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Fault Classification Method for Inverter Based on Hybrid Support Vector Machines and Wavelet Analysis

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Abstract: A new classification method for fault waveform is proposed based on discrete orthogonal wavelet transform (DOWT) and hybrid support vector machine (hybrid SVM) for fault type of a three-phase voltage inverter. The waveforms of output voltage obtained from the faulty inverter are decomposed by DOWT into wavelet coefficient matrices, through which we can obtain singular value vectors acted as features of time-series periodic waveforms. And then a multi-classes classification method based on a new Huffman Tree structure is presented to realize 1-v-r SVM strategy. The extracted features are applied to hybrid SVM for determining fault type. Compared to employing the structure based on ordinary binary tree, the superiority of the proposed SVM method is shown in the success of fault diagnosis because the average Loo-correctness of the SVM based on Huffman tree structure exceed the general SVM 3.65%, and the correctness reaches 99.6%.

Keywords: Electronic power devices, fault diagnosis, support vector machine, wavelet transform.

1. INTRODUCTION

Over the past two decades, model based fault diagnosis technique has made a significant progress and received considerable attentions in both research and application domains. It is most important for model based fault diagnosis to obtain a mathematic model, for example observer-based scheme for fault detection [1,2]. But it is very difficult to build mathematical models for fault diagnosis of electronic power devices because of nonlinear power devices involved. With the wide use of fault recorders, a lot of fault waveforms are stored in the form of time-series sequences, which contain rich information for fault diagnosis. In general, fault diagnosis based on time series analysis includes the steps such as feature extraction, classification, similarity matching, and fault determination. Both the feature extraction and classification are very important steps because so many waveforms are stored with high dimensions in historical data bases.

Many approaches and techniques about the feature vectors extraction for time-series sequences have been suggested. Normally, the traditional methods of time series analysis are based on Fourier transform, by which the outputs waveforms are sinusoid on different frequencies. The strongest coefficients of a discrete Fourier transform are supposed to represent sequences in Ref. [3,4]. But in such a system the desirable information may be located in both frequency and time domain, and the strongest coefficients cannot reflect the local information of time domain. Considering the limits of Fourier transforms in time series analysis applications, a Plain Wavelet Transform (PWT) method has been proposed as an alternative tool in [5]. It can extract features in both frequency domain and time domain because of good ability of time-frequency localization. However, the vector of wavelet coefficients is too long for calculation and searching process in a large database. A Wavelet Singular Value Decomposition (W-SVD) method is introduced in [6,7], by which the matrices of wavelet coefficients are decomposed. The singular value vectors are viewed as feature vectors with low dimension for similarity searching process in large databases. But these methods have been not applied to waveform classification because of high dimensions of their features.

So many traditional methods on pattern classification, which are expert in linear classification problems, include Bayesian classification, Fisher distinguishing, Principal Component Analysis (PCA) [8]. Among the various methods for nonlinear classification, artificial neural network (ANN) techniques have become in the recent decades due to the outstanding method exploiting their non-linear pattern classification properties, offering advantages for automatic detection and identification of gearbox failure conditions [9,10]. These methods are based on an empirical risk minimization principle and have some disadvantages such as local optimal solution, low convergence rate, obvious "over-fitting" and

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especially poor generalization when the number of fault samples is limited [11].

Support vector machines (SVMs) is a very effective method for general purpose of pattern recognition based on structural risk minimization principles. This characteris-tic is very important for fault diagnosis under the condition that the fault samples are few [12]. The difference in risk minimization leads to a better generalization performance for SVMs than ANNs [13]. However, SVM theory is proposed for binary classification. Many approaches have been proposed to extend the binary SVM to multi-class problems. The common scheme is that a multi-class SVM is designed to deal with the problem as a collection of two-classifications that can be solved by binary SVM. A hybrid SVM scheme is proposed for multi-fault classification, which integrates two SVM strategies, 1-*v*-1 (one versus one) and 1-*v*-*r* (one versus rest), respectively adopted at different classification levels, parallel classification and serial classification levels [14]. But this design is too subjective for selecting which two nodes are classified firstly. So it is difficult to ensure the generalization ability of the hybrid SVM.

In this paper, the object of the fault diagnosis is the three-phase voltage source inverter. For designing W-SVD and hybrid SVM based fault design system, the features of the three-phase voltage source inverter are used for training and testing of hybrid SVM after preprocessing. And then an improved serial classification method based on 1-v-r SVMs strategy is proposed in our research.

2. FEATURE EXTRACTION FOR OUTPUT WAVEFORMS OF CONVERTER

The model of three-phase voltage source inverter consists of six IGBTs shown as Fig. 1. This paper focuses on fault classification of three-phase voltage source inverter through its voltage output waveforms which can be obtained when one or two of power components IGBTs are break. In fact, the output waveforms are periodic because of symmetrical structure of the inverter.

Given that there is a time-series sequence set of fault waveforms, which is set $\mathbf{S}=(\mathbf{s}_1;\mathbf{s}_2;\cdots;\mathbf{s}_n)$. The sequence $\mathbf{s}_i$ ($\mathbf{s}_i=(s_{i,1},s_{i,2},\cdots,s_{i,m})$) is one of the periodic waveforms, $1\le i\le n$, n is the number of sequences, and m is the length of each sequence.

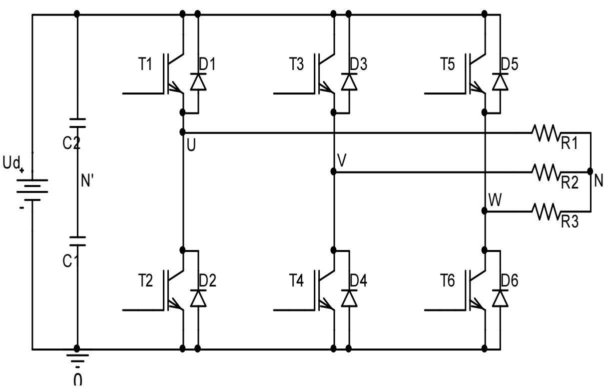


Fig. 1. The model of three-phase source inverter.

Discrete Orthogonal Wavelet Transform (DOWT) is an irredundant wavelet transform process, by which orthogonal basics can be constructed on the foundation of the discrete framework. We transform each sequence $\mathbf{s}_i$ into l+1 wavelet coefficient vectors by DOWT, where l is the level of DOWT. The length of each coefficient vector at different levels of DOWT is extended to n/2 by padding zeros in the rear. And then l+1 wavelet coefficient vectors are stacked into a matrix $\mathbf{A}\in \mathrm{R}^{\frac{n}{2}\times(l+1)}$, given by

$$A=\begin{bmatrix}\mathbf{x}_l^0 & \mathbf{x}_l^1 & \dots & \mathbf{x}_{l-1}^1 & \mathbf{x}_1^1\end{bmatrix} =\begin{bmatrix} x_{l,1}^0 & x_{l,1}^1 & \cdots & x_{1,1}^1 \\ x_{l,2}^0 & x_{l,2}^1 & \cdots & x_{1,2}^1 \\ \cdots & \cdots & \cdots & \cdots \\ x_{l,n/2}^0 & x_{l,n/2}^1 & \cdots & x_{1,n/2}^1 \end{bmatrix}, \tag{1}$$

where $\mathbf{x}_l^0$ represents the l^{th} layer approximate coefficient vector, $\mathbf{x}_j^1$ represents the j^{th} layer detailed coefficient vector and $1\le j\le l$. The process of DOWT with $l=3$ is shown as Fig. 1.

It is obvious that matrix $\boldsymbol{A}$ can entirely represent time-frequency information of time series sequences according to the properties of SVD and wavelet analysis. More detailed information about SVD can be obtained in [15].

By SVD of the matrix $\boldsymbol{A}$, the singular value vector $\boldsymbol{\lambda}_i$ ($\boldsymbol{\lambda}_i=[\lambda_{i,1}\ \ \lambda_{i,2}\ \dots\ \lambda_{i,l+1}]^{\mathrm{T}}$, $1\le i\le n$) can be obtained. So $\mathbf{S}$ can be transformed into a $n\times l$ singular matrix as follow:

$$Q=[\boldsymbol{\lambda}_1\ \ \boldsymbol{\lambda}_2\ \dots\ \boldsymbol{\lambda}_n]^{\mathrm{T}}. \tag{2}$$

Because the level of DOWT is far smaller than the length of each sequence, and namely $l\ll n$, the waveforms can be compressed by DOWT. Singular values possesses many characteristics such good stability, the property of proportion of invariant and the property

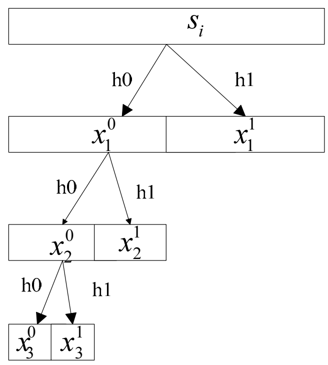


Fig. 2. Discrete orthogonal wavelet transformation process.

of rotation invariance, so it can express the characteristics of matrices, and it is effective to select singular value vectors of wavelet coefficient matrix acting as feature vectors.

Assume that there are a maximum of two IGBT failures at the same time. Namely there is only one IGBT failure, or there are simultaneously two IGBT failures in the same bridge, the different bridge but both are top or bottom among three bridges. So there are 21 types of fault waveforms and 1 type of normal waveform at each phase. Thus there are 66 types of fault waveforms in total if the normal waveform is also considered as one type of 'fault' waveform. Different input condition and different circuit condition would lead to different fault waveforms in the same type of fault waveforms.

The simulation experiment is carried out using Matlab/Simulink environment, PWM pulse generator is employed to generate pulse signal with carrier frequency 800Hz, and DC supply voltage is 500V. In this experiment, the length of each sequence is 5000, and then there are 66×5000 sequences because there are 66 types of fault/normal waveforms, and $\mathbf{S} = (\mathbf{s}_1; \mathbf{s}_2; \cdots; \mathbf{s}_{66})$. Set $l = 3$, and it means that each sequence is transformed by 3 levels of DOWT and there are 4 wavelet coefficient vectors obtained by padding zeros in the rear. So a 4×2500 wavelet coefficient matrix is stacked as follow:

$$s_i = \left[\mathbf{x}_3^0;\ \mathbf{x}_3^1; \mathbf{x}_2^1; \mathbf{x}_1^1\right],\quad 1 \le i \le 66. \tag{3}$$

Do SVD of the wavelet coefficient matrix s_i, and achieve the feature vector as $\lambda_i = [\lambda_{i,1}; \lambda_{i,2}; \lambda_{i,3}; \lambda_{i,4}]^{\mathrm{T}}$ where $1 \le i \le m$. Then the matrix $\mathbf{S}$ with 66×5000 is transformed into a feature vector matrix Q with 66×4 as follow:

$$Q = \left[\boldsymbol{\lambda}_1\ \ \boldsymbol{\lambda}_2\ \ \dots\ \ \boldsymbol{\lambda}_{66}\right]. \tag{4}$$

The distribution of 66 feature vectors with 4 dimensions, which are derived from 66 fault waveforms by DOWT, is shown as Fig. 3.

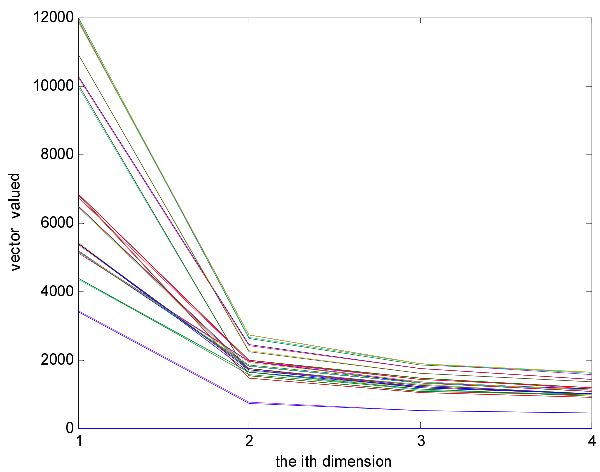


Fig. 3. The distribution of 66 feature vectors with 4 dimensions.

Table 1. The Fault classification of the three phase voltage.

Fault type	Fault waveform U	Fault waveform V	Fault waveform W	Sample number
F1	Normal, T1, T3 T1T4,T2T3	Normal, T1,T5 T1T6, T2T5	Normal, T3,T5, T3T6,T4T5	15
F2	T2,T4, T5,T1T3 T2T6,T4T6	T2,T3, T6,T1T5 T4T6,T2T4	T1,T4, T6,T2T4, T2T6,T3T5,	18
F3	T6,T1T6, T2T4,T2T5 T3T6,T4T5	T4,T1T4 T2T3,T2T6 T3T6,T4T5	T2,T1T4, T2T3,T1T6 T2T5,T4T6	18
F4	T1T2,T3T4	T1T2,T5T6	T3T4,T5T6	6
F5	T1T5 T3T5,T5T6	T3T4 T1T3,T3T5	T1T2 T1T3, T1T5	9

The 66 fault waveforms can be divided into 5 types of faults according to Fig. 3, set $F = (F_1, F_2, F_3, F_4, F_5)$, which corresponds to the distribution of 66 fault waveforms in Table 1, and $\mathrm{T_i}\,(i = 1, 2, \dots, 6)$ represent the i^{th} IGBT.

3. MULTI-CLASS CLASSIFICATION MODEL OF FAULT WAVEFORMS

3.1. Basic theory of SVMs

The SVM introduced by Vapnik is a learning method on the foundation of statistical learning theory [16]. SVM can create a line or a hyperplane between two sets of data for classification. We assume that a training set of n data points is given by

$$I = \{\boldsymbol{\lambda}_i, y_i\}_{i=1}^{n}, \tag{5}$$

where $\boldsymbol{\lambda}_i (\boldsymbol{\lambda}_i \in R^l)$ is the feature vectors and corresponding binary class labels $y_i \in \{-1, +1\}$. According to Vapnik's original, the SVM classifier is to find an optimal hyperplane formulation satisfies the following conditions:

$$\begin{aligned} &\mathbf{w}^{\mathrm{T}}\boldsymbol{\varphi}(\boldsymbol{\lambda}_i) + b \ge 1 \qquad \text{if} \quad y_i = +1, \\ &\mathbf{w}^{\mathrm{T}}\boldsymbol{\varphi}(\boldsymbol{\lambda}_i) + b \le 1 \qquad \text{if} \quad y_i = -1, \end{aligned} \tag{6}$$

where $\mathbf{w}$ is the weight vector and b is the bias.

If the inequality in (6) holds for all training data, it will be a linearity separable case [17,18]. The non-linear function $\boldsymbol{\varphi}(\boldsymbol{\lambda}_i)$ maps the input space to a high (possibly infinite) dimensional feature space. Therefore, in the linearly separable case, for finding the optimal hyperplane, we can solve the following constrained optimization problem:

$$\text{Minimize} \quad \phi(\mathbf{w}) = \frac{1}{2}\mathbf{w}^{\mathrm{T}}\mathbf{w}, \tag{7}$$

$$\text{Subject to} \quad y_i(\mathbf{w}^{\mathrm{T}}\boldsymbol{\varphi}(\boldsymbol{\lambda}_i) + b) \ge 1,\ \ i = 1, 2, .., n. \tag{8}$$

By introducing kernel function $\mathbf{K}(\boldsymbol{\lambda}, \boldsymbol{\lambda}_i)$, SVM maps the input vector into a higher dimensional feature to solve the nonlinear case. $\mathbf{K}(\boldsymbol{\lambda}, \boldsymbol{\lambda}_i)$ is the inner product kernel performing the nonlinear mapping into feature space

$$\mathbf{K}(\boldsymbol{\lambda},\boldsymbol{\lambda}_i)=\mathbf{K}(\boldsymbol{\lambda}_i,\boldsymbol{\lambda})=\boldsymbol{\varphi}(\boldsymbol{\lambda})^{\mathrm{T}}\boldsymbol{\varphi}(\boldsymbol{\lambda}_i). \tag{9}$$

We can resolve the optimization problem (7), (8) using two Lagrange multipliers as a dual problem [17]. So the decision function can be expressed as

$$f(\boldsymbol{\lambda})=\mathrm{sgn}\left(\sum_{i=1}^{n}\mathbf{a}_i^* y_i \mathbf{K}(\boldsymbol{\lambda}\cdot\boldsymbol{\lambda}_i)+b^*\right), \tag{10}$$

where 'sgn' is the signal function.

3.2. Hybrid SVMs based on 1-v-r strategy

The initial motivation of SVM is to deal with binary classification problems, but fault diagnosis is a typical multi-class classification problem. In this paper, we presented a hybrid SVM using 1-*v*-*r* SVM strategy which is designed to realize fault classification for the inverter that involved 5 fault types. This strategy is realized using binary tree. It is clear that the upper nodes of binary tree affect the classification performance of SVM classifier model more than the lower nodes if we view these classes as tree nodes. So in this paper, we employed a special binary tree called Huffman Tree to realize multi-class classification. It is the most different from other ordinary binary-tree based model that we construct this tree from bottom to top in the process of constructing Huffman Tree. Because Huffman Tree posseses minimal Weight Path Length(WPL), we put the two nearest classes on the lowest level of the Huffman tree which are classified firstly, and put the second two nearest classes on the second lowest level of the Huffman tree until the two farthest classes are put on the top level. It means that the two nearest classes are put on the bottom level of the Huffman tree. It will ensure the good generalization performance of the Huffman tree SVM. However, the two nodes of each node of the ordinary binary are selected so subjective that it may lead to more fault classifications.

The distance between each two classes is calculated using the mean of each class as follow:

$$d_{i,j}=\left\|\frac{1}{n_i}\sum_{k=1}^{n_i}\boldsymbol{\lambda}_{ik}-\frac{1}{n_j}\sum_{k=1}^{n_j}\boldsymbol{\lambda}_{jk}\right\|, \tag{11}$$

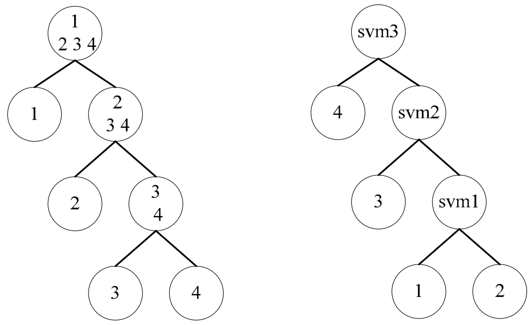
where n_i and n_j represent the numbers of i^{th} class and j^{th} class respectively. Then all distances of each two classes are calculated according to (11), and results are shown as Table 2.

As shown in Table 2, the distance between F1 and F4 is the smallest, and the distance between F1 and F2 is the second smallest, and so on. So the difference between the ordinary binary tree and proposed Huffman tree is shown as Fig. 4.

Table 2. Distances of each two classes.

Class	Distance	Class	Distance
F1 and F2	1394.2	F2 and F3	4265.8
F1 and F3	5600.7	F2 and F4	2266.0
F1 and F4	924.19	F2 and F5	3452.1
F1 and F5	2351.11	F3 and F4	6511.8
F4 and F5	1537.2	F3 and F5	7684.0

Because of the energy regressive property of singular value of the matrices, we select the first two dimensions of the feature vectors, and 5 types of faults are shown as Fig. 5. The Huffman-Tree based SVMs model is constructed as Fig. 6.



(a) Ordinary binary tree. (b) Huffman tree.

Fig. 4. The ordinary binary tree and proposed Huffman tree.

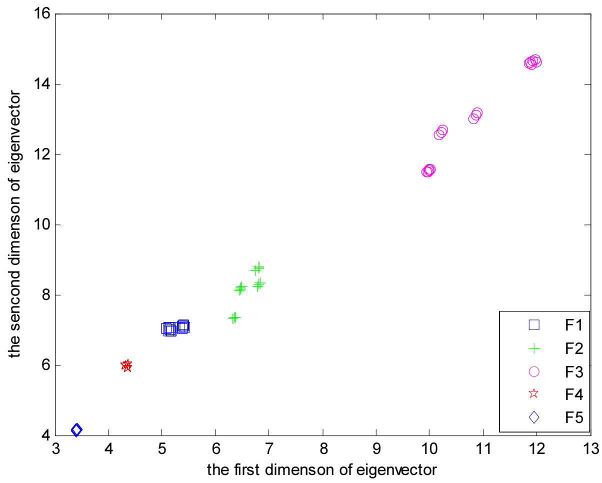


Fig. 5. The distribution of 5 types of faults.

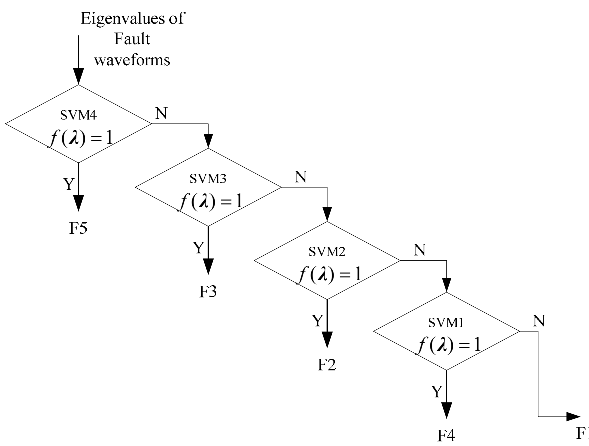


Fig. 6. Scheme of fault waveforms of the inverter based on 1-*v*-*r* SVM strategy.

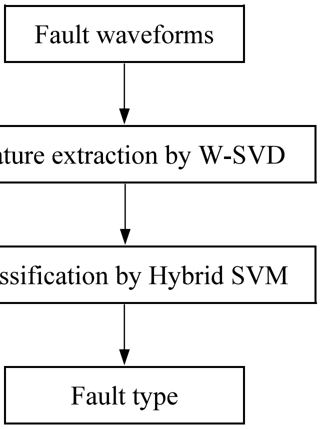


Fig. 7. Flow chart of fault diagnostic procedure.

As shown in Fig. 6, SVM4 is trained to separate F5 from the other four fault types. When the feature input is F5, the output of SVM4 is set to +1 and the classification process is over; otherwise the output is set to -1 and fault diagnosis from will be transferred to SVM3.

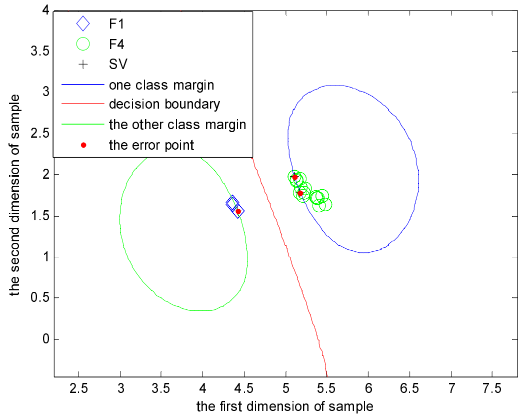
SVM3 is trained to classify F3 and the other three fault types. When the feature input is F3, the output of SVM3 is set to +1 and the classification process is over; otherwise -1 and fault diagnosis will be transferred into SVM3. SVM2 is trained to classify F2 and the other two fault types. When the feature input is F2, the output of SVM2 is set to +1 and the classification process is over; otherwise -1 and fault diagnosis will be transferred into SVM1. SVM1 is trained to classify F1 and F4 because these two classes are the nearest. When the feature input is F4, the output of SVM1 is set to +1; otherwise -1 indicates F1.

The fault diagnosis includes two main parts: fault feature extraction and fault classification. W-SVD is used as a feature extractor which gave distinguishable characteristic features about fault waveforms. Therefore, dimensions of the input patterns can be reduced and useful information can be extracted for the training of the proposed hybrid SVMs model. The wavelet analysis is performed with three-level decomposition by DOWT. All of these values would be transferred into serial classification level SVMs as inputs. The training of the proposed SVMs model is carried out using the Platt's SMO algorithm [17]. The process is shown as Fig. 7.

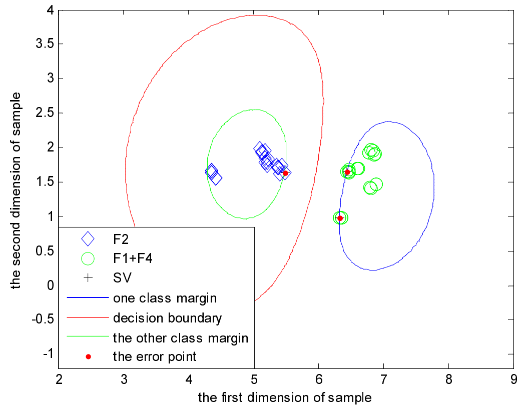
4. EXPERIMENTS AND ANALYSIS

4.1. Training and testing of the SVM

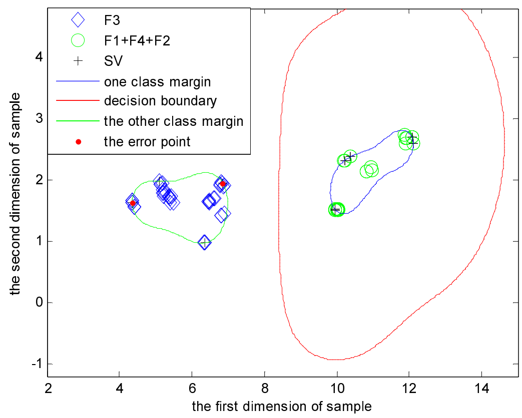
The training experiments are conducted on a small data set (66 fault waveforms). Using these samples, the proposed SVMs model based on Huffman Tree using 1-*v*-*r* SVMs strategy are trained. The Gaussian RBF kernel has been used for training and testing of the SVM and the values of the parameters gamma (r) and regularization parameter (C) have been chosen as 0.5 and 100, respectively. The results of four classifiers are shown as Fig. 8.



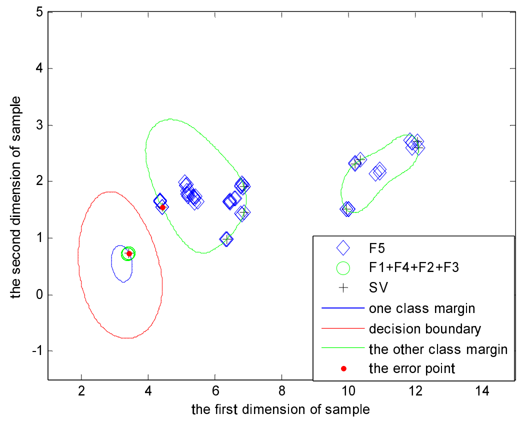
(a) SVM1.



(b) SVM2.



(c) SVM3.



(d) SVM4.

Fig. 8. The simulation results of four training classifier.

Table 3. Testing results of the proposed classifier.

Sample No	SVM4	SVM3	SVM2	SVM1	Decisive result
1	-1	-1	1	-	F2
2	-1	1	-	-	F3
3	-1	-1	-1	-1	F1
4	1	-	-	-	F5
5	-1	-1	1	-	F2
6	-1	-1	-1	1	F4
7	-1	1	-	-	F3
8	-1	-1	1	-	F2
9	-1	1	-	-	F3
10	-1	-1	1	-	F2
11	-1	-1	-1	-1	F1
12	-1	1	-	-	F3
13	-1	-1	1	-	F4
14	-1	1	-	-	F3
15	-1	-1	1	-	F2
16	1	-	-	-	F5
17	-1	1	-	-	F3
18	-1	-1	-1	-1	F4
19	-1	-1	1	-	F2
20	-1	-1	-1	-1	F1

In order to test the performance of the proposed hybrid SVM model, we change the experimental conditions of the inverter: carrier frequency is set to 1000Hz, and DC supply voltage is set to 700V. 60 testing samples are chosen randomly in 66 samples obtained from the experiment. In order to test the sensitivity of the proposed method, Gaussian noise is added to the fault waveforms given as below.

$$S_{new} = S + \rho U_{no}, \tag{12}$$

where U_{n0} is the white noise, ρ is the noise coefficient and set ρ =15 here. The decisive results of the front 20 fault waveforms are shown as Table 3.

4.2. Parameters of the SVM

Currently in literatures, there is no method available for deciding the value of C, for choosing the best kernel function, and for setting the kernel functions. As a result, the most appropriate kernel function and the values of kernel function parameters C as well as of the parameter are decided by trial and error procedure. The selection of RBF kernel width is one of the major problems in SVMs for good classification performance. The kernel width determines the radius of the hypersphere enclosing part of the data as a classifier boundary in a multi-dimensional feature spaces.

For choosing the optimum values of the parameters C and r of the RBF kernel, a large number of studies had been carried out by varying the values of these two parameters. We change the experimental conditions of the inverter once again: carrier frequency is set to 1000Hz, and DC supply voltage is set to 100V, and achieved 100 fault waveforms as training samples. The variation of these two parameters, which had been considered, are shown as follows:

$$\begin{aligned} &C = (10, 10^2, 10^3, 10^4, 10^5, 10^6, 10^7), \\ &r = (0.3, 0.5, 0.7). \end{aligned} \tag{13}$$

Table 4. Results of different combinations of C and r.

r = 0.3			r = 0.5			r = 0.7		
C	SV	Accuracy	C	SV	Accuracy	C	SV	Accuracy
10	8	96.1%	10	9	96.1%	10	10	96.1%
10^2	13	96.1%	10^2	12	96.1%	10^2	12	96.1%
10^3	7	96.1%	10^3	9	96.1%	10^3	7	96.1%
10^4	5	96.1%	10^4	6	96.1%	10^4	6	96.1%
10^5	5	96.1%	10^5	6	99.8%	10^5	6	99.8%
10^6	6	99.8%	10^6	5	99.8%	10^6	6	98.2%
10^7	9	96.1%	10^7	6	96.1%	10^7	5	95.8%

Table 5. Comparison results of two different structures.

	Huffman Tree		Ordinary binary Tree	
	SV	Loo-correctness	SV	Loo-correctness
SVM1	5	90.7%	13	92.5
SVM2	7	93.5%	8	95.8
SVM3	5	94.9%	5	89.7
SVM4	6	96.8%	3	83.3

The classification accuracies acquired for different combinations of C and r are shown in Table 4. From Table 4, it can be observed that, the maximum classification accuracy (99.8%) is obtained for $r = 0.5$ and C=10^6, and there are 5 support vectors. Therefore, as already mentioned earlier, these values had been finally chosen in this paper.

4.3. Comparison between Huffman Tree based method and ordinary binary tree based method

To show the efficiency of the classifier algorithm, a comparison between the Huffman-Tree based method and ordinary binary-tree based method has been done.

We changed the experimental conditions of the inverter again: carrier frequency is set to 2000Hz, and DC supply voltage is set to 300V. 100 testing samples are chosen randomly from the experiment, and also added white noise using (12). The comparison results between the two methods are shown as Table 5. From Table 5, it can be observed that, two types of classifiers possess the same accuracy for each class, but the average Loo-correctness [19] of the proposed method is 3.65% higher than ordinary binary tree based classification method. It means that the proposed method possesses lower expected risk, and the decisive function can obtain lower predictive falseness for unknown samples because the Loo-correctness represents the generalization performance of the classifier.

5. CONCLUSIONS

The aim of this paper is to determine the fault type on the three-phase voltage source inverter accurately and quickly. Both Wavelet Analysis and Singular Value Decomposition are well-known signal processing techniques for fault detection and identification. This paper describes a new approach with the combination of Wavelet Analysis and of Singular Value Decomposition for extraction of features from output voltage waveforms of the three-phase voltage source inverter, and the hybrid

SVM to classify the faults inherent in the features extracted through the W-SVD of different fault types. The results show the applicability and effectiveness of this method to determine the fault types of the three-phase voltage source inverter, and bright potential in application of fault diagnosis for similar electronic power devices.

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