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# Analog Circuit Fault Diagnosis with Small Samples Based on Selective SVM Ensemble

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**Abstract.** A method of selective SVM ensemble base on clustering analysis is presented in this paper. Then it is applied in analog circuit fault diagnosis with small samples. The method overcomes disadvantages of single SVM and greatly improves the generation ability for problems with small samples. In the end of paper, simulation experiments on a CTSV filter circuit are carried out. Experimental results indicate that the method obtains higher accuracy than single SVM.

**Keywords:** Support vector machines; selective ensemble learing; clustering analysis; analog circuit fault diagnosis; small samples

## 1. Introduction

Circuit fault diagnosis is still an extremely challenging research field in the world nowadays. Many different methods of fault diagnosis, especially some machine learning algorithms, have been improved and introduced into the field of circuit fault diagnosis in the past few years. Most of these methods are designed to solve problems with large samples. However, circuit fault diagnosis with small samples is the common case in real-world application. As a result, the application of these methods is limited by the quantity of sample data.

Compared with other machine learning algorithms, Support Vector Machines (SVM), a kind of machine-learning algorithm based on the Structural Risk Minimization (SRM) principle, presents high performance in solving small sample problems. But when the number of samples is decreased to some extent, the experimental result shows that the classification accuracy of SVM will decline sharply. Faced with the problem, ensemble learning theory provides a promising way for overcoming the shortcomings of SVM.

Ensemble learning algorithms have captured an increasing interest in the research community because of their capability of improving the classification accuracy of any single classifier [1]. In order to make further improvement of ensemble learning, the concept of selective ensemble is proposed, i.e. by selecting a subset of the originally generated classifiers according to certain strategy, the classification accuracy could be improved with less memory cost and higher classification speed [2]. In this paper, a method of circuit fault diagnosis base on selective SVM ensemble is proposed to solve small samples problems.

The rest of this paper is organized as follows. The principles of SVM and ensemble learning are briefly introduced in Section II. Then, in the same section, the selective SVM ensemble learning algorithm based on clustering analysis is proposed. In Section III, fault diagnosis experiments on a continuous-time state-variable filter circuit are carried out. The experimental results indicate that the proposed method has higher performance in fault diagnosis with small samples. Finally, conclusions are drawn in Section IV.

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## 2. Selective Svm Esemble Algorithm

### 2.1 Principle of support vector machines

In this paper, we merely take the nonlinear two-class classification problem as an example to analyze the principle of SVM briefly. Given a set of training vectors belonging to two classes

$$T = \{(x_1, y_1), \cdots, (x_l, y_l)\},$$
$$x_i \in R^n, y_i \in \{1, -1\}, i = 1, \cdots, l. \tag{1}$$

The training vectors are mapped into a high dimensional feature space to solve the nonlinear problem. Then we seek a linear separating hyperplane, called optimal separating hyperplane, with the maximal margin in this high dimensional feature space.

The problem mentioned above leads to the following optimization problem,

$$\min_{\omega,b,\xi} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{l}\xi_i,$$
$$s.t.\ y_i((\omega \cdot \phi(x_i)) + b) \geq 1 - \xi_i, i = 1, \ldots, l, \tag{2}$$

where $C > 0$ is the penalty parameter of the error term, and ξBi B≥ 0 is the slack variable. The primal problem can be transformed to its dual problem, which is easier to solve. The dual problem is given by,

$$\min_{\alpha} \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} y_i y_j \alpha_i \alpha_j K(x_i, x_j) - \sum_{i=1}^{l}\alpha_i,$$
$$s.t.\ \sum_{i=1}^{l} y_i \alpha_i = 0, \alpha_i \geq 0, i = 1, \cdots, l, \tag{3}$$

where $\alpha$ is the Lagrange multiplier. After solving the dual problem, the decision function is given by,

$$f(x) = \operatorname{sgn}\left[\sum_{i=1}^{l}\alpha_i^* y_i K(x_i, x) + b^*\right]. \tag{4}$$

Here, $K(x_i, x_j)$ is the kernel function. Generally, there are four common kernel functions as follows: linear, polynomial, radial basis function (RBF), sigmoid. And RBF kernel is usually a reasonable first choice among these kernel functions [3]. RBF kernel is defined as

$$K(x, x_i) = \exp\left(-\|x - x_i\|^2 / 2\sigma^2\right). \tag{5}$$

SVM was originally designed for binary classification. In order to solve the multi-class problem, the typical method is to construct a multi-class classifier by combining several binary classifiers. There are three main methods based on binary classifiers: "one-against-all", "one-against-one" and DAGSVM [4].

### 2.2 Ensemble learning theory

Ensemble learning has gradually become the most popular research direction in machine learning since the mid-1990s. An ensemble of classifiers is constituted by a set of predictors that, instead of yielding their individual decisions to classify new examples, combine them together by adopting some strategy. High diversity and relatively high accuracy of member classifiers are two essential conditions for the improvement of ensemble accuracy. Bagging [5] and Boosting [6] are two most representative algorithms of ensemble learning. In Bagging, classifiers are trained independently via a bootstrap method, while in Boosting the selection of training samples depends on the effect of last learning.

Selective ensemble theory is a new ensemble learning paradigm proposed by Zhou and its main idea is many could be better than all [7]. Compared with Bagging and Boosting, selective ensemble can generate classifier ensembles with far smaller sizes but stronger generalization ability. Meanwhile, Zhou proposed a genetic algorithm based approach named GASEN (Genetic Algorithm based Selective ENsemble), which trains a number of individual neural networks and then employs a genetic algorithm to select an optimum subset of individual networks to constitute an ensemble [8]. In order to improve the diversity of individuals in neural networks ensemble, clustering algorithm based selective ensemble (CLUSEN) is proposed by Li and Yang [9], which substitutes clustering algorithm for genetic algorithm. The experimental results on UCI data sets show that CLUSEN is more efficient than GASEN. Inspired by Li's work, clustering algorithm based selective ensemble is applied in SVM in this paper.

### 2.3 Selective SVM ensemble based on clustering algorithm

The selective SVM ensemble learning algorithm in this paper employs bootstrap sampling to generate $T$ different training sets from the original training set for training $T$ SVM classifiers. Then these SVM classifiers are partitioned into $K$ clusters by the use of K-means clustering analysis, which could improve the diversity of sub-classifiers. And the classifier which is nearest to clustering centroid in every part is chosen to compose selected SVM classifiers set. Finally, the ensemble SVM model is obtained by plurality voting. The algorithm is shown in Fig.1.

**Input**: training set $S$, number of bootstrap samples $T$, number of clusters $K$
**Output**: ensemble $N^*$
1. for $i = 1 : T$
    $S_i$ = bootstrap sample from training set $S$
    $N_i$ = SVM model trained by bootstrap sample $S_i$
    $F_i$ = classification accuracy of SVM model $N_i$ on set $S$
  end
2. generate $K$ clusters from $N$ by using clustering analysis
3. for $i = 1 : K$
    for $j = 1 : T$
      $D_i(j)$ = distance from each point to every centroid
      $M_i$ = SVM model with the maximum element in set $D_i$
    end
  end
4. for $i = 1 : K$
    $R_i$ = classification result of SVM model $M_i$ on testing sample set
  end
$N^*$ = ensemble SVM model by using plurality voting on set $R$

Figure 1. Selective SVM Ensemble based on Clustering Algorithm.

## 3. Simulation Experiment and Result Analysis

### 3.1 The circuit under test (CUT) and parameters settings

A Continuous-Time State-Variable (CTSV) filter circuit [10] chosen from ITC'97 benchmark circuits is shown in Fig.2. And this circuit serves as experimental circuit in this paper. The tolerance of resistors and capacitors is 10% in the circuit.

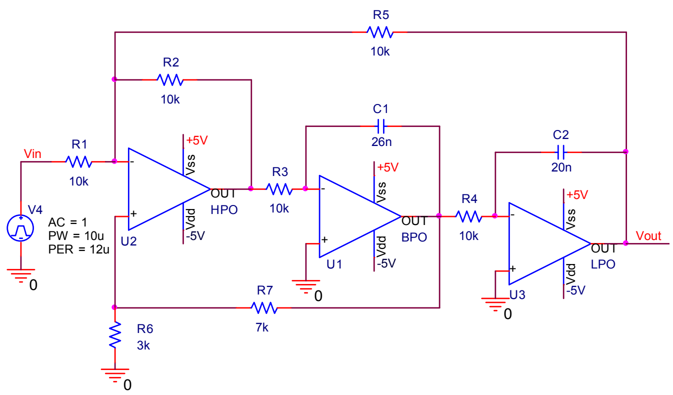


Figure 2. Continuous-Time State-Variable Filter Circuit

Fault models for analog circuits can be classified into two categories: hard faults and soft faults. Hard faults mainly consist of stuck-open fault and stuck-short fault. Soft faults are deviations of component parameters which are out of specified tolerance limits, as shown in Table 1. Compared with hard faults, soft faults are more difficult to diagnose. Thus nine different soft faults, including single fault and multiple faults modes, are chosen randomly for simulation experiments. The nine soft faults are shown in Table 2.

Table 1 Single Soft Faults of the Circuit

| ***Fault Class*** | ***Normal Value*** | ***Fault Value*** |
|---|---|---|
| R1~R5 ↑ | 10kΩ | 11.8kΩ |
| R1~R5 ↓ | 10kΩ | 8.2kΩ |
| R6 ↑ | 3kΩ | 3.54 kΩ |
| R6 ↓ | 3kΩ | 2.46 kΩ |
| R7 ↑ | 7kΩ | 8.26kΩ |
| R7 ↓ | 7kΩ | 5.74kΩ |
| C1 ↑ | 20nF | 26.0nF |
| C1 ↓ | 20nF | 14.0nF |
| C2 ↑ | 20nF | 23.6nF |
| C2 ↓ | 20nF | 16.4nF |

We generate the training and testing data in our experiments by the use of OrCAD/Pspice 10.5. For all the SPICE simulation, we input a single impulse of height 5V and duration 10 μs into the filter. To obtain multiple data within tolerance of 10%, 1000 Monte-Carlo analyses of each fault class are performed. The fault samples are extracted from output frequency response curve. We extract 10 points with equal space from output curve. Thus every sample date consists of 10 voltage values. Then fault samples data are scaled to the range [0, 1]. For each fault class (including no-fault class), we divide the 1000 samples into two parts: first 5 samples used for training; the other 995 samples used for testing. Finally, the training set has 50 samples and testing set has 9950 samples.

In the experiments, we choose the RBF kernel for SVM. Meanwhile, considering the characteristics of analog circuit testing, we use one-against-one method due to its high accuracy for classification. The related parameters contain the penalty parameter $C$ and kernel parameter $\sigma$. And the parameters ($C$, $\sigma$) are set at (10000, 7) which could obtain relatively high classification accuracy in most cases. Other parameters are setting as follows: number of bootstrap samples $T = 100$, number of clusters $K = 15$.

## 3.2 Experiment Results and Analysis

The average accuracy of selective SVM ensemble in testing experiment is 70.41%. Meanwhile, we test the same samples by using single SVM. The parameters of SVM are set by k-fold cross-validation method. Then the single SVM obtains the average accuracy of 57.43%. Table II shows the results of two fault diagnosis methods. From the data in table II, it is clear that the accuracy of our algorithm is higher in all kinds of fault modes.

In addition, experiments of the two methods with different number of training samples are carried out. The numbers are, respectively, set to 100, 200, 300, and 400. The experimental results, shown in Fig.3, indicate that the gap between the results of selective SVM ensemble and single SVM is gradually reduced along with the increase of sample number. When the number of samples is 400, single SVM obtains higher accuracy than selective SVM ensemble.

Table 2 Comparison of results of two fault diagnosis methods with 50 training samples

| ***Fault ID*** | ***Fault Class*** | ***Selective SVM Ensemble (%)*** | ***Single SVM (%)*** |
|---|---|---|---|
| F0 | No-fault | 76.78 | 41.3 |
| F1 | R2 ↑ | 51.53 | 11.05 |
| F2 | R3 ↓ | 67.93 | 47.93 |
| F3 | R3 ↑ & R5 ↑ | 97.58 | 90.15 |
| F4 | R4 ↓ & R5 ↓ | 64.3 | 27.73 |
| F5 | C1 ↑ | 70.95 | 88.04 |
| F6 | C1 ↑ & C2 ↓ | 50.55 | 70.45 |
| F7 | R4 ↑ & C1 ↓ | 39.65 | 34.67 |

| | | | |
|---|---|---|---|
| F8 | R1↓ & C2↑ | 85.2 | 64.42 |
| F9 | R1↓ & R5↑ | 99.69 | 98.59 |

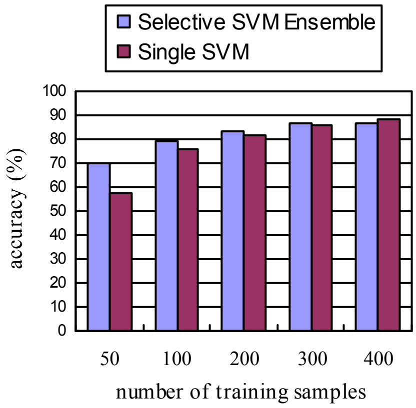


Figure 3. Accuracies Obtained by Two Fault Diagnosis Methods with Different Number of Training Samples

## 4. Conclusion

In this paper, selective SVM ensemble base on clustering analysis is applied to solve small samples problems. It overcomes disadvantages of single SVM for problems with small samples. Experimental results indicate that the method obtains higher accuracy than single SVM. Meanwhile, another set of experiments are carried out by changing the number of training samples. And the results show that the proposed method merely presents good performance in solving sample problems.

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