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Signal Defects Classification Using Wavelet Transform and Multiclass Support Vector Machine

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Abstract—In this paper I have represented a new method for detection and classification of signal defects or disturbances. Before actual classification the database of signal is applied for wavelet transform. Two discrete wavelet transforms filters are used in the classification with feature extraction process. It improves the performance using pair of wavelet transform than single. For the classification of the signal disturbances I have used a support vector machine. For the computational purpose one can use binary decision tree is created and a support vector machine (SVM) classifier is trained for every node of the tree. It can be implemented using binary as well as multiclass classification of SVM.

Index Terms—signal disturbances, classification, wavelets, support vector machine (SVM).

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I. INTRODUCTION

It is very much important that signal must be noise free or disturbance less. The signal quality has great importance due to damage caused by disturbances. Small variations in signal causes more damage in industrial appliances or equipments at which small scale is used and which is noticeable. In order to improve the performance of signals its defects/disturbances should be known before respective controlling action can be taken. So these signals are to be classified on the basis of its various types.

This can be performed by detection of different signal defects. Various defects which are detected are subsequently classified and information related to it is reported using display or stored in database form. Manual approach of detection and identifying disturbances is complicated because small defects are not identified. In some applications after detecting the type of defect in signal automatic controlling action is taken in such cases manual detection has no use. The conventional techniques for analyzing these problems are too simple and rigid to capture all the relevant disturbance structure. A reliable automated system for disturbance detection and classification has many advantages over a manual one. These technique increases the speed of processing, amount of data that can be processed, ease of data collection and storage, reliability and cost. Generally two methods for automated detection and classification of disturbances have been proposed recently. Some frequently used artificial intelligence based classifiers are rule-based expert systems. artificial neural networks and support vector machines (SVM) techniques use feature vectors derived from disturbance waveforms to classifysignal quality events. Different digital signal processing techniques can be used in the process of extraction features that characterize various disturbances among them [3].Wavelet transform analysis approach is able to give information about frequency contents of the recorded signal is in wav format. Wavelet transform is better method for feature extraction. These features make the wavelet transform well suited for the analysis of various signals. Using wavelet transform approach it gives more accuracy than other types of transforms. Here, we will consider various wavelet based methods that are used for comparison purposes. A decision tree is created, using wavelet analysis in the feature extraction process. The signal, which is tested for various defects, is decomposed in 21 levels and the database of every obtained signal is compared with reference database. The reported overall accuracy is 94.3%. The reported overall accuracy is 95.85%. The disturbance classification scheme is performed with the different pairs of wavelets. It performs a feature extraction and a classification algorithm composed of a wavelet feature extractor. Multiclass classifier performs the sorting process to detect the appropriate type.

In this paper, I have used new wavelet based method for signal defects detection and classification. In order to overcome the problem with the choice of the appropriate wavelet we use a pair of discrete wavelet transforms (DWT), one with filter type one e.g. DB2 and another with filter type two e.g. DB4 in the proposed automatic defects recognition and classification procedure. The idea is to equally treat the analyzed data by the both filters and to use representation that emphasizes the uniqueness, selectivity and characterization of every distinctive class of disturbance. The feature vector can be constructed by concatenating the feature vectors obtained after applying wavelet transform with both filters. In most wavelet based methods RMS values of different sub-bands are used as feature vectors. In order to classify the voltage disturbances we use multiclass SVM as a classification method. Identifying the properties of the signal disturbances, one can classify into particular type using any two discrete wavelet transforms.

II. DISCRETE WAVELET FILTERS(DWF):

The continuous wavelet transform of a signal $f(t)$ is defined as

$$CWT(a,b)=\int_{-\infty}^{\infty} f(t)\,\psi ab(t)\,dt \qquad \ldots(1)$$

Where $\psi ab(t)=1/\sqrt{a}\,\psi(t-b)/a$ and $a,b\in k; a\neq 0$.

The function $\psi(t)$ is the base function or the mother wavelet and a and b, are the dilation and translation parameters

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respectively. Since the transformation is achieved by dilating and translating the mother wavelet continuously, it generates substantial redundant information. The resulting expression is given with

$$\mathbf{DWT[m,n]} = \frac{\mathbf{1}}{\sqrt{\boldsymbol{a_o^m}}} \sum_{k=-\infty}^{\infty} \boldsymbol{f[k]}\,\psi\left[\frac{k - nb_0 a_0^m}{a_0^m}\right]$$

Input Voltage Signal

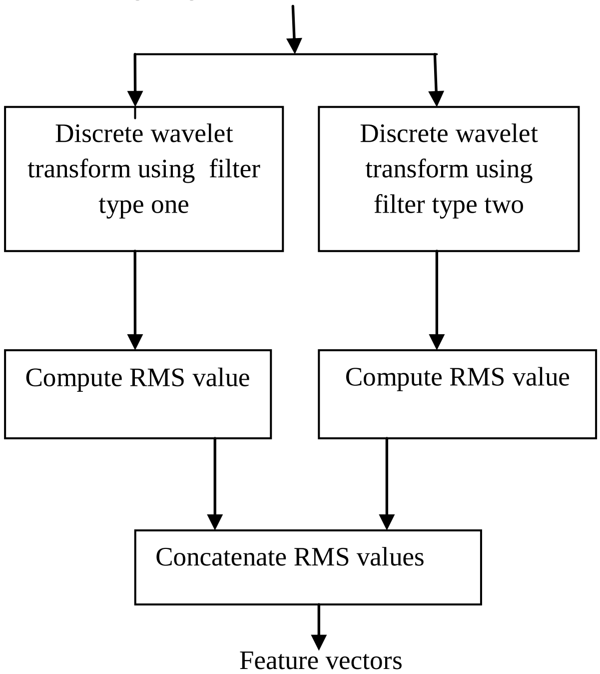

Fig.1 Generation of Feature Vector

Wavelet transform is called a **Dyadic-Ortho normal** wavelet transform, and can be easily and quickly implemented by filter bank techniques normally known as **Multi-Resolution Analysis** (MRA) which consists of two filters: a high-pass filter with impulse response $h[n]$ i.e.Ca1 and its low-pass mirror version with impulse response $g[n]$i.e. Cd1. These filters are related to the type of mother wavelet and can be chosen according to the application. At each stage, the input signal is decomposed for low pass and high pass conditions. The approximation signal is further decomposed to produce new coarser representation of the signal. After *specific* levels of decomposition, we can get two parts after feature extraction, which is the reference signal at the next higher resolution.

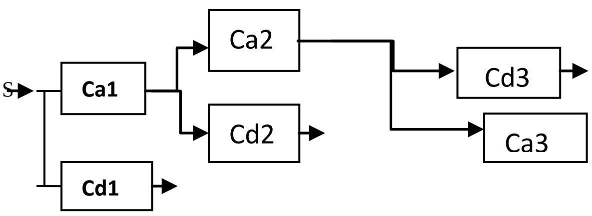

Fig.2 Feature extraction using three levels.

III. Support Vector Machines (SVM) :

The support vector machine (SVM) is a powerful method for statistical classification of data used in a number of different applications. However, the usefulness of the method in a commercial available system is very much dependent on whether the SVM classifier can be pre trained from a factory since it is not realistic that the SVM classifier must be trained by the customers themselves before it can be used. This paper proposes a novel SVM classification system for signal defects. Support vector machines are a very popular supervised machine learning methods used for classification and regression analysis. Given a set of n training examples x_i which belong in one of two classes c_i ={-1,1} using SVM we can create a model which can separate new samples of the classes. The task of the classification process is to choose a hyper plane which can best separate the two classes. The hyper plane is described as

$$P_0: w.x - b = 0$$

Where $w.x$ denotes the dot product and w the normal vector to the hyper plane. The parameter b determines the offset of the hyper plane from the origin along the normal vector w. We want to choose the parameters w and b to maximize the margin, or distance between the parallel hyper planes that are as far apart as possible while still separating the data. These hyper planes can be described by the equations:

$$P_1: w.x - b = 1$$
$$P_2: w.x - b = -1$$

The problem can be solved by minimizing

$$\frac{1}{2}||w^2||$$

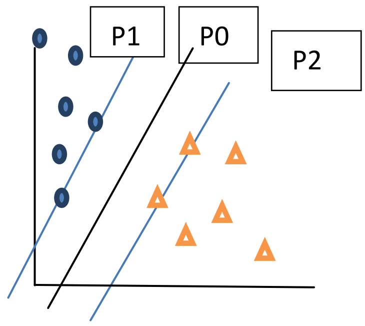

Fig.3 Support vectors and hyper plane.

Table-I Voltage disturbances equations

Type of disturbance	Function/Model used	Parameters
NORMAL(C1)	$x(t) = \sin w(t)$	-
SWELL(C2)	$x(t) = A(1 + \alpha(u(t-t1) - u(t-t2)))\sin w(t)$	0.1≤α≤0.8,T≤t2-t1≤9T
SAG(C3)	$x(t) = A(1 - \alpha(u(t-t1) - u(t-t2)))\sin w(t)$	0.1≤α≤0.8,T≤t2-t1≤9T
HARMONIC(C4)	$x(t) = A(\alpha_1 \sin(wt) + \alpha_3 \sin(3wt) + \alpha_5 \sin(5wt) + \alpha_7 \sin(7wt))$	0.05≤α3≤0.15,0.05≤α5≤0.15,0.05≤α7≤0.15,$\sum \alpha i^2 = 1$
OUTAGE(C5)	$x(t) = A(1 - \alpha(u(t-t1) - u(t-t2)))\sin(wt)$	0.9≤α≤1,T≤t2-t1≤9T
SAG WITH HARMONIC(C6)	$x(t) = A(1 - \alpha(u(t-t1) - u(t-t2)))(\alpha_1 \sin(wt) + \alpha_3 \sin(3wt) + \alpha_5 \sin(5wt))$	0.1≤α≤0.9,T≤t2-t1≤9T 0.05≤α3≤0.15,0.05≤α5≤0.1, $\sum \alpha i^2 = 1$
SWELL WITH HARMONIC(C7)	$x(t) = A(1 + \alpha(u(t-t1) - u(t-t2)))(\alpha_1 \sin(wt) + \alpha_3 \sin(3wt) + \alpha_5 \sin(5wt))$	0.1≤α≤0.9,T≤t2-t1≤9T 0.05≤α3≤0.15,0.05≤α5≤0.1, $\sum \alpha i^2 = 1$

IV. PROPOSED METHOD

For the feature extraction process we use two DWT, as used in[1] and [2]. The DWT has been used intensely for the analysis of the signal defects, compared to the discrete Fourier transform (DFT), since it provides not only frequency information, but also information about location of the components. The wavelet analysis is in fact a measure of similarity between the basis function (wavelets) and the signal itself. Therefore, the selection of the most adequate wavelet mother function to be used in the analysis is one of the key factors in successful application of wavelets, not only in power quality applications. In order to reduce the influence of the choice of the wavelet we propose the use of two DWT with two different wavelets, one with high support and one with low support. Introducing the second wavelet transform in the feature extraction process provides additional information about the analyzed signal, which makes the classification more accurate.

The increased accuracy comes with the price of increased computational complexity of the algorithm. However, the additional wavelet transform allows fewer levels of decomposition to be used, which reduces the computational complexity of the algorithm. Additionally, we design a classification algorithm which also reduces the number of operations in the test phase. The signal, which is tested for various defects, is first decomposed in n-levels using discrete wavelet transform. The energy of the detail and approximation coefficients at each level of decomposition is used as feature vector using formula,

$$EDi = \sum_{j=1}^{N} d^2 ij \qquad i = 1 \dots \dots n$$

$$EAi = \sum_{j=1}^{N} a^2 ij$$

where *dij i=1 to n* the wavelet detail coefficient in the wavelet decomposition from level 1 to level *n* and *aij* is the wavelet approximation coefficient in the wavelet decomposition at level *n*. *N* is the total number of wavelet coefficients at each level of decomposition, *EDi* is the energy of detail coefficients at the decomposition level *i* and *EAi* is the energy of the approximate wavelet coefficients at decomposition level n. In this way, the size of the analyzed data is significantly reduced The overall feature vector is obtained after applying another wavelet transform and calculation of the energy of detailed and approximation coefficients in the same manner. With aim to make length of the feature vector and computational cost comparable with other wavelet based methods for detection and classification of voltage disturbances, although there are many classification methods we have chosen multiclass SVM learning method. We have constructed tree of types where, for every node a liner-SVM model is created. The tree is designed analyzing the properties of the seven signals. At the root node we have grouped the seven types of signals into two groups in such way that they would be easiest to separate. In the first group signals without harmonic disturbances and in the other with harmonic disturbances. Grouping the signals into two groups in a way that will make the classification easiest. At the leaf nodes the algorithm separates the signals which are hardest to separate. The results with the use of the decision tree are similar with the results using the typical one-against-all or one against-one approach. However, in the testing phase only three decisions are made instead of seven, thus making this approach faster. The experimental results shown high accuracy in classification with training data from one network and unseen testing data from another. High accuracy was also achieved when the SVM classifier was trained on data from a real power network and test data originated from synthetic data.

V. EXPERIMENTAL RESULTS

For comparison purposes the power disturbances are

Table II(a):

Wavelet	Coif 2	Coif30	Db2	Db20
Overall Efficiency	91.53%	92.53%	92.60%	92.8%

Table II(b):

Class\Wavelet	Db2	Db6	Coif2	Dmey	V24	Db20
Normal	100	100	100	100	100	100
Swell	100	100	100	98	100	100
Sag	89	92	90	85	88	90
Outage	100	100	100	100	100	100
Harmonic	88	91	89	87	90	88
Sag_Harmonic	100	100	100	100	100	100
Swell_Harmonic	100	100	100	97	100	100

VI. EXPERIMENTAL RESULTS

All these work include the same defects and the same pattern numbers generated by parametric equations of data (Table. I) for training and testing of the classification stage. Seven different classes are considered, including the case with no power disturbances: *normal*, *swell*, *sag*, *harmonic*, *outage*, *sag with harmonic* and *swell with harmonic*, denoted with C1, C2, C3, C4, C5, C6, C7, respectively. Ten cycles are included in every signal with a sampling frequency of 256 samples/cycle i.e. every signal has 2560 samples. The normal frequency is assumed to be 50Hz.The data sets with same size were used in the testing process. The choice of the number of decomposition level *n* has significant influence on the process of classification.

Table III:

	Db2 & coif2	Db4 & coif30	Coif30 & db6	Db6 & V24	Db6 & V24	Db20 & Coif 20
C1	100	100	100	100	100	100
C2	100	100	100	98	100	100
C3	90	92	94	89	90	91
C4	100	100	100	100	100	100
C5	89	90	92	88	89	90
C6	100	100	100	100	100	100
C7	100	100	100	97	100	100

Choosing higher n will generally bring more information in the system and in that way higher accuracy. On the other hand, higher number of decompositions means more calculations Since two DWTs are used for extraction of feature vectors in the proposed method we reduce the level of decomposition to *n*=7.wavelet transforms with different wavelets are applied, significant improvements in the classification processes are obtained. Some of obtained results are given in Tables II(a) & II(b).These results have very high classification accuracy rate. The results also show that the filter v24, which is mainly used for harmonic analysis [3], is not appropriate db4 wavelet in 10 and 12 levels, respectively The results are comparatively presented in Table III the performance of the proposed wavelet classification methods exceeds the performance of the classification methods proposed in [1]–[3].In order to analyze the computational complexity of the proposed method we analyze the number of support vectors obtained in the training process. The classification function of the linear SVM is

$$f(x) = sign(\sum_{i=1}^{m} \alpha iyi\, xi^{T} x + b)$$

Where x_i are the support vectors and *m* is the number of the support vectors. It can be seen that the number of operations depends of the number of the support vectors. It can be seen that due to the correct grouping of the signals in most cases the classification is very easy and the SVM requires very few support vectors. The number of support vectors is largest for the SVM that distinguishes the sags from the outages. However, the proposed classification method does not use all of the support vectors for a given test sample and in the case when the signal is not sag or outage the number of calculations is significantly reduced.

VII. Conclusions

This paper proposes a novel method based on the SVM algorithm for classification of common types of voltage disturbances. The results from the conducted experiments have shown high classification accuracy, implying that the SVM classification technique is an attractive choice for classification of this type of data using DWT and support vector machine. High classification accuracy rate of the proposed method is obtained by the use of two wavelets.

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