Analog Circuit Fault Diagnosis Using Ada Boost and SVM

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***Abstract*-A fault diagnosis method for analog circuits based on Support Vector Machine (SVM) and AdaBoost algorithm is developed in this paper. Firstly, output voltage signals from the test nodes are obtained from analog circuits test points and the fault feature vectors are extracted from haar wavelet packet transform coefficients. Then, after training the AdaBoostSVM by faulty feature vectors, the SVM ensemble model of the circuit with tolerances fault diagnosis system is built. Simulation results of diagnosing a two stage four op-amp biquad low-pass filter circuit, compared with several existent fault diagnosis methods, show us the proposed technique has the highest classification accuracy and have confirmed the validity of the method.**

I. INTRODUCTION

The fault diagnosis of Analogue electronic circuits is known to be difficultly. Apart from the huge number of possible faults and the lack of efficient fault models, this difficulty is a consequence of the inherent nonlinearity of these circuits. Even linear circuits exhibit nonlinear relations between circuit parameters and the output response. Normally the techniques used in the field can be divided into two categories: the estimation methods and pattern recognition methods. The estimation methods require mathematical process models that represent the real process satisfactorily. However, no mathematical model of the process is required in the pattern recognition methods as the operation of the process is classified by matching the measurement data. Some intelligent classification algorithms, such as artificial networks (ANNs) and support vector machines (SVMs) have been successfully applied to fault diagnosis for analog circuit [1-5]. The difference in risk minimization leads to a better generalization performance for SVMs than ANNs. However, the SVM has two drawbacks. First, since it is originally a model for the binary-class classification, we should use a combination of SVMs for the multi-class classification leading to the performance do not seem to improve as much as in the binary classification. Second, since learning of the SVM is a very time consuming for a large scale of data, we should use some approximate algorithms [6]. Using the approximate algorithms can reduce the computation time, but degrade the classification performance. To address this problem, several ensemble methods, such as bagging, boosting and nonlinear ensemble approaches [7, 8], have been proposed to improve SVM performance by combining multiple SVMs. However, there exists accuracy/diversity dilemma of the original boosting. So, we propose improved boosting algorithm with RBFSVM as component classifiers to classify analog circuit fault. Using Logistic map to adjust parameters of RBFSVMs, the distributions of accuracy and diversity over RBFSVM component classifiers are tuned to maintain a good balance between them and promising results have been obtained on analog circuit fault diagnosis experiment.

This paper proceeds as follows. Section II introduces the SVM theory and ensemble structure for pattern recognition. Section III presents fault diagnosis methods combining RBFSVM with AdaBoost and Logistic map. Section IV shows the simulation results when the proposed method is applied to the fault diagnosis for a two stage four op-amp biquad low-pass filter circuit. The conclusions are presented in Section V.

II. SVM AND ENSEMBLE STRUCTURE FOR PATTERN RECOGNITION

The support vector machine (SVM) was first developed by Vapnik for pattern recognition and function regression. It has also been proved to be very successful in many other applications such as handwritten digit recognition, image classification, face detection, object detection, text classification, etc. Given an identically independent distributed (i.i.d) training example set $\{(x_1,y_1),...,(x_N,y_N)\}$, where $X \in R^N$, $y \in \{-1,1\}$.The kernel function can map the training examples in input space into a feature space such that the mapped training examples are linearly separable. In order to have a better classification result, we maximize the margin of separation between patterns. The problem can be converted to maximize the following dual optimization problem:

$$W(\alpha) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j K(x_i, y_j) \quad (1)$$

$$\text{Subject to } \sum_{i=1}^{N} \alpha_i y_i = 0, \alpha_i \in [0, C] \quad (2)$$

The decision function becomes:

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$$f(x) = sign\left(\sum_{i=1}^{N} \alpha_i y_i K(x, x_i) + b\right) \tag{3}$$
$$b = y_r - \sum_{i=1}^{l} \alpha_i y_i K(x_r, x_i)$$

Where (x_r, y_r) is any training example, l is the number of support vectors, C is a positive number, $K(\bullet)$ denotes the kernel function used in SVMs classifiers, In this paper, we use Gaussian radial basis function:

$$K(x, x') = \exp\left(-\frac{\|x - x'\|}{2\sigma^2}\right).$$

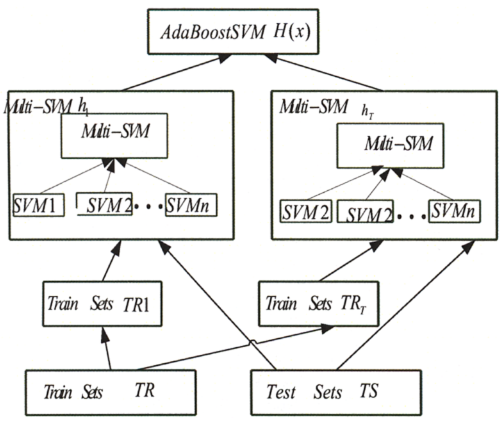

Figure.1 The structure of SVMs ensemble

Since SVM is originally a model for the binary-class classification, we should use a combination of SVMs for the multi-class classification which frequently meets in fault diagnosis problems. Usually there are two schemes to obtain a multi-class pattern recognition system, one of which is to combine several binary classifiers, and another is to consider all the classes in one big optimization problem. Several common multi-classification methods based on above schemes are: one-against-all, one-against-one, decision directed acyclic graph (DDAG) SVMs and error correcting output codes (ECOC) [9]. In the paper, we use one-against-all method, which is probably the earliest used implementation, to construct multiclass SVM classifiers. The SVM ensemble is built in the level of multi-class classifiers and the structure show in Fig.1. We obtain the final decision from the decision results of many multi-class classifiers via an appropriate aggregating strategy of the SVM ensemble. We propose a novel AdaBoostSVM ensemble algorithm in following section.

III. SVM ENSEMBLE BASED ON LOGISTIC MAP AND ADABOOST ALGORITHM

As mentioned in section I, we can also improve the classification performance in the multi-class classification by taking the SVM ensemble where each SVM classifier is designed for the multi-class classification. Two of the commonly used techniques for constructing Ensemble classifiers are Boosting and Bagging. As the most popular Boosting method, AdaBoost be attributed to its ability to enlarge the margin, which could enhance the generalization capability of AdaBoost. Diversity is known to be an important factor which affects the generalization performance of Ensemble classifiers. It is also known that there is an accuracy/diversity dilemma in AdaBoost [10], which means that the more accurate the two component classifiers become, the less they can disagree with each other. Only when the accuracy and diversity are well balanced, can the AdaBoost demonstrate excellent generalization performance. However, the existing AdaBoost algorithms do not explicitly take sufficient measures to deal with this problem.

Valentini and Dietterich[8] suggest that Adaboost with heterogeneous SVMs could work well. The classification performance of SVM is affected by its model parameters. For RBFSVM, the model parameters include the Gaussian width σ, and the regularization parameter C. AdaBoostSVM provides a convenient way to control the classification accuracy of each RBFSVM component classifier by simply adjusting the values of σ and C; it also provides an opportunity to deal with the well known accuracy/diversity dilemma in Boosting methods. We obtained a set of moderately accurate and diversity RBFSVM component classifiers by Logistic map to adjusting their σ and C values in each Boosting iteration.

A. Logistic map

Because the Logistic map is more convenient to use and the computer efficiency is better than other chaos iteration maps to generate chaos variables, the following Logistic map is used to generate the chaos sequence:

$$z_{k+1} = \eta z_k (1 - z_k) \tag{4}$$

Where z is the chaos variable, $0 \le z_i \le 1$, k is the times of iteration, $k = 1, 2, \dots$, and η is the control parameter. It is easy to testify that the system is entirely in chaos situation when $\eta > 3$ and the chaos space is [0, 1].

B. Main steps of the chaos AdaBoostSVM algorithm

1). Input: a set of training samples with labels $S = \{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$, $x_i \in R^n$, $i = 1, 2, \dots, N$, $y_i \in \{1, 2, \dots, K\}$ is the class of x_i; the iterations T; classifier h (SVM); the initial vector σ and C, the threshold of diversity $D_{threshold}$; the threshold of accuracy-diversity $E_{threshold}$; the control parameters of logistic mapping μ_σ and μ_c; the trade off parameters of accuracy and diversity w_{div}.

2). Initialize: the weights of training samples: $w_i^1 = \frac{1}{N}$, for all $i = 1, 2, \dots, N$.

3). Change the value of parameters σ and C of SVM by Logistic map:.

(a) Map the parameters space to the chaos space [0, 1] as follows:

$$z_i = \frac{\sigma_i - \min_{i=1}^{T}(\sigma_i)}{\max_{i=1}^{T}(\sigma_i) - \min_{i=1}^{T}(\sigma_i)} \tag{5}$$

Or $z_i = \frac{C_i - \min_{i=1}^{T}(C_i)}{\max_{i=1}^{T}(C_i) - \min_{i=1}^{T}(C_i)}$ (6)

(b) Perform chaos iteration on according to Eq. (4).

(c) Map the chaos space to the parameters space. Solve the value in original parameters space which corresponds to the chaos variable z_i.

4).Train a multi-RBFSVM classifier, $h_t : X \to Y$, on the weighted training set.

5). Calculate the training accuracy of h_t:

$A(h_t) = \sum_{i=1}^{N} a_i$, $\forall a_i = \begin{cases} 0, if & y_i \neq h_t(x_i) \\ w_i^t, if & y_i = h_t(x_i) \end{cases}$. If $A(h_t) < \frac{1}{2}$, go to 3.

6). Calculate the diversity of h_t:

$D(h_t) = \frac{1}{N}\sum_{i=1}^{N} d_t(x_i)$, $\forall d_t(x_i) = \begin{cases} 0, if & h_t(x_i) = f(x_i) \\ 1, if & h_t(x_i) \neq f(x_i) \end{cases}$.

if $D(h_t) < D_{threshold}$, go to 3.

7). Calculate the trade off measure between accuracy and diversity of h_t:

$E(h_t) = (1 - w_{div}) * A(h_t) + w_{div} * D(h_t)$. If $E(h_t) < E_{threshold}$, go to 3.

8). Set the weight of component classifier h_t: $\beta_t = \left(\frac{A(h_t)}{1 - A(h_t)}\right)$.

9). Update the weights of training samples:

$w_{t+1}(i) = \frac{w_t(i)}{Z_t} \times \begin{cases} -\beta_t & if \quad h_t(x_i) = y_i \\ \beta_t & if \quad h_t(x_i) \neq y_i \end{cases}$, where Z_t is a normalization constant, and $\sum_{i=1}^{N} w_i^{t+1} = 1$.

10).Output: $H(x) = \arg\max_{y \in Y} \left[\sum_{t=1}^{T} \log \beta_t\right][h_t(x) = y]$.

In the algorithm, the diversity RBFSVM component classifiers are obtained by virtue of the randomicity and ergodicity of the chaos iterations, and the distributions of accuracy and diversity over the RBFSVMs are tuned to maintain a good between them. By the novel algorithm, we can construct SVM multi-classifiers which have high classification and generalization performance.

IV. THE SIMULATIONS AND RESULTS ANALYSIS

A. The Circuit under Test (CUT)

Fig.2 shows a two-stage four-op-amp biquad low-pass filter circuit [2, 3] used in our study. The faults associated with this circuit are assumed to C1↑,C2↑,C3↑,C4↑, R16↑, R17↓, R19↑, R21↓, R22↑, R3↑, R4↓, R6↑, R7↓, R8↑ and R9↑, which are the same as in Ref.[2] and Ref.[3] for comparation. In this notation, ↑and↓ imply significantly higher or lower than nominal values. In order to generate training data for the fault classes, we set the value for faulty components and vary other resistors and capacitors within their standard tolerances of 5% and 10%, respectively. Fault diagnosis of this circuit requires recognizing 16 fault classes, 15 fault classes indicated above and the fault-free class (NFT). The impulse response of the filter can be very well approximated by the output generated from a narrow pulse whose width T is much smaller than the inverse of the filter's bandwidth [2]. For all our PSpice simulations, we have taken the filter input to be a single pulse of height 5 V and duration of 10us. 100 sample signals of each fault pattern are obtained from all 1600 Monte Carlo PSpice simulations.

The Haar wavelet packet transform is applied to decompose all the samples using the MATLAB Wavelet toolbox 3.0.4 (MathWorks, Natick,MA). Each sample signal is transformed into a set of five-dimension feature vectors based on the feature extraction methods in Ref. [4].

B. Simulation Results and Analysis

All the training feature vectors from Haar wavelet packet transform are inputted into the AdaBoostSVM, and then all the testing feature vectors are tested. In the experiment, we initiate all parameters value as follows:

σ_i=1,C_i=5,$\eta_\sigma = 3.5, \eta_C = 4$, $i = 1,2,...,N$, $w_{div} = 0.4$, $T = 10$, $0 < C < 100$, $D_{threshold} = 0.7D_{\max}$ (there $D_{\max}$ is the max value of $D(h_t)$).

In order to evaluate the effectiveness of our AdaBoostSVM in analog fault diagnosis, we have applied it to the sample filter circuit and the diagnosis results are compared with those in Ref. [2] and Ref. [3]. Ref.[2] develops an analog circuit fault diagnostic system based on Bayesian neural networks using wavelet transform, normalization and principal component analysis as preprocessors and can correctly classify 96% the faults when R6↑, R7↓, and R9↑are placed in one ambiguity group. Ref.[3] obtains seven DICs (diagnosisable components) using testability analysis and uses an off-line trained neural network as a classifier to diagnosis circuit's seven DICs fault, and reach a relatively high diagnosis accuracy 97%. Our present approach is able to identify the actual 16 kinds of fault classes very accurately with correct classification rate of 97.5%. Moreover, we compare the performance of the AdaBoostSVM with several kinds fault diagnosis methods based on SVM multi-classification algorithm: one-against-all SVMs, one-against-one SVMs and DDAGSVMs, all the trainings are under the same condition. The average correct classification rates for the testing data of the fault classes are given in TABLE I.

From TABLE I we can know that the average classification accuracy rate of the multi-classifiers based on AdaBoostSVM is 96.57% which is higher obviously than other methods, for the proposed method using AdaBoost and Logistic map creates a collection of diversity component classifiers which improve classifier's classification and generalization ability by maintaining a set of weights over training samples and adaptively adjusting these weights after each Boosting iteration: the weights of the training samples which are misclassified by current component classifier will be increased while the weights of the training samples which are correctly classified will be decreased. Classification results for the experiment prove the performance improvement of the proposed multi-classifier fault diagnosis method.

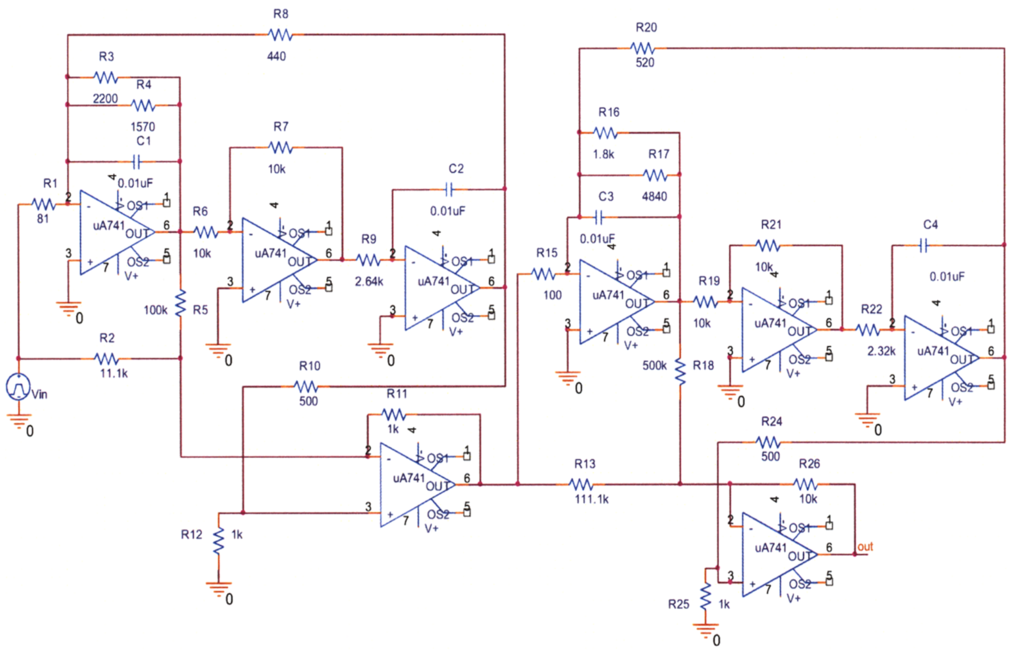

Figure.2 Two-stage four op-amp biquad low-pass filter used in our study. All resistors are in ohms

TABLE I. COMPARISON OF SEVERAL MULTI-CLASS CLASSIFICATION METHODS

Method	No. of training samples	No. of testing samples	Accuracy (%)
o-a-a	*960*	*640*	*92.32*
o-a-o	*960*	*640*	*93.54*
DDAG	*960*	*640*	*94.46*
RBFNN	*960*	*640*	*90.13*
AdaBoostSVM	*960*	*640*	*96.57*

V. CONCLUSIONS

Aiming at the characteristic of fault diagnosis of analog circuit with tolerances, we propose a novel algorithm combining SVM, Logistic map and AdaBoost. The result of simulation for verification shows that the accuracy ratio of fault diagnosis for a two-stage four op-amp biquad low-pass filter using AdaBoostSVM is highly. The AdaBoostSVM classifiers applied to fault diagnosis of the analog circuits are effective.

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