A New Fault Diagnosis Approach for Switched Current Circuit based on preferred wavelet packet and Support Vector Machine

Zhang Zhen\textsuperscript{1}, Duan Zhenmin\textsuperscript{1}, Long Ying\textsuperscript{2}

1. School of Electronics and Information, Northwestern Polytechnical University, Xi'an 710072, China
2. Department of Electronic and Electrical Engineering, Changshu University, Changsha 410022, China

Abstract: In order to improve the effectiveness of collecting faults in the switched current circuit and accurately classify the patterns of faults, this thesis puts forward a new fault diagnosis approach for switch current circuit based on preferred wavelet packet and particle swarm support vector machine. Firstly, the original signal can be transformed by the wavelet packet. Then, the normalized energy of each frequency band can be calculated out as the only feature parameter. Distance criterion is introduced as a way to judge the measures of different wavelet-basis packet functions. Finally, the optimal fault features are input into support vector machine which is optimized by particle swarm. It can be verified through simulation experiment using the sixth order Chebyshev Low-Pass Filter, in which the accuracy rate of fault diagnosis reaches 99%. As a result, this approach is superior in fault-diagnosis of switched current circuit.

Keywords: switched current circuit; fault diagnosis; wavelet packet; particle swarm support vector machine

1. Introduction

In all the analog sample signal processing technologies, switch-capacitor technology is the mainstream technology in the analog circuit to achieve digital-analog hybrid. However, with the development of CMOS technology into the era of deep submicron and nanometer, the voltage becomes lower and lower. As a result, operational amplifier with high speed and high gain is difficult to achieve and the cost to achieve linear capacitor increases \cite{1}. Switched current (SI) technology is a kind of analog sampled data signal processing technology, which appeared in the late 1980s. Different from the voltage mode of switch-capacitor technology, switch current circuit is a technology based on current mode. It deals the continuous time signals with discrete time sampled data, which develops rapidly in recent decades \cite{2} and is superior for low source voltage, high speed, low power consumption, small chip area and so on. Meanwhile, SI technology can be completely compatible with standard CMOS technology and achieve large-scale integration without linear capacitor and high-performance operation.

As the key to guarantee the operation of the complex electronic system, fault-diagnosis technology to circuit is always the research hotspot in modern circuit theory. Although great progress has been made in analog circuit test and fault-diagnosis in recent years \cite{3-13}, studies on these aspects of switched current circuit lag behind the design and manufacture of switched current circuit as a kind of digital analogue technique, which hinders the development of the SI technology. Besides, those non-ideal effects, charge injection effects and device adapter effects in SI circuit increase the difficulty of testing and collecting fault features of SI circuit. There are many aspects in fault-diagnosis of SI circuit worth studying.

In recent years, many efficient and pragmatic diagnosis approaches \cite{14-21} appear in the fault-diagnosis area of switched current circuit. In all the fault-diagnosis approaches, test and diagnosis technology of hard fault are mature to achieve correct diagnosis. But there are many problems to be solved in the area of soft fault diagnosis because feature extraction and classification technologies have great impacts on the performance of diagnosis system. Reference [14] refers the test and diagnosis approaches of analog circuit, studies the test of basic SI storage unit and makes fault diagnosis for basic storage unit of switched current circuit. Owing to the test of current parameters, the fault information for test and diagnosis is uncomplete and fault location is inaccurate. Reference [15-16] put forward a pseudo random test approach for switched current circuit. But they didn’t talk about the selection of labeled sample and didn’t solve the problem of high misjudgment rate. Reference [17] put forward a pseudo-random implicit function test based on fault identification, which can overcome the shortcomings of reference [15-16]. Large scales of labeled samples were used for the analysis of faulty circuit. Detailed discussions about tolerance range from performance space to feature space were made. Boundary division on catastrophic faults and parametric faults in signal feature space was made. As a result, the misjudgment rate was lowered. Reference [18] diagnosed the SI circuit through wavelet neural network. But the diagnostic rate is only about 80% when soft faults happen to transistor with low sensitivity. The reference [19] first introduced the concept of pretreatment of fault key feature into the test and diagnosis of SI circuit. Information entropy pretreatment was made to collected fault response signals and the fuzzy set of information entropy was calculated out to construct a fault dictionary. Then those faults were classified and diagnostic rate can reach about 95%. Reference [20], there is a new feature parameter, which is kurtosis. The author of this thesis put forward a pretreatment of information entropy and kurtosis test and diagnosis approach to SI circuit based on particle swarm support vector machine. Compared with the reference [19], the diagnostic rate of soft fault was raised to about 99%. Reference [21] adopted wavelet transform and calculate the kurtosis and entropy of low-frequency and high-frequency signals. Like the reference [19], it only constructed a fault dictionary and didn’t realize automatic classification and identification of faults.

Aimed at these problems, this thesis put forward a new fault-diagnosis approach to switched current Circuit based on preferred wavelet packet and support vector machine. Firstly, take the pseudorandom sequence produced from linear feedback shift register (LFSR) as test vector to collect original response signals. Then, use the preferred wavelet packet which makes judgments based on distance criterion to classify the patterns of faults, this thesis puts forward a new fault diagnosis approach for switch current circuit based on preferred wavelet packet and particle swarm support vector machine. Firstly, the original signal can be transformed by the wavelet packet. Then, the normalized energy of each frequency band can be calculated out as the only feature parameter. Distance criterion is introduced as a way to judge the measures of different wavelet-basis packet functions. Finally, the optimal fault features are input into support vector machine which is optimized by particle swarm. It can be verified through simulation experiment using the sixth order Chebyshev Low-Pass Filter, in which the accuracy rate of fault diagnosis reaches 99%. As a result, this approach is superior in fault-diagnosis of switched current circuit.

2. Support vector machine based on particle swarm optimization

Particle Swarm Optimization (PSO), which was put forward by Kennedy \cite{22-23}, which is an intelligence algorithm simulating birds who find food in a mutual cooperative way. The solution to the objective optimization problem M can be judged based on fitness function F. The product of the initialization of Particle Swarm Optimization is a group of random particles. The approximate optimum solution can be found through iteration. The movements of particle are influenced a lot by the best position where it can search by pbest and the best position where all the particles in the group can search by gbest in every iteration.

The formulas for the update of particles' speed and position are as follows:

\[
s_m(t+1) = s_m(t) + v_m(t+1)
\]

\[
(1)
\]

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\[ v_m(t+1) = \omega v_m(t) + c_1 r_1(t)[p_m(t) - s_m(t)] + c_2 r_2(t)[p_{gm}(t) - s_m(t)] \] (2)

In the two formulas, \( \omega \) means inertia weight, \( v_m(t) \) means the original speed of particle, \( v_m(t+1) \) means the new speed of particle, \( p_m \) is the optimal position of particle \( m \) and \( p_{gm} \) means the optimal position of the whole group. \( s_m(t) \) is the original position of particle \( m \), \( s_m(t+1) \) is the new position of particle \( m \). \( c_1 \) and \( c_2 \) are learning factors, while \( r_1(t) \) and \( r_2(t) \) are random numbers from 0 to 1.

Support Vector Machine (Support Vector Machine, SVM) is a machine learning method based on statistical theory [29], which has gradually become the first choice to deal with the classification of modes. Given a labeled classified sample set \( \{X_i, y_i\}, i = 1, 2, \ldots, n \). In this sample set, \( x_i \in R^d \), \( X \) is a feature vector, \( n \) is the number of sample, \( y \in \{+1, -1\} \) is the class label to divide them with maximum margin by looking for an optimal hyperplane. At the same time of enlarging the interval, this thesis introduce penalty to optimize itself. Besides, SVM often introduces kernel function \( K(x, y) \) to substitute the inner product operation in optimal classification function. Choose proper kernel function can effectively improve the classification ability of SVM.

As the classifier of SVM is parameterized, the selection of parameter has great impact on its generalization performance. PSO has a strong global searching ability and can optimize and adjust the parameters in the process of SVM modeling. In this way, higher precision of SVM classifier can be gained. Detailed steps on SVM based on PSO are as follows:

Step 1: Extract feature vector from original sample data to construct a sample training set \( X \).

Step 2: Every support vector in \( X \) can gain a group of parameters from SVM classifier. Each parameter constructs a particle and the entire particles construct group \( X' \).

Step 3: Initialize the group \( X' \). Set the initial parameter of the particle group as \( C_1 \) and \( C_2 \). Identify the optimal position of each original particle \( p_m \) and the optimal position of the entire group \( p_{gm} \).

Step 4: Select \( F(x) \) as the fitness function of particle group and calculate the fitness function value of each particle in the group.

Step 5: Adjust the optimal position of particle \( p_m \) and the entire group \( p_{gm} \) according to the fitness function value.

Step 6: Update the position and speed of particle according to formula (1) and (2) and get new SVM classifier parameters.

Step 7: When the fitness function value meets the requirement or when iterative times reach the limit, the iteration will be stopped and the results will be output. Otherwise, continue to do the steps from step 4.

3. Extraction of optimal fault features

3.1 Approach to extract wavelet packet energy feature

Wavelet packet analysis is a method extended from wavelet analysis to do more precise multiresolution analysis [23]. It can make stratified division on frequency band. On each level, more precise dissociation to low frequency and high frequency parts are made to raise the time frequency resolution. It is feasible to extract the fault signal features efficiently.

The two-scale equations of transformation of wavelet packet are as follows:

\[
\begin{align*}
    w_{0}(t) & = \sqrt{2} \sum_{k \in Z} h_{0k} w_{0}(2t-k) \\
    w_{1}(t) & = \sqrt{2} \sum_{k \in Z} h_{1k} w_{0}(2t-k)
\end{align*}
\] (3)

In the equation, \( h_{0k} \) means using multiresolution analysis to analyze low and middle pass filtering coefficients and \( h_{1k} \) means using multiresolution analysis to analyze high pass filtering coefficient. When \( n = 0 \), \( w_{0}(t) = \phi(t) \), \( w_{1}(t) = \psi(t) \) respectively refer to scaling function and wavelet function. The recursion formulas of the wavelet packet coefficient are:

\[
\begin{align*}
    d_{j+1}^{2n} & = \sum_{k} h_{0k-2j} d_{j}^{n}(k) \\
    d_{j+1}^{2n+1} & = \sum_{k} h_{1k-2j} d_{j}^{n}(k)
\end{align*}
\] (4)

In the formula, \( d_{j}^{n}(k) \) means the NO. \( k \) coefficient of node \((j, n)\) after the dissociation of wavelet packet. The node \((j, n)\) represents the NO. \( n \) frequency band on the NO. \( j \) level.

The theoretical foundation of frequency band analysis based on wavelet packet is Parseval equation of energy integral. The signal \( X \)'s wavelet packet transform coefficient \( d_{j}^{n}(k) \)'s square has energy dimensions. When the tested circuit malfunctions, the signal energy in each frequency band will be greatly influenced. As a result, normalized energy of frequency bands can be used as feature vector to reflect the states of circuit. Steps about the extraction of wavelet packet energy feature are as follows:
(1) Do j level wavelet packet decomposition to the original signals from tested circuits. On $j$ level, the wavelet packet coefficient $d^j_{jk}(k)$ with $2^j$ frequency bands from low frequency to high frequency can be gained.

(2) The energy of each frequency band can be gained and the energy value of the NO. $i$ is:

$$E_i = \sum_{k=1}^{N} \left\| d^j_{jk}(k) \right\|^2, \quad i = 1, 2, ..., 2^j$$

$N$ means the length of the NO. $i$ frequency band. Energy is taken as an element to construct feature vectors to reflect faults $F = \left[ E_1, E_2, \cdots, E_{2^j} \right]$. The total energy of the signals is $E = \sum_{j=1}^{2^j} E_i$. And it be normalized according to $E' = \frac{E_i}{E}$.

(3) Input the feature vector extracted from normalized wavelet packet as classifier.

$$F' = \left[ E'_1, E'_2, \cdots, E'_{2^j} \right]$$

### 3.2 Optimization of wavelet basis function

Different wavelet basis function has different reflection performance to the local information of faults. As a result, the optimized wavelet basis should be picked to do the wavelet packet decomposition. In this way, the optimal fault feature can be extracted. In this thesis, distance criterion is taken as the measure to identify the optimal wavelet basis and achieve the optimization of fault feature extraction.

Suppose that there are $c$ kinds of fault modes $f_1, f_2, \ldots, f_c$ in the circuit. Wavelet packet decomposition is done to the original signals in this circuit. The normalized energy of each frequency band is extracted as fault feature vector. A feature vector set $\{x_i^j, i = 1, 2, \ldots, c, j = 1, 2, \ldots, n_i\}$ can be gained. Among them, $n_i$ is the number of the feature vectors in the fault class $f_i$. The average distance of feature vectors in $f_i$, $f_j$ is:

$$d_i = \frac{1}{2n_i} \sum_{k=1}^{n_i} \frac{1}{n_j} \left\| x_i^j - x_i^k \right\|$$

Based on the above, the average distance intra-class is:

$$d_f = \frac{1}{c} \sum_{i=1}^{c} \frac{1}{n_i} \sum_{k=1}^{n_i} (x_i^j - u_i)^2$$

$u_i$ is the mean value of the feature vector $f_i$, it is :

$$u_i = \frac{1}{n_i} \sum_{j=1}^{n_i} x_i^j$$

Calculate the mean value of all the feature vectors in fault category, it is:

$$u = \frac{1}{c} \sum_{i=1}^{c} u_i$$

The definition of the average distance among the fault category is:

$$d_c = \frac{1}{c} \sum_{i=1}^{c} \left\| u_i - u \right\|$$

Inter-category distance to intra-category distance is the definition of distance ratio criterion, which is represented by $J$:


\[ J = \frac{\partial J}{\partial f} = \frac{1}{c} \sum_{i=1}^{c} \left( \sum_{j=1}^{n} \left( x_{ij} - u_{ij} \right) \right)^2 \]  

(12)

Use the value of \( J \) after the above calculation to distinguish the validity of different fault categories. When the value of \( J \) is maximal, the corresponding wavelet packet basis is the optimal wavelet basis function.

4. Fault diagnosis based on preferred wavelet packet and particle swarm support vector machine

Firstly, this thesis uses preferred wavelet packet decomposition to extract optimal feature vector. Then, the optimal feature vector is trained in Support Vector Machine which is optimized by particle swarm. Finally, judge the fault category of the new samples by the trained Support Vector Machine model. The flow chart of fault diagnosis is as the Fig. 1. Besides, the detailed steps are as follows:

Step 1: Generate pseudorandom test vector. Adopt pseudorandom sequence as vector to enlarge the differences among the responses of fault states.

Step 2: Define fault mode. In order to get the first order change of the circuit system feature to the change of the component parameter, the thesis analyzes the sensitivity of circuit and locates the fault component.

Step 3: Collect the original response data of circuit. Simulate the fault states of the circuit using the ASIZ which is the dedicated software for switched current circuit. In this way, finish the collection of the original response data.

Step 4: Extract the fault feature samples in various states. Optimize wavelet packet based on distance criterion. Calculate the fault feature set constructed by normalized energy.

Step 5: Classify the faults of Support Vector Machine which is optimized by particle swarm. Train the training sample set in Support Vector Machine which is optimized by particle swarm to construct the optimal classifier and achieve fault classification.

5. Simulation experiment

5.1 Diagnostic circuit and fault setting

The fault-diagnosis of switched current circuit is aimed at catastrophic (hard) fault and parametric (soft) fault. Compared with soft fault, hard fault is easy to be diagnosed. In order to test the validity of the method, the author will take the soft fault diagnosis experiment using the sixth order Chebyshev Low-Pass Filter to test it. The circuit is as shown in the figure 2.

In this figure, the normalized trans-conductance values of the transistor are as follows:

M_a = 1, M_b = 0.4255, M_c = 1.9845, M_d = 0.3455, M_e = 0.9845, M_f = 0.5827, M_g = 1.9134, M_h = 0.085, M_i = 0.8577, M_j = 2.1021, M_k = 0.2787. The cut-off frequency of the circuit is 5MHz. The cut-off frequency to the clock frequency is 1 to 4. The clock frequency is 20MHz and the ripple is 0.5dB.

Set tolerance range of trans-conductance \( g_m \) as 5%. After the analysis of sensitivity, the author can know that the number of malfunctioned transistors is 5, including M_g, M_f, M_e, M_d and M_j. When one of the trans-conductance \( g_m \) values of the transistor deviates 50% of the normal value and the other four transistors change within the tolerance range, the circuit has soft faults. At this time, the time-domain response is fault category. Just as the table 1, there are 10 soft fault modes. In this table, ↑ and ↓ respectively represent 50% above or below the normal value.
5.2 Preferred wavelet packet

Simulate the 10 fault modes of the switched current circuit. Tested vector signals adopt a 255 bit pseudorandom sequence generated by an 8th order LFSR. First, do time-domain analysis to all the fault states of the circuit and a fault response signal with 158 sampling sites can be gained. Collect 60 time-domain response sample in each fault mode. Divide these 600 data into two parts. Choose 300 data as the learning sample of SVM and another 300 data as the verification sample. Test the trained SVM classifier.

Choose four wavelet basis functions Haar, Db2, Db3, Db4 to do the three layers decomposition respectively to 300 sample data. The normalized energy of each frequency band is gained to construct the feature vector set. In table 2, the class distance measurements of fault feature sample set corresponding to each wavelet are listed out. From this table, we can see that the class distance measurement decomposed by Db4 wavelet is superior to the results of the other three. Db4 wavelet is the optimal wavelet basis.

<table>
<thead>
<tr>
<th>wavelet basis</th>
<th>Haar</th>
<th>Db2</th>
<th>Db3</th>
<th>Db4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance measure value $J$</td>
<td>4.761</td>
<td>5.147</td>
<td>6.254</td>
<td>8.325</td>
</tr>
</tbody>
</table>

5.3 The Diagnosis and Analysis

In this thesis, radial basis function (RBF) is selected as the kernel function. $K(x_i, x_j) = \exp(-r \|x_i - x_j\|^2)$. Suppose $r = 1.0$. The original value of penalty factor $C = 2.0$, the scale of particle swarm $n = 300$ and the maximum iteration number is 300. The training sample is iterated by PSO and the change curve of fitness is as the figure 3. We can see from the figure that the average fitness of PSO reaches 99%. After the global search of the algorithm, penalty factor $C$ takes 0.7536 and parameter $\sigma$ of the kernel function takes 89.
After the determination of the penalty factor $C$ and parameter $\sigma$ of kernel function, 300 test sample data from 10 fault categories are input into the support vector machine to be trained. In this way, the optimal classification model is generated. Input the other 300 verification sample data into support vector machine to classify them and the result is as figure 4. From the result, we can see that all the faults are well classified except when $Md\downarrow$ what belong to $F_2$ category are wrongly classified into $F_4$ category. The accuracy rate of the diagnosis reaches 99%.

The actual classification and prediction of the test set

![Figure 4 Results of PSO-SVM prediction-based classification](image)

In order to verify the superiority of this approach over the approaches in other papers, the author compares the fault-diagnosis approaches and the results are as table 3.

<table>
<thead>
<tr>
<th>Using method</th>
<th>fault-pattern</th>
<th>Number of characteristic parameters</th>
<th>Diagnostic rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Method of reference[18]</td>
<td>4</td>
<td>1</td>
<td>80%</td>
</tr>
<tr>
<td>Method of reference[19]</td>
<td>11</td>
<td>2</td>
<td>95%</td>
</tr>
<tr>
<td>Method of reference[20]</td>
<td>11</td>
<td>2</td>
<td>99%</td>
</tr>
<tr>
<td>The method of this paper</td>
<td>11</td>
<td>1</td>
<td>99%</td>
</tr>
</tbody>
</table>

Reference [18] uses wavelet neural network to do the fault test for the sixth order Chebyshev Low-Pass Filter. This approach adopted sensitivity as the feature parameter. As a result, transistors with low sensitivity are shielded. The diagnosis rate of the four soft fault modes is only 80%. But in this thesis, the normalized energy of each frequency band is the only feature parameter, which has a good classification effect to the soft faults of transistor with low sensitivity.

In the reference [19], the number of the soft fault categories is 11. No more optimization to fault feature leads to the unsatisfied diagnosis effect. The diagnosis rate of the soft fault is only about 95% which can’t distinguish the four soft fault categories $Mg\downarrow$, $Mj\uparrow$, $Mg\uparrow$ and $Mj\downarrow$. The soft fault categories in this thesis are the same with reference [19]. But the diagnosis rate of the soft fault reaches 99%, which successfully distinguishes the four fault categories that cannot be distinguished in reference [19]. In the fault-diagnosis approach of reference [20], information entropy and kurtosis are two classifiers. But in this thesis, only one feature parameter is extracted and the same classification effect is achieved.

In table 4, results extracted by 4 wavelet basis functions and diagnosed by PSO-SVM are shown. From this table, we can see that the accuracy rank from high to low of the four wavelet basis functions is: Db4, Db3, Db2 and Haar, which is the same as the rank of the J value. Distance criterion can be seen as a measure to choose the optimal wavelet basis.

<table>
<thead>
<tr>
<th>Wavelet basis</th>
<th>Diagnostic accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haar</td>
<td>95.3%</td>
</tr>
<tr>
<td>Db2</td>
<td>96.7%</td>
</tr>
<tr>
<td>Db3</td>
<td>97.5%</td>
</tr>
<tr>
<td>Db4</td>
<td>99.3%</td>
</tr>
</tbody>
</table>

6. Conclusion

The diagnosis results of this thesis show that fault-diagnosis approach to Switched Current Circuit based on preferred wavelet packet and Support Vector Machine can diagnose effectively on the switched current circuit. And the correct rate of the fault diagnosis is relatively high. Besides, the author compares the approach of this thesis with approaches of other references. Wavelet packet transform can do more precise decomposition both to low frequency and high frequency parts. Normalized energy of each frequency band is gained as the only feature parameter. Wavelet basis function is preferred to get the optimal fault feature based on distance criterion. Finally, use the Support Vector Machine which is optimized by particle swarm as the classifier to identify fault modes. This approach verifies its efficiency through simulation experiment using the sixth order Chebyshev Low-Pass Filter. In view of its good performance, the author plans to use it to do studies on the online fault diagnosis of the switched current circuit.
Reference