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Analog circuit fault diagnosis via FOA-LSSVM

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ABSTRACT

At present, the research on fault detection and diagnosis technology is very significant to improve the reliability of the equipment, which can greatly improve the safety and efficiency of the equipment. This paper proposes a new fault detection and diagnosis means based on the FOA-LSSVM algorithm. Experimental results demonstrate that the algorithm is effective for the detection and diagnosis of analog circuit faults. In addition, the model also demonstrate good generalization ability.

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1. INTRODUCTION

According to statistics, at present, 80% of devices in electronic systems are digital, but 80% of faults occur on analog devices. At the same time, the test cost of the analog circuit part accounts for 80% of the total test cost, thence, it is very important to carry out discuss on fault diagnosis of analog circuits. In recent years, many scholars have conducted extensive research in the field of analog circuit fault diagnosis and have achieved many excellent results [1-9]. However, the analog circuit itself has the characteristics of poor fault model, component tolerance, fault parameter continuity and circuit nonlinearity. Such characteristics make the development of analog circuit fault diagnosis technology slow, and there is still no practical method.

In analog circuit fault diagnosis, the extraction of fault features is a very important link, and the quality of the extraction results will directly affect the final diagnosis accuracy rate. Ordinary feature extraction methods mainly include PCA, wavelet analysis, kernel analysis, etc. [10-13]. These methods have their limitations. For example, the PCA method is only suitable for linear feature extraction. Wavelet analysis and nuclear analysis involve the selection and consideration of many factors such as wavelet base and nuclear parameters, which are greatly influenced by experience. Moreover, in essence, these analysis methods and data are isolated from each other, and it is difficult to ensure that the extracted features are the essential characteristics of the data.

Fault classification and identification is another key point of fault diagnosis for analog circuits. In recent years, the continuous development of various artificial intelligence algorithms has gave birth a new ideas for analog circuit fault diagnosis. They are neural networks (NN) [14-19], support vector machine (SVM) [20-24], deep learning [25-27] and so on. The main idea of the fault diagnosis method of neural network is: the mapping between fault symptoms and fault types is established through learning between network layers. The nodes of the input layer are caused to correspond to fault symptoms, and the nodes of the output layer correspond to fault types. Thus, the reasoning process from fault symptom to fault type can be realized. The neural network can set the network structure according to requirements and approximate the nonlinear function with arbitrary precision. But the learning of the network requires a large number of circuit failure samples. Therefore, for systems that cannot obtain a large amount of fault data, the use of neural networks will be limited. At the same time, how to ensure the integrity and typicality of the fault sample and the convergence, training speed and real-time diagnosis of the method are the bottlenecks restricting the development of analog circuit fault diagnosis technology based on neural network.

As a pattern recognition method based on statistical learning theory, SVM has many unique advantages, for example solving small samples, nonlinear and high-dimensional pattern recognition, and can be applied to other machine learning problems, such as function fitting. However, when constructing the optimal classification hyperplane, SVM only pays attention to the separability between the data classes and ignores the structural information of the data within the class. This results in the classification boundary of the data being too smooth when the data has a nonlinear manifold structure, which seriously affects the classification performance of the SVM. In practical problems, most of the samples are highly correlated, that is, they are at least partially distributed on a low-dimensional manifold. In particular, there is often a nonlinear relationship between the output of the general circuit and the fault mechanism of the circuit. Therefore, the traditional SVM only pays attention to the inter-class spacing information, which is not enough for the analog circuit fault diagnosis classification problem.

At present, the research results based on deep learning are relatively few in analog circuit fault diagnosis. The difficulty in the field of fault diagnosis lies in the adjustment of parameters. The parameter selection affects the accuracy of fault sign extraction. There is no systematic theoretical system to guide the adjustment of deep learning parameters. The adjustment of relevant parameters often needs to be selected according to actual experience.

Deep learning training is time consuming. For machine learning, the verification process of model correctness is complex and the features found are not intuitive enough. Fault diagnosis requires the model to identify the type of fault in a timely and rapid manner. This is a difficult point to overcome in the application of the deep learning method. In this paper, we were inspired to receive the above method, we present FOA-LSSVM model for circuit fault diagnosis. The example of Sallen-Key band pass filter circuit display that our resulting diagnostic system can effectively classify the faulty components of analog circuits when it is tested, and it has a competitive classification performance.

2. FLY OPTIMIZATION ALGORITHM

Fruit Fly Optimization Algorithm (FOA) [28, 29] is an emerging swarm intelligent optimization algorithm based on the bionics principle of fruit fly foraging behavior. It is based on the food searching behavior of the fruit fly. In comparison to any other species, fruit fly has exceptional olfactory and visual senses. The organ responsible for the sense of smell with-in fruit flies can search of all kinds of smells floating in the air, also it is able to smell the food taste that is nearly 40 km. It has a built-in olfactory organ that allows them to pick up different odor molecules in the air and to determine the source of their food. Thereafter, it gets closer to the sources, and its sharp eyesight was used to find food, also it uses the way back to its swarm. FOA's operation is simple, easy to implement, and has strong local search capabilities. The steps for an iterative search for food by the Drosophila population are as follows:

- Step 1. Define a fruit fly swarm's location randomly.

$$InitX\_axis;\ InitY\_axis \tag{1}$$

- Step 2. Give fruit fly individuals random distance and direction to search for food using their sense of smell.

$$\begin{cases} X_i = X\_axis + RandomValue_x \\ Y_i = Y\_axis + RandomValue_y \end{cases} \tag{2}$$

- Step 3. Since the position of the food is unknown,first of all ,the distance from the origin ($Dist_i$) is estimated, and then the taste concentration judgment value (S_i) is calculated, which is the inverse of the distance.

$$Dist_i = sqrt(X_i^2 + Y_i^2);\ S_i = 1/Dist_i \tag{3}$$

- Step 4. Substituting the taste concentration judgment value (S_i) into the taste concentration judgment function (or called fitness function), so that the taste concentration ($Smell_i$) of the individual position of the fruit fly

$$\text{Smell}_i = Function(S_i) \tag{4}$$

- Step 5. Find the highest-dose fruit fly in this population (maximum value)

$$[bestSmellbestIndex] = \max(\text{Smell}) \tag{5}$$

- Step 6. Maintain the best smell concentration value and x, y coordinate; the Drosophila swarms will detect this position and fly towards it.

$$\begin{cases} Smellbest = bestSmell \\ X\_axis = X(bestIndex) \\ Y\_axis = Y(bestIndex) \end{cases} \tag{6}$$

- Step 7. Perform iterative optimization, repeat steps 2-6 and determine whether the taste concentration is better than that in the previous iteration; if so, go to step 6.

3. LEAST SQUARES SUPPORT VECTOR MACHINES

The support vector machine (SVM) [30, 31] maps the sample space to a high-dimensional or even infinite-dimensional feature space through a non-linear mapping, so that the non-linearly separable problem in the original sample space is transformed into a linearly separable problem in the feature space. Starting from the machine learning loss function, Suykens et al. proposed a least squares support vector machine (LSSVM) [32], which uses the second norm in the objective function of its optimization problem. The equality constraint condition is used instead of the inequality constraint condition in the SVM standard algorithm, so that the optimization problem of the LSSVM method becomes a solution of a set of linear equations obtained by Kuhn-Tucker condition.This makes it possible to reduce the computational complexity, increase the generalization ability and the solution speed when the extreme conditions are met, and it can be effectively applied to pattern recognition and function estimation.

In LSSVM, the regression is expressed as given below:

$$\min_{w,b,e} J(w,e) = 1/2\, \|w\|^2 + \frac{\gamma}{2}\sum_{i=1}^{l} e_i^2 \tag{7}$$

$s.t. y_i = w^T\varphi(x_i) + b + e_i, i = 1,2, \ldots, 1$, where γ is the regularization parameter, determining the tradeoff between the fitting error minimization and smoothness, and e_i is error variable. The Lagrangian equation is defined as follows:

$$L(w,b,e,a) = J(w,e) - \sum_{i=1}^{l} \alpha_i[w^T\varphi(x_i) + b + e_i - y_i] \tag{8}$$

optimize (8), we get the optimal solution of the following conditions:

$$\begin{cases} w = \sum_{i=1}^{l} \alpha_i\varphi(x_i), \sum_{i=1}^{l} \alpha_i - 0, \alpha_i = \gamma e_i \\ y_i = w^T\varphi(x_i) + b + e_i \end{cases} \tag{9}$$

omitting e_i and w leads to the Karush–Kuhn–Tucker (KKT) conditions:

$$\begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} 0 & e^T \\ e & \Omega + I/\gamma \end{bmatrix} \begin{bmatrix} 0 \\ Y \end{bmatrix} \tag{10}$$

where $Y = [y_1, y_2, \ldots, y_l]^T$, $\alpha = [\alpha_1, \alpha_2, \ldots, \alpha_l]^T$, $e = [1,1, \ldots, 1]^T$, $\Omega\left(\varphi(x_i)\varphi(x_j)\right)_{l\times l}$ is kernel function matrix, I represents the identity matrix.

Define $K(x_i, x_j) = \varphi(x_i)^T\varphi(x_j)$, which is satisfied with Mercer's condition. In the paer, We choose Gaussian Radial Basis Function (RBF) as the kernel function, as is meaned in:

$$K(x_i, x_j) = \exp\left\{-\frac{|x_i - x_j|}{2\sigma^2}\right\} \quad (11)$$

where σ introduces a positive real number, taken into account as the kernel function. So, the following relationship is found as the final result:

$$y(x) = \sum_{i=1}^{l} a_i K(x, x_i) + b \quad (12)$$

It should be noted that the performance of the LSSVM model is significantly affected by the kernel function width coefficient σ and the regularization factor γ, the width of the RBF is affected by the width σ, and the complexity and punishment are affected by γ.

4. FOA-LSSVM ALGORITHM

In this section, among the methods proposed in this paper, the optimization of the LSSVM classifier by FOA is shown as follows:

- No. 1. Let us assume the maximum number of iterations (maxgen), population size (sizepop), and we also can randomly emerge a fruit fly swarm's starting position (InitX_axis, InitY_axis) in order to create random flight distance (FR).
- No. 2. Surppose gen = 0, it's assigned that each fruit fly ($\mathrm{Fly_i}$) respectively looks for food toward a random direction, and it goes for a random amount of distance.

$$\begin{aligned} X(i,:) &= X\_axis + a \times rands - b \\ Y(i,:) &= Y\_axis + a \times rands - b \end{aligned} \quad (13)$$

a, b are Constants which can be selected.

- No. 3. Calculate the distance of the initial position $\mathrm{Dist_i}$, then we can determine the value of the smell concentration $\mathrm{S_i}$. Program $\mathrm{Dist_i}$ which is denoted by $(\mathrm{D(i,1), D(i,2)})$, so we have:

$$\begin{aligned} D(i,1) &= \sqrt{X(i,1)^2 + Y(i,1)^2} \\ D(i,2) &= \sqrt{X(i,2)^2 + Y(i,2)^2} \end{aligned} \quad (14)$$

Let

$$S(i,1) = 1/D(i,1), S(i,2) = 1/D(i,2) \quad (15)$$

so, we can get the conclusion that S_i is represented by $(S(i,1), S(i,2))$.

Let's put S_i into the model of LSSVM. We assume $\gamma = v \times S(i,1), \sigma^2 = S(i,2)$, where v is Constant which can be selected. $[\gamma, \sigma]$ are Parameters of LSSVM, which can be represented by $[S(i,1), S(i,2)]$. As the result of classifications, the smell concentration can be calculated $Smell_i$, which is used to be the mean square error (RMSE) in order to measure the predicted and actual value. n is a sample capacity, y_i is a measured value, and $\hat{y}_i$ is a predictive value.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (16)$$

- No.4. Surpposed gen = gen + 1, according to (13)-(15) iterations, and put the value of iterations into LSSVM model. Thereafter, calculate the smell concentration.
- No. 5. When gen reaches the maximum iterations, it can decide to stop. Then, we will have the best model that meets LSSVM model parameters. Otherwise, we will return to No.2.
- No. 6. We get the optimized parameters, and we establish FOA-LSSVM models.

5. ILLUSTRATIVE EXAMPLE

The Sallen-Key is tested as a lowpass filter circuit to verify effectiveness and correctness in this section. The resistors and capacitors are assumed to meet 5% tolerances respectively. The Sallen-Key bandpass filter in Figure 1 under C1, C2, R2 and R3 vary within their tolerances. NF represents non-fault class. The normal values for each component are shown in Table 1. Resistors and capacitors have 5% tolerances respectively. Every normal value is: $C_1 = 5nF$, $C_2 = 5nF$, $R_1 = 1k\Omega$, $R_2 = 3k\Omega$, $R_3 = 2k\Omega$, $R_4 = R_5 = 4k\Omega$. Here, we suppose resistors and capacitors in this interval $[(50\%X, 95\%X) \cup (105\%X, 150\%X)]$ (X is the regular value). Then faults can be classified to 8 fault pattern: C_1↑, C_1↓, C_2↑, C_2↓, R^2↑, R_2↓, R_3↑, R_3↓. In this way, training and test samples generated after preprocessing can be trained and tested after FOA-LSSVM optimization. The single fault categories and the nominal and fault component values for the Sallen-Key bandpass filter are listed in Table 1.

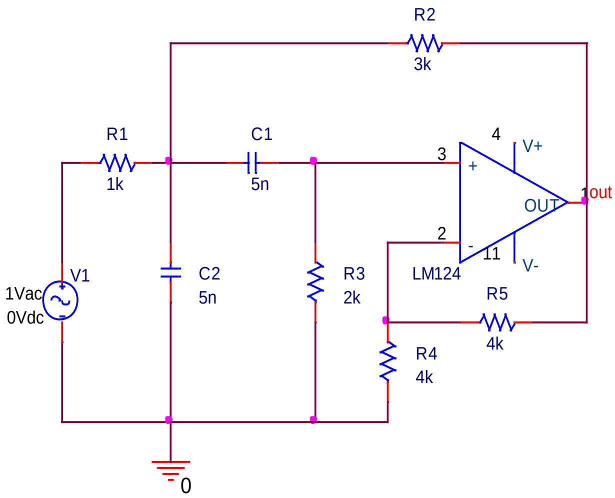

Figure 1. Sallen-Key bandpass filter

Table 1. Single fault classes and the nominal and faulty component values

Fault code	Fault class	Normal	Faulty value
1	C1↑	5nF	7.5nF
2	C1↓	5nF	2.5nF
3	C2↑	5nF	7.5nF
4	C2↓	5nF	2.5nF
5	R2↑	3kΩ	4.5kΩ
6	R2↓	3kΩ	1.5kΩ
7	R3↑	2kΩ	3kΩ
8	R3↓	2kΩ	1kΩ
9	NF	-	-

We carry out 50 times Monte Carlo analysis to the diagnosis circuit by PSpice 10.5 software where the acquisition value of the output voltage Vout as source data, through Haar wavelet transform and fault data which were obtained 450 samples, of which 40% will be used as training data sample, 60% of the data as a test samples. We suppose the fruit fly population is 100, and the number of iterations is 30 steps, flies swarm original position is a random generator by matlab rands function. After the simulation, FOA-LSSVM optimization iteration convergence is shown in Figure 2. We can see that FOA-LSSVM optimization iteration steps converge to 0.02, when the iteration step is between 1109 and 2699 under the local optimal area. According to several tests of the downward trend, we have found that the optimal iteration can converge 0 to 4000 steps. Finally, we have obtained the optimal parameters (see Table 2).

As is seen from Table 3, five kinds of fault modes can diagnose the correct ones. Then, NF, C1↓, R2↓ fault modes of 7 tested sample data are diagnosed unsuccessful. Using the optimized parameters is classified, diagnostic accuracy of Sallen-Key band-pass filter circuit is 97.04% by FOA-LSSVM methods.

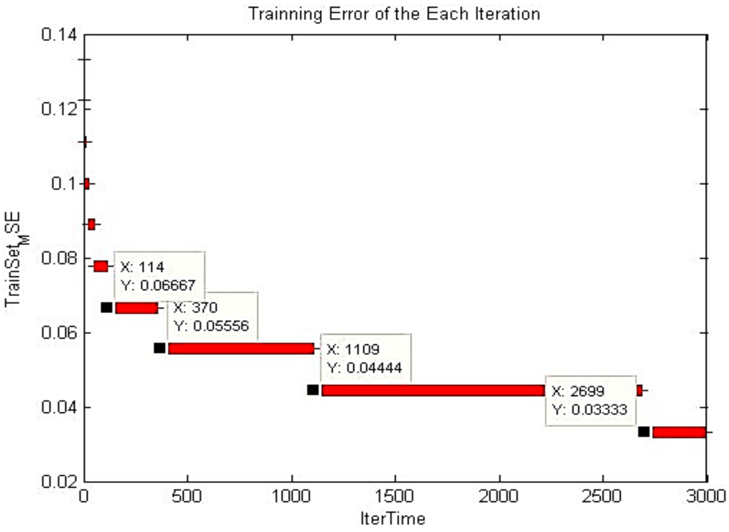

Figure 2. Training error of each iteration

Table 2. Single fault diagnostic test parameter results

Sizepop	maxgen	gambest	sigbest
100	30	2.0521	0.0806
X_axis		Y_axis	
[-6.4958,-6.9183]		[10.3066,10.4556]	

Table 3. Sallen-Key band-pass filter circuit single fault diagnosis

	NF	C1↑	C1↓	C2↑	C2↓	R2↑	R2↓	R3↑	R3↓
NF	27		1				2		
C1↑		30							
C1↓	2		27 (Inf)						
C2↑			1	30					
C2↓					30				
R2↑						30			
R2↓	1						28		
R3↑								30	
R3↓									30

6. CONCLUSION

In this paper, the use of FOA has a good global searching ability linked with LSSVM in pattern recognition of superior performance. We present FOA-LSSVM model circuit fault diagnosis as the Sallen-Key band-pass filter, which shows that the algorithm obviously improves the accuracy of fault diagnosis and recognition of faults. This shows that the method is an efficacious and reliable method for fault diagnosis of analog circuits.

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