localization of difficult faults.

Keywords

Analog circuit; MODA algorithm; Adaptive learning rate; Deep belief network; Fault diagnosis.

1. Introduction

As an important pillar of military, defense, and aerospace [1], accurate and efficient fault diagnosis in analog circuits has become a hot research topic 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]. However, due to the complex fault phenomena and multiple concurrent faults in analog circuits, the fault states of analog circuits are infinite and the fault characteristics can be continuous, while the input-output relationship of analog circuits is often nonlinearly mapped and there are nonlinear components in the circuits, making it difficult to establish an accurate mathematical model of the circuit response in practice.

In recent years, Zhao et al [7] used DBN networks to adaptively extract features of signals and automatically classify them, which can diagnose faults in analog circuits flexibly and efficiently and provide new solutions to different diagnostic problems. liu et al [8] proposed Gauss-bernoulli deep confidence network (GB-DBN) can capture the higher-order semantic features in the original output signal more effectively and make the diagnosis results more accurate. Zhong et al [9] proposed an overall average empirical mode decomposition (EEMD) based on the intermittent faults in analog circuits and DBN-based intermittent fault diagnosis method for analog circuits. The experimental results show that this method is more efficient than the traditional DBN in diagnosis. Gan et al [10] used a model combining wavelet packet transform (WPT) and hierarchical diagnosis network (HDN), where the HDN consists of two layers DBN is used to extract and feature and perform fault diagnosis respectively.

The DBN uses the BP algorithm to reverse the fine-tuning weights, however, the BP algorithm has the problem of easily falling into the local minimum, so the performance of the DBN will

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also be affected by this. In order to obtain a DBN model with strong robustness and avoiding local minima, the MODA algorithm is used to fine tune the weights and verify its convergence and stability. Finally, simulation experiments are conducted using a two-stage quad op-amp dual second-order complex circuit to verify the superiority of the diagnostic model in this paper.

2. MODA-DBN learning algorithm

2.1. DBN Structure

DBN is a probabilistic generative model consisting of multiple restricted Boltzmann machine stacks.The process of DBN feature extraction is divided into two phases: a pre-training phase and a fine-tuning phase, respectively. In the pre-training phase, all the RBMs are first pre-trained unsupervised layer by layer, resulting in an unsupervised learning feature model. Next, reverse training is performed with a supervised algorithm to fine-tune the initial connection weights of all RBMs, thus reducing the errors generated by training and facilitating DBN to extract the essential features of the input data, the structure of which is shown in Figure 1.

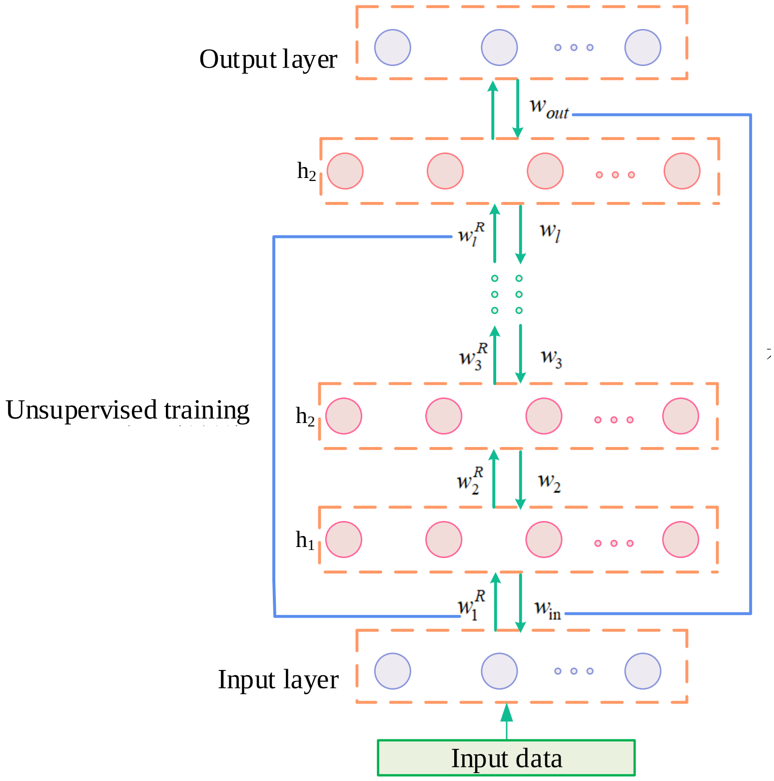

Figure 1: Structure diagram of DBN

2.2. Supervised fine-tuning based on multi-objective dragonfly optimization

There are three main types of insect swarm behavior [10]:

(a) Separation, which refers to the avoidance of static collisions between individuals and their neighbors;

(b) Alignment, which indicates that individuals match the velocity of neighboring individuals;

(c) Coalescence refers to individuals‘ to cluster to the center of the surrounding group.

(1) Movement model

One of the main behaviors of insect swarms is to be attracted by food, and the other is to avoid natural enemies. Therefore, the location renewal of dragonfly individuals is mainly influenced by 5 factors, and the mathematical model of the 5 factors is as follows:

1) Separation:

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In a static swarm, dragonflies will cluster into groups in order to hunt other flying prey such as butterflies and mosquitoes. In order to avoid collision with other dragonflies during flight its, the separation expression is as follows:

$$S_i = -\sum_{j=1}^{N} X - X_j \tag{1}$$

where, X denotes the position of the current individual, X_j denotes the position of the *j*-th neighboring individual, and *N* denotes the number of neighboring individuals.

2) Alignment:

$$A_i = \sum_{j=1}^{N} V_j / N \tag{2}$$

where, V_j denotes the velocity of the *j*-th neighboring individual.

3) Cohesion:

$$C_i = \frac{\sum_{j=1}^{N} X_j}{N} - X \tag{3}$$

where X denotes the position of the current individual, X_j denotes the position of the *j*-th neighboring individual, and *N* denotes the number of neighboring individuals.

4) Food attraction:

$$F_i = X^+ - X \tag{4}$$

where X denotes the current individual location and X^+ denotes the location of the food source.

5) Natural enemy dispersal:

$$E_i = X^- + X \tag{5}$$

where X denotes the current individual location and X^- indicates the location of natural enemy.

The MODA algorithm assumes that the behavior of the dragonfly is a combination of these five correction modes. In order to update the position of the artificial dragonfly in the search space and to simulate its movement, two vectors are considered: step (ΔX) and position (X), defined as follows:

$$\Delta X_{t+1} = \left(sS_i + aA_i + cC_i + fF_i + eE_i\right) + \omega \Delta X_t \tag{6}$$

$$X_{t+1} = X_t + \Delta X_{t+1} \tag{7}$$

where *s* denotes the separation weight, S_i denotes the separation of the *i*-th individual, *a* denotes the alignment weight, A_i denotes the alignment of the *i*-th individual, *c* denotes the cohesion weight, C_i denotes the cohesion of the *i*-th individual, *f* denotes the food factor, F_i denotes the food source of the *i*-th individual, *e* denotes the enemy factor, E_i denotes the location of the *i*-th individual's enemy, ω denotes the inertia weight, and *t* denotes the number of iterations.

3. Simulation experiments and research analysis

The MODA-DBN fault diagnosis model proposed in this paper is based on the following five processes:

(1) Applying pulse signals at both ends of the circuit under test and collecting fault data;

(2) Fault coding of the data;

(3) Dividing the data set into training set and test set;

(4) Fine-tuning the weights using the MODA optimization algorithm during supervised learning;

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(5) Model testing: the real codes of the test set are compared with the predicted codes of the model, and if the predicted codes are consistent with the real codes, the classification is correct; if the predicted codes are inconsistent with the real codes, the classification is incorrect.

3.1. Complex filter diagnostic example

In this paper, the two op-amp double-quadratic low-pass filter (Figure 2) is used to verify the MODA-DBN model proposed in this paper. The tolerances of the resistors and capacitors in the circuit are both set to 5%, respectively. In this experiment, a single resistor or capacitor in the filter is set to fail, while the other resistors or capacitors vary randomly within the tolerance range, that is, in a normal state. And according to the sensitivity test results, two components of resistors R_9, and C_4 were selected as the study objects for experimental analysis, as shown in Table 1.

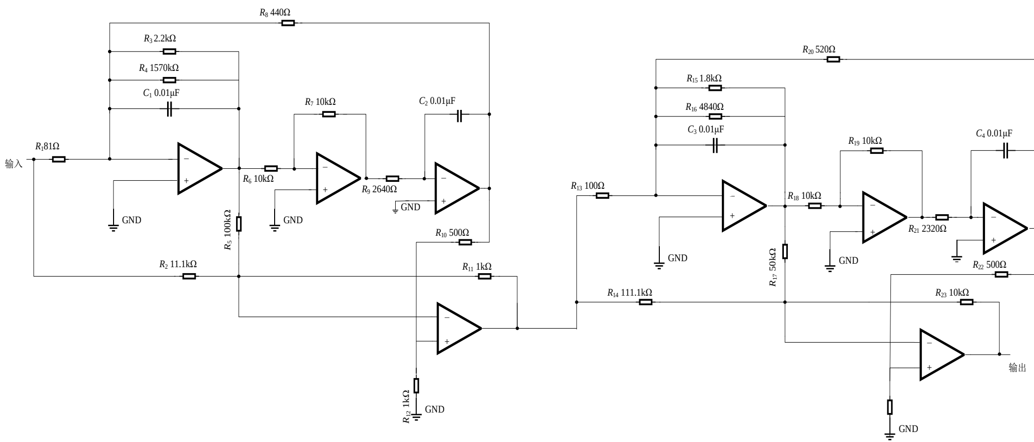

Figure 2: Structure diagram of DBN

Table 1: Three Scheme comparing

Fault code	Fault Type	Tolerance /%	Nominal Value	Fault value
1	Normal	-	-	-
2	R9 ↑	5	2640Ω	3960Ω
3	R9 ↓	5	2640Ω	1320Ω
4	C4 ↑	5	0.01nF	0.015nF
5	C4 ↓	5	0.01nF	0.005nF

The proposed method is compared with some common analog circuit fault diagnosis and classification methods to prove the effectiveness and superiority of the MODA-DBN model for complex circuit fault diagnosis and classification. In the superficial aspect, BP, SVM are used for classification diagnosis, and in the deep aspect, traditional DBN is used for comparison.

The above model was compared with the MODA-DBN proposed in this paper for 10 independent diagnostic experiments, as shown in Table 2, where the comparison indexes included average time and average accuracy rate.

Method	average time/s	average accuracy rate /%
BP	46.12	75.92
SVM	53.07	82.17
DBN	43.91	91.08
MODA-DBN	45.94	97.23

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It can be seen from Table 2 that the main advantages of the MODA-DBN proposed in this paper are as follows: (1) Compared with the shallow layer, the essential features of the data can be effectively extracted; (2) Reasonable optimization of DBN can improve the accuracy and performance to varying degrees; Therefore, MODA-DBN has certain advantages in the accurate identification of faults.

4. Conclusion

This paper presents a fault diagnosis method for analog circuits based on IMODA-DBN. The supervised fine-tuning process of DBN was optimized by MODA algorithm, and the simulation experiment was verified by complex low-pass filter. The experimental results show that the MODA-DBN model can realize efficient fault classification and location, and can be used as a new solution in the field of analog circuit fault diagnosis.

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