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Fault Classification Research of Analog Electronic Circuits Based on Support Vector Machine

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With the rapid development of microelectronics and semiconductor technology, integrated analog electronic systems become more sophisticated and complex functions. It has become increasingly high reliability requirements, but the corresponding testability positive change it was getting worse. How to use signal processing and artificial intelligence techniques and diagnose faults in the system analog electronic components or subsystems, is currently a hot simulation diagnostics. Fault feature extraction and selection is the key technology in the field of analog electronic system testing, for subsequent fault classification is very important. Current research focuses on the fault feature extraction, feature selection. To solve this problem, a new feature based on fault scalar wavelet coefficients selection method. In this paper, some analog electronic system fault characteristics and difficult to obtain a small number of samples and other issues, study the characteristics of a fault simulation method based on a sample cloud model generation method, and the use of neural network expansion sample sets the newly created training. The results show that the new sample training practiced neural network has better noise robustness.

1. Introduction

Simulation of analog electronic circuits (or mixed) electronic system testing and diagnostic problems have attracted more and more attention of researchers, it has become a hot issue in the field of fault diagnosis (Sarathi, 2013; Duan, 2015). Engaged in related research not only has important theoretical significance, but also has a very important practical significance and engineering application (Tong and Zhou, 2014). Testing and fault diagnosis technology development analog electronic circuit system nearly half a century of research time, it has become the circuit network analysis, the third largest branch network after the integrated electrical circuit network theory. Circuit fault diagnosis technology development so far, test theories and test standard digital circuits has matured, however, for fault diagnosis theory and nonlinear tolerance analog circuits have not yet formed a mature theoretical system, associated analog test standard IEEE1149.4 has not been widely used. Therefore, the study engaged in related technology has important theoretical significance (Vasan and Long, 2014).
Support vector machine is CorinnaCortes and Vapnik equal first proposed in 1995, it exhibits many unique advantages in solving small sample, nonlinear and high dimensional pattern recognition, and can be generalized to other machine learning problems such as function fitting (Wang, 2015). SVM basic idea is derived from the optimal classification surface linearly separable development mode, which solve the optimal hyperplane (Lang and Ding, 2013). SVM effectively overcome the local optimal learning models and artificial neural network technology is difficult to determine the presence of other shortcomings, effectively solve the high dimensionality of samples, small samples, a series of non-linear learning problems, at present, support vector machines have been widely used at fault classification, handwriting recognition (Long, 2012; Mata, 2015). Face recognition and other fields, and have achieved relatively good results (Huo, 2014; Sivasubramaniam, 2015).
Since the beginning of research on analog circuit fault diagnosis, it has raised many basic theory and method of fault diagnosis. Lack of standard analog circuit fault model, there is a component parameter tolerances and other factors make extensive nonlinear analog circuit fault diagnosis technical difficulty is large, therefore, fault diagnosis of analog circuits has been challenging. The small sample based on statistical learning theory under

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the support vector machine has many advantages in solving the above problems, an analog circuit fault diagnosis provides a new method. The main contents of this paper the method according to SBT intelligent fault dictionary method, which mainly relates to the analog electronic system testing fault classification technique; in addition, and other fault feature extraction and selection of key technologies were also studied.

2. The fault classifier design based on SVM

2.1 The basic principle of support vector machines

Basic support vector machine classifier (SVC) binary classification can be achieved, namely a binary support vector machine classifier (BSVC), can be achieved with positive data negative label classification. BSVC can be divided into two types: linear and nonlinear BSVC, the former can classify linearly separable data; the latter can be achieved on the nonlinear separable data classification, the type BSVC in the actual testing and troubleshooting the larger the value of the field. Suppose to be classified in the two kinds of collections:

$$\{(x_i, y_i)\} \quad (i = 1, 2, \ldots, n, \quad and \quad x_i \in R^d, y_i \in \{+1, -1\}) \tag{1}$$

Where, O represents the output data class labeled "-1", and O2 represents the output data class labeled "+1" tag. Two types of data in the original d-dimensional feature space can be divided into linear (see Figure 1 below).

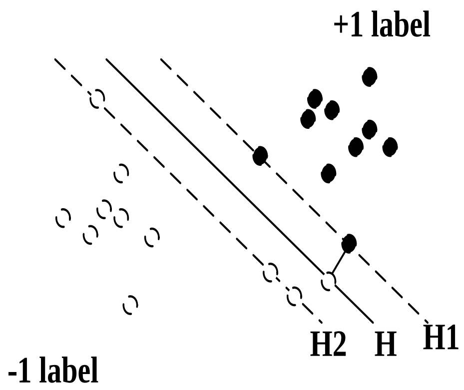

Figure 1: Classification of schematic BSVC

For positive and negative sample label label samples sequentially corresponding decision becomes:

$$\begin{cases} W \bullet x_i + b \ge +1; y_i = +1 \\ W \bullet x_i + b \le -1; y_i = -1 \end{cases} \tag{2}$$

The following two classifications calculate surface H1, the distance between the Margin H2, assuming that px H1 on this point from the nearest point on record over the surface H is qx, then:

$$W \bullet x_q + b = 0 \tag{3}$$

$$W \bullet x_p + b = +1$$

Then

$$W \bullet (x_p - x_q) = +1 \tag{4}$$

Both sides take away from the norm, then the distance between the H1 to H:

$$L(W, b, \Lambda) = \frac{\| W \|^2}{2} - \sum_{i=1}^{q} \lambda_i [y_i \bullet (W \bullet x_i + b) - 1] \tag{5}$$

The antithesis is a typical quadratic function convex optimization problem, with the proviso that

$$\sum_{i=1}^{q} \lambda_i y_i = 0, \lambda_i \geq 0 \tag{6}$$

2.2 Decision symbol and nuclear spatial distance analysis SVC

In the electronic circuit diagnosis, some researchers one-against-rest SVC decision method as follows: Output calculated in turn a function of the decision, if the output of a decision function is valid, then the sample is then determined home, regardless of the subsequent decision output function. This decision method has certain computational advantages: only part of the calculation of decision function, thus reducing decision time and improve decision-making efficiency; sequentially reads decision function, indicating that the decision function corresponding to the first reading of the fault class decision-making priority. But this method also has some disadvantages: If multiple output effective decision-making function exists, resulting in the possibility of misdiagnosis great; if no decision-making function output is active, indicates that the sample must not fall into the classification zone, resulting be refused recognition. This paper presents a method of analysis based on the spatial distance, this method can better solve the problem sample rejection problem can not fall into the classification zone caused.

When the number of non-border support vector (UBSV) occupies a large proportion of the calculated directly UBSV effects and use all the support vector obtained effect close, therefore, can be used to calculate UBSV, thus appropriate to reduce the amount of computation; but when the number of UBSV occupy a smaller proportion, still we need to use all the support vector calculation. Consider Nene high-dimensional vector space law kernel mode is the vector product of evolution:

$$\| W_i \| = \sqrt{(W_i \bullet W)_i} \tag{7}$$

Instead of using the kernel function vector inner product, it produces:

$$\| W_i \| = \sqrt{\sum_{j=1}^{n'_{yy}} y_{ij} \lambda_{ij} \sum_{j=1}^{n'_{yy}} y_{ij} \lambda_{ij} (x_{ij} \bullet x_{ij})} \tag{8}$$

The new method of analog electronic circuit fault classification process shown in Figure 2:

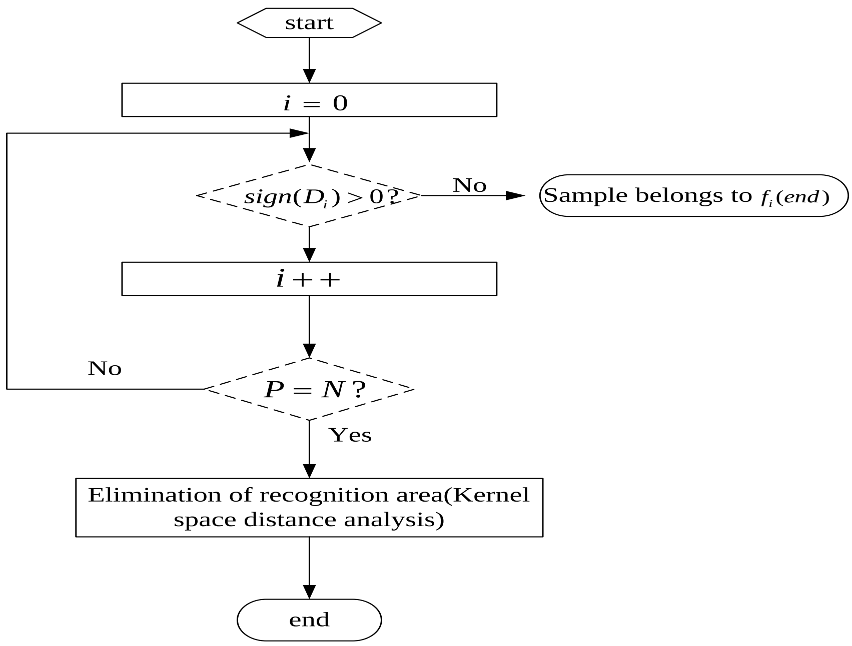

Figure 2: Fault classification process based on the improved SVC

3. Experiments and results

3.1 Low-pass filter circuit and SVM basic diagnostics

Figure 3 is a fourth-order Butterworth low-pass filter circuit, now the circuit analog circuit fault diagnosis, the diagnosis, the output terminal out as the sole test point "In addition, this article only for analog circuit single soft fault single resistor or the occurrence of a single capacitor carried SVM diagnosis, SVM analog circuit diagnosis is not considered more soft faults and hard faults conditions.

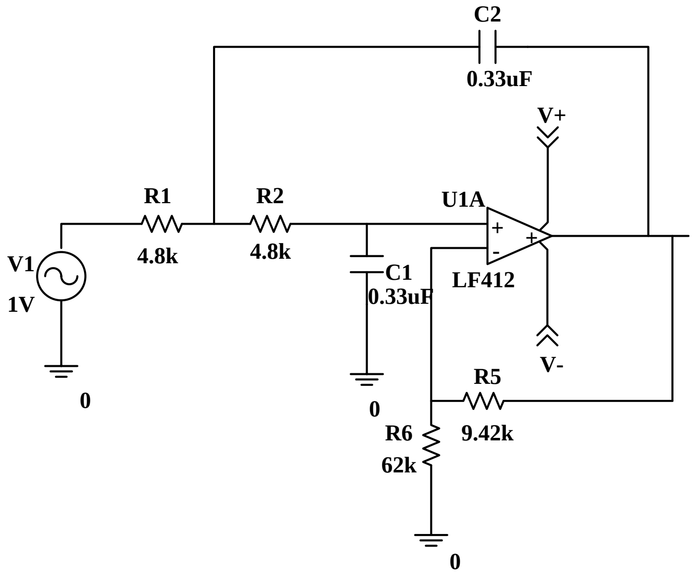

Figure 3: Butterworth low-pass filter circuit

Fault feature extraction analog circuit fault diagnosis system is an important part, since different extraction methods from the failure characteristics of the signal in the frequency domain, so the realization of simulation and process analysis of analog circuit fault diagnosis are slightly different, here are sampling from the effective implementation of the sampling points and the wavelet transform fault feature extraction, SVM fault diagnosis were achieved on the final results of fault diagnosis further comparative analysis.

3.2 Test results and analysis

In this experiment, a number of experimental nuclear parameters, select radial basis function as the kernel function, wherein the radial basis kernel parameter σ^2 = 16 (penalty coefficient C = 100). Listed here, the overall performance of each classifier comparison, Table 1 below:

Table 1: Test results of several SVC for high pass filter

Index / SVC	F_r	F_1	F_f	F_m	F_j	T_{te}	T_{tr}	SV
l-v-r(extremum)	1	0	0	0	0	19.698	1.2356	292
l-v-r(Symbol)	0.98846	0	0	0.0125	0.011538	10.691	1.2356	292
l-v-r(Symbol)+KP	1	0	0	0	0	10.702	1.2356	292
KP+1-v-r	1	0	0	0	0	3.2815	1.2356	292
l-v-l	1	0	0	0	0	53.371	2.0604	526
DAGSVC	1	0	0	0	0	7.7729	2.0604	526
RBSVCl	0.91731	0.052083	0	0.089475	0	3.9735	0.87461	132
CBSVC	0.99808	0	0	0.0020833	0	3.6948	0.87461	166

Above table can be seen in the corresponding fault tolerance and model of the device settings, in addition to random binary RBSVC1, design algorithms have been 100 percent or close to 100% over the diagnosis, indicating that support vector machine fault diagnosis method is very effective. Aminian, who used in the diagnosis of the same fault circuit (fault models are also the same) neural network fault classification can be obtained 95% of the fault classification results, in order to further improve the diagnosis of neural networks, they modular neural network (small scale neural network combined method) for diagnosis, and the result was 100%. Taken together, these results show that support vector machine can be used in analog electronic circuit fault diagnosis and classification, and neural network performance close to or even better.

Here, the op amp with four high-pass filter will be described as an example. In order to facilitate the comparison of several conventional SVC multiple classifiers effect feature selection, also designed one-against-one SVC as a feature selection classification. Figure 4 shows the three SVC in the selection process of S5 ~ S32 features a total of 28 groups subset Comparative Accuracy of the curve. Among them, the curve "proposed SVC" refers to this chapter of the proposed hybrid one-against-rest SVC.

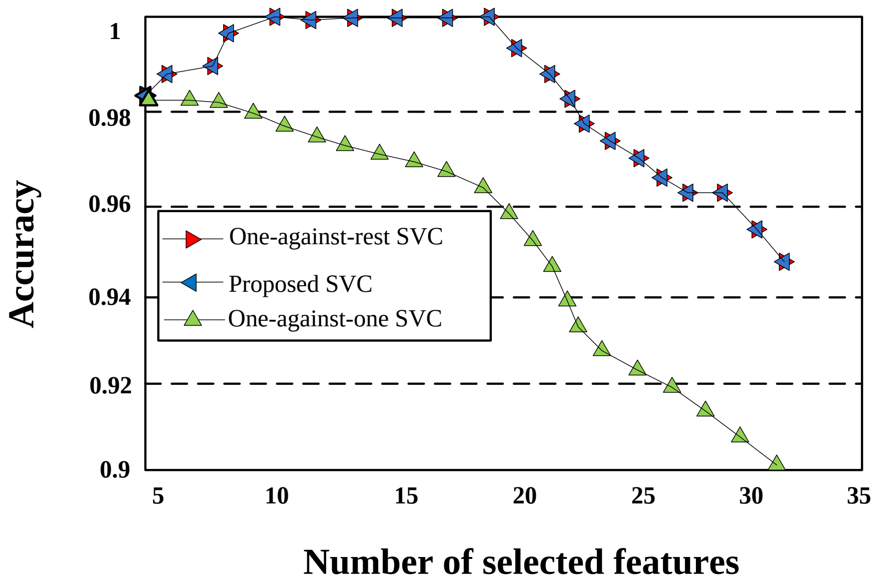

Figure 4: Three kinds of SVC select HPF wavelet feature comparison of the performance curve

The figure shows the performance of the mixed one-against-rest SVC performance and classic one-against-rest SVC almost completely consistent, but the test time is much lower than the former; one-against-one SVC to be slightly in performance testing worse than the other two SVC, and the test of time as well. In addition, from time curve comparison point of view, when increasing the fault feature samples of dimension three SVC test time is also increasing, indicating that the higher dimensional characteristics required to calculate the amount of the higher test, therefore, reduce the number of features not only beneficial to improve the performance of the classifier generalization, but also helps to reduce the amount of calculation and storage space.

4. Conclusion

The corresponding testability positive change It was getting worse. How to use signal processing and artificial intelligence techniques to test and diagnose faults in the system analog electronic components or subsystems, is currently a hot simulation diagnostics. Fault feature extraction and selection is the key technology in the field of analog electronic system testing, for subsequent fault classification is very important. Current research focuses on the fault feature extraction, feature selection. To solve this problem, a new feature based on fault scalar wavelet coefficients selection method. In this paper, some analog electronic system fault characteristics and difficult to obtain a small number of samples and other issues, study the characteristics of a fault simulation method based on a sample cloud model generation method, and the use of neural network expansion sample sets the newly created training. The results show that the new sample training practiced neural network has better noise robustness.

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