Analog Circuit Soft Fault Diagnosis based on PCA and PSO-SVM

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Abstract—Regarding to the complexity and diversity of analog circuit fault, a principal component analysis (PCA) and particle swarm optimization (PSO) support vector machine (SVM) analog circuit fault diagnosis method is proposed. It uses principal component analysis and data normalization as preprocessing, then reduced dimension fault feature is putted into support vector machine to diagnosis, and particle swarm optimization is used to optimize the penalty parameters and the kernel parameters of SVM, that improve the recognition rate of the fault diagnosis. The simulation results show that the proposed diagnosis model can perform analog circuit fault diagnosis effectively, and has higher fault diagnosis rates.

Index Terms—Analog Circuit; Fault Diagnosis; Principal Component Analysis; Particle Swarm Optimization; Support Vector Machine

I. INTRODUCTION

Circuit fault diagnosis has become the third largest branch of modern circuit theory except for circuit analysis and network synthesis [1]. Currently, digital circuit fault diagnosis technology has been very mature; however, analog circuit fault diagnosis technology requires further in-depth research. The reason is that analog circuit has tolerance, non-linear, fault diversity, etc [2]. In recent years, many experts and scholars use artificial neural networks, wavelet decomposition, information technology and fuzzy theory to diagnosis analog circuit fault, and achieve good results [3-9].

Fault feature extraction and fault classification are two key steps of analog circuit fault diagnosis. Owe to the characteristics of analog circuits, analog circuit fault feature is not strong regularity. However, through fault feature extraction can significantly improve the simulation circuit fault recognition performance. Principal component analysis (PCA) is an effective information processing, compression and extraction method based on the covariance matrix [10]. PCA distinguish fault feature information by extracting main components and removing redundant components, which provide favorable conditions for fault classification and identification. Support vector machine (SVM) is a new machine learning method based on statistical learning theory [11]. It is the approximate realization of structural risk minimization. It shows many unique advantages in resolving the small samples, nonlinear and high dimensional pattern recognition. It has better generalization ability and shows superior performance in analog circuit fault diagnosis [12]. Diagnosis accuracy is influenced by SVM parameters. In order to improve the fault diagnosis accuracy, the optimal parameters must to be found. At present, intelligent optimization algorithms is used to automatically find the optimal parameters. Particle swarm optimization (PSO) is a random search optimization algorithm derived from bird predation behavior and based on group collaboration. Its advantages are simple structure, easy to implement, fast convergence, no need to adjust many parameters, scalability, etc [13]. It has been successfully applied in many fields.

In this paper, PCA is used to reduce dimension for collecting fault information. Then PSO is used to optimize the punishment parameter and kernel parameter of SVM. At last, the normalized fault feature is inputted optimized SVM to diagnosis analog circuit fault.

II. PREPROCESSING TECHNIQUES

A. Principal Component Analysis and Normalization

PCA is a statistical analysis method that turns multiple variables into a few independent comprehensive variables. It is used to reduce data dimensionality [14]. Let \(X = [x_1, x_2, \ldots, x_n]\). \(X\) is a sample space that has \(n\) samples, where each sample has \(m\) feature. Covariance matrix of the sample space \(X\) is:

\[
C = \frac{1}{n} \sum_{i=1}^{n} (x_i - E(X))(x_i - E(X))^T
= \frac{1}{\sqrt{n}} \sum_{i=1}^{n} (x_i - E(X))(x_i - E(X))^T = AA^T
\]

\[
E(X) = \frac{1}{n} \sum_{i=1}^{n} x_i
\]

is the mean of the sample space.

Eigenvalues of \(C\) is \(\lambda_1, \lambda_2, \ldots, \lambda_m\), and \(\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_m\). Eigenvectors is \(u_1, u_2, \ldots, u_m\):

\[
C u_i = \lambda_i u_i, \quad i = 1, 2, \ldots, m
\]
is feature vector projection. Let \( U = [u_1, u_2, \ldots, u_m] \), the sample space is reconstructed to:

\[
Y = U^T A
\]  

Formulas (3) convert the \( m \)-dimensional sample space \( X \) into \( m \)-dimensional sample space \( Y \) through eigenvectors \( U \). In sample space \( Y \), \( y_j \) is the \( j \)-th principal component of the \( i \)-th sample.

In order to select principal component and discard secondary component in the feature space, define variance contribution rate:

\[
\Phi(L) = \frac{\sum_{i=1}^{L} \lambda_i}{\sum_{i=1}^{m} \lambda_i}
\]  

First \( L \) eigenvectors \( U_L = [u_1, u_2, \ldots, u_L] \) act low-dimensional projection space when variance contribution rate \( \Phi(L) \) is large enough.

Data normalization turn the number of all data into \([0, 1]\). Its purpose is that cancels the order of magnitude difference between data, then avoid magnitude difference of the input and output data to identify the poor effect. In this paper the data normalization function following form is:

\[
x_i = \frac{x_i - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}
\]  

where, \( x_{\text{min}} \) is the minimum number of data sequence, \( x_{\text{max}} \) is the maximum number of data sequence.

**B. Support Vector Machine**

The support vector machine evolve from optimal separating line in the case of linearly separable, the optimal classification line is the optimal classification surface in the high dimensional feature space [15]. If linearly inseparable, there can add to a slack variables \( \xi (\xi \geq 0) \) and solve the optimization problem:

\[
\begin{align*}
\text{min} & \quad \Phi(w, \xi) = \frac{1}{2} (w \cdot w) + C \sum_{i=1}^{n} \xi_i \\
\text{s.t.} & \quad y_i ((w \cdot x_i) + b) \geq 1 - \xi_i 
\end{align*}
\]  

where, \( w \) is weight vector, \( b \) is offset, \( C \) is punishment parameters.

There use Lagrange multiplier method to turn the optimization problem into a dual quadratic programming problem, optimal classification decision function as follows:

\[
f(x) = \text{sgn} \left( \sum_{i=1}^{n} a_i^{*} y_i (x \cdot x_i) + b^{*} \right)
\]  

If it is nonlinear classification problem, input variables \( x \) are transformed into a high dimensional space, and solve optimal classification surface in transform space. Use a kernel function \( K(x_i, x_j) \) that corresponds to the inner product of transform space to obtain the nonlinear optimal classification decision-making function, as follows:

\[
f(x) = \text{sgn} \left( \sum_{i=1}^{n} a_i^{*} y_i K(x_i, x_j) + b^{*} \right)
\]  

Choose a different kernel function will be different support vector machine. In this paper, use radial basis function as kernel function of SVM.

The standard SVM is a binary classification problem. In dealing with analogy circuit fault diagnosis multi-classification need to construct multiple classifiers. The combination of a number of binary classifiers can be used to construct multi-classification, such as one against all, one against one, decision directed acyclic graph SVM. This paper use one against all to construct multi-classification. For \( K \) classification problems, firstly construct \( K(1) \) classifier, the samples are inputted into model to vote results. The highest number of votes shall be final classification results.

**C. Particle Swarm Optimization**

Particle swarm optimization that is proposed by Eberhart doctor and Kennedy doctor in 1995 is a global optimization method [16]. Each potential solution of the optimization problem is a particle in the search space. All particles are determined fitness value by a fitness function. Each particles move in space, the direction and distance of flight are determined by the particle velocity. Initialize a group of random particles to find the optimal solution by iteration. In every iteration, the particles find
the individual optimal solution $p_{best}$ and the global optimal solution $g_{best}$ to update itself. Particle populations evolve rules as follow:

$$v_i(t+1) = w \times v_i(t) + c_1 \times \text{rand} \times (p_{best} - x_i(t)) + c_2 \times \text{rand} \times (g_{best} - x_i(t))$$

$$x_i(t+1) = x_i(t) + v_i(t+1)$$

where, $v_i$ is velocity of particle, $x_i$ is position of particle, $w$ is inertia factor, $c_1$, $c_2$ is learning factor, $\text{rand}$ is the random number between(0, 1).

D. PSO Optimized SVM Parameter Model

Support vector machine is a very superior classifier, but its classification effect is greater impacted by setting parameters (penalty parameter $C$ and kernel parameter $\sigma$) [17]. Mostly use cross-validation method to obtain SVM parameters, but the effect is no better. In this paper, use PSO algorithm to optimize penalty parameter $C$ and kernel parameter $\sigma$. The initial population that is generated by PSO as SVM parameters input SVM model to training and testing. Through cluster, rear-end, foraging behavior iterative optimization to produce the next generation population parameters, until fulfill the termination condition is set by PSO algorithm. Figure 1 is PSO algorithm optimize SVM parameters flowchart.

The algorithm steps as follows:

Step 1: Determine fitness function. Cross-validation accuracy is as fitness function value of PSO.

Step 2: Particle swarm initialization. Randomly generate moderate size particle swarm in the solution space. The particle swarm individual representative SVM parameters. Set particle initial velocity, maximum iteration number, inertia factor and learning factor.

Step 3: Calculate individual fitness value. Set penalty parameter $C$ and kernel parameter $\sigma$ of SVM. Sample set is inputted SVM to train. Obtain the recognition rate of test sample. According to SVM classifier performance evaluation function calculate individual fitness.

Step 4: Determine $p_{best}$ and $g_{best}$. Compare updated particle swarm fitness value with $p_{best}$ corresponding fitness value, if excellent update it, otherwise retain the original value. Compare updated each particle $P_{best}$ with global extremum $g_{best}$, if excellent update it, otherwise retain the original value.

Step 5: Determine whether termination condition is met, if meet output optimal SVM parameters, algorithm end; otherwise, it returns Step 3 until termination condition is met, output optimal SVM parameters value.

III. ANALOG CIRCUIT FAULT DIAGNOSIS MODEL

A. Determination of Analog Circuit Fault Information

Figure 2 is a quad op amp pairs of secondary high-pass filter circuit. The nominal value of the respective elements is shown in the figure. Where, resistors and capacitors each have 5% tolerance. If resistors and capacitors component values outside the tolerance range and less than 50%, circuit is soft fault.

Excitation signal is applied to the circuit, and a response signal at this time can be obtained by simulation. Amplitude of 1V sinusoidal voltage excitation signal is applied to the circuit shown in Figure 2. When some of the components in the circuit deviate from the nominal value measured amplitude-frequency characteristic curve shown in Figure 3.
As can be seen from Figure 3, the amplitude-frequency characteristic curve of deviating from nominal value and normal state is inconsistent. Therefore, the amplitude-frequency characteristic curve information can be collected to use as circuit fault information.

B. Analog Circuit Fault Diagnosis Model based on PCA and PSO-SVM

If not dealt with analog circuit fault information that was collected, directly input classifier fault to diagnosis, not only the efficiency of diagnosis is poor, but also the accuracy of diagnosis is not ideal. Figure 4 is analog circuit fault diagnosis model based on PCA and PSO-SVM that is presented in this paper.

IV. NUMERICAL RESULTS

Quad op amp pairs of secondary high-pass filter circuit shown in Figure 1 is used as example to verify the feasibility and effectiveness of the proposed method in this paper.

In the circuit, each of the passive components of the nominal values is shown in Figure 3, resistors and capacitors have 5% tolerance. If resistor and capacitor components values outside the tolerance range and less than 50%, the circuit is soft fault.

<table>
<thead>
<tr>
<th>Fault code</th>
<th>Fault category</th>
<th>Nominal value</th>
<th>Fault value</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1</td>
<td>C1</td>
<td>5nF</td>
<td>7.5nF</td>
</tr>
<tr>
<td>F2</td>
<td>C1</td>
<td>5nF</td>
<td>2.5nF</td>
</tr>
<tr>
<td>F3</td>
<td>C1</td>
<td>5nF</td>
<td>6nF</td>
</tr>
<tr>
<td>F4</td>
<td>C1</td>
<td>5nF</td>
<td>2.5nF</td>
</tr>
<tr>
<td>F5</td>
<td>R1</td>
<td>6.2kΩ</td>
<td>9.3kΩ</td>
</tr>
<tr>
<td>F6</td>
<td>R1</td>
<td>6.2kΩ</td>
<td>3.1kΩ</td>
</tr>
<tr>
<td>F7</td>
<td>R1</td>
<td>6.2kΩ</td>
<td>9.3kΩ</td>
</tr>
<tr>
<td>F8</td>
<td>R1</td>
<td>6.2kΩ</td>
<td>3.1kΩ</td>
</tr>
<tr>
<td>F9</td>
<td>R1</td>
<td>6.2kΩ</td>
<td>9.3kΩ</td>
</tr>
<tr>
<td>F10</td>
<td>R1</td>
<td>6.2kΩ</td>
<td>3.1kΩ</td>
</tr>
<tr>
<td>F11</td>
<td>R1</td>
<td>1.6kΩ</td>
<td>2.4kΩ</td>
</tr>
<tr>
<td>F12</td>
<td>R1</td>
<td>1.6kΩ</td>
<td>1.2kΩ</td>
</tr>
<tr>
<td>F13</td>
<td>NF</td>
<td>--</td>
<td>--</td>
</tr>
</tbody>
</table>

Single soft fault is considered in this paper, that only one component in the circuit is fault, and the component values is in [50% X, 95% X] ∪ (105% X, 150% X] (X is nominal value of the component), while the other component only changes within the respective tolerance range. Normal and soft fault value of a quad op amp pairs of secondary high-pass filter is shown in TABLE I. Where, ↑ indicates component is larger fault, ↓ indicates component is smaller fault. There are a total of 13 kinds of fault modes including a no-fault state.

OrCAD10.5 software is used to simulate the circuit shown in Fig. 2. Amplitude of 1V sinusoidal voltage excitation signal is inputted to the circuit and collect amplitude-frequency response information in the output. Use fault modes shown table1 to AC Sweep analysis. The start frequency is set to 1 Hz; the stop frequency is set to 25 kHz, obtain 60 sampling points. Monte Carlo analysis is applied to 13 fault modes respectively, and obtains 50 samples of each fault classification with 60 characteristics. PCA is used to reduce the dimension of these samples; select the maximum contribution rate of 7 characteristics constitute the fault feature, and normalization the fault eigenvalue. Fault eigenvalue of PCA reduce dimension and normalization is shown as TABLE II.

The sample is divided into two parts: 30 samples of each fault mode as training samples; 20 samples of each fault mode as test samples. Altogether there are 390 training samples and 260 test samples. These samples are inputted into optimized SVM classifier to identify. Let
TABLE II. FAULT MODES OF QUAD OP AMP PAIRS OF SECONDARY HIGH-PASS FILTER

<table>
<thead>
<tr>
<th>Fault category</th>
<th>Eigenvalue</th>
<th>V1</th>
<th>V2</th>
<th>V3</th>
<th>V4</th>
<th>V5</th>
<th>V6</th>
<th>V7</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1 :</td>
<td>0.2147762811</td>
<td>0.4332654045</td>
<td>0.6435283812</td>
<td>0.1688999957</td>
<td>0.8600303120</td>
<td>0.2973400631</td>
<td>0.8496252783</td>
<td></td>
</tr>
<tr>
<td>C1 :</td>
<td>0.0813955179</td>
<td>0.8023247825</td>
<td>0.3307205825</td>
<td>0.5451867606</td>
<td>0.7257072511</td>
<td>0.7663424893</td>
<td>0.4362908243</td>
<td></td>
</tr>
<tr>
<td>C1 :</td>
<td>0.1712885453</td>
<td>0.5539884357</td>
<td>0.5868189186</td>
<td>0.4696581556</td>
<td>0.8423154184</td>
<td>0.4922262634</td>
<td>0.4976065696</td>
<td></td>
</tr>
<tr>
<td>C1 :</td>
<td>0.3852667839</td>
<td>0.9167196294</td>
<td>0.4962201460</td>
<td>0.7109761560</td>
<td>0.1278108937</td>
<td>0.7237387004</td>
<td>0.5001795176</td>
<td></td>
</tr>
<tr>
<td>R1 :</td>
<td>0.3195273770</td>
<td>0.5060377810</td>
<td>0.8240135565</td>
<td>0.7531269050</td>
<td>0.9444367961</td>
<td>0.3113920490</td>
<td>0.1034103616</td>
<td></td>
</tr>
<tr>
<td>R1 :</td>
<td>0.0537275883</td>
<td>0.6352848987</td>
<td>0.3897214381</td>
<td>0.4801027374</td>
<td>0.7925482904</td>
<td>0.7417172694</td>
<td>0.4449599156</td>
<td></td>
</tr>
<tr>
<td>R1 :</td>
<td>0.3509762538</td>
<td>0.3106850292</td>
<td>0.5215505300</td>
<td>0.1836177844</td>
<td>0.7534512007</td>
<td>0.4649604229</td>
<td>0.6694909595</td>
<td></td>
</tr>
<tr>
<td>R1 :</td>
<td>0.0678263340</td>
<td>0.7860505642</td>
<td>0.0582704664</td>
<td>0.5223024263</td>
<td>0.4989576617</td>
<td>0.8287203871</td>
<td>0.5673568515</td>
<td></td>
</tr>
<tr>
<td>R1 :</td>
<td>0.0945992008</td>
<td>0.6539785196</td>
<td>0.4133698654</td>
<td>0.8203400673</td>
<td>0.8351726302</td>
<td>0.6231620450</td>
<td>0.4391948061</td>
<td></td>
</tr>
<tr>
<td>R1 :</td>
<td>0.809675147</td>
<td>0.1158884388</td>
<td>0.8616459319</td>
<td>0.5596783900</td>
<td>0.7478817505</td>
<td>0.1280996518</td>
<td>0.3169705897</td>
<td></td>
</tr>
<tr>
<td>R1 :</td>
<td>0.1368724822</td>
<td>0.5262354835</td>
<td>0.5275029891</td>
<td>0.3171775022</td>
<td>0.8187603211</td>
<td>0.5472914996</td>
<td>0.6107060699</td>
<td></td>
</tr>
<tr>
<td>R1 :</td>
<td>0.2752375068</td>
<td>0.6907023872</td>
<td>0.6482149844</td>
<td>0.8395501709</td>
<td>0.6216429217</td>
<td>0.7739117301</td>
<td>0.3899606259</td>
<td></td>
</tr>
<tr>
<td>NF</td>
<td>0.206304048</td>
<td>0.5919910866</td>
<td>0.6278054955</td>
<td>0.8208408476</td>
<td>0.5394177980</td>
<td>0.3666234206</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

and $c_i$ is 1.5 and 1.7 respectively, inertial factor $w$ is 1. PSO optimization SVM parameter curve is shown as Fig. 5, x-axis represents the evolution number, and y-axis represents the fitness value. The best fitness curve outset to reach stability as can be seen from Figure5. The optimal penalty parameter $C$ is 66.998, and the kernel function parameter $\gamma$ is 1.8028.

Use PSO optimized SVM to diagnosis analogy circuit fault, the final diagnosis results are as shown in Figure 6.

In Figure 6, “+” represent test samples. It can be seen that there are four samples are wrong diagnosis in 260 samples, and diagnosis rate is 98.5%. Where, two samples of fault 3 categories are error diagnosis for fault 11 categories; two samples of fault 13 categories are error diagnosis for fault 3 categories.

TABLE III is comparison of common method and the method in this paper.

TABLE III. FAULT MODES OF QUAD OP AMP PAIRS OF SECONDARY HIGH-PASS FILTER

<table>
<thead>
<tr>
<th>Diagnosis rate</th>
<th>PCA-PSO-SVM</th>
<th>SVM</th>
<th>Reference[18]</th>
</tr>
</thead>
<tbody>
<tr>
<td>98.5%</td>
<td>98.5%</td>
<td>93%</td>
<td>95%</td>
</tr>
</tbody>
</table>

As shown in the TABLE III, although traditional SVM method is simple, but fault diagnosis rate is lower, only is 93%. Reference [18] use neural networks to diagnosis fault, diagnosis rate is 95%. This shows that the proposed method for analog circuit fault diagnosis has a great advantage.

V. CONCLUSION

Results of this study show that analogy circuit fault diagnosis system use PCA to reduce dimension of fault feature and PSO to optimize parameters of SVM can implement analogy circuit fault diagnosis effectively. A quad op amp pair of secondary high-pass filter diagnosis rate is 98.5% through this method. Through comparison of this method and other methods verify the advantage of
method in this paper. It is an effective method of analogy circuit fault diagnosis.

REFERENCES


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