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Power quality detection and classification using wavelet and support vector machine

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Abstract. This work presents the identification and classification of various disturbances that affect the quality of energy, seen as the quality of the voltage wave (harmonics, sag, swell and flicker). For this, the wavelet transform is used, which allows to have characteristic patterns as input signals of the support vector machine, these are evaluated in their different configurations, bi-class, minimum output coding, error correcting output and one versus all. For all of them, in the first instance they were trained with 200 samples, then the results were validated with 100 samples and finally the evaluation was made with 500 different samples, obtaining that the best result is presented with the minimum output coding configuration.

1. Introduction

The power quality that the final user receives, be it residential or industrial, must be guaranteed for the proper functioning of the equipment and the system itself. However, multiple phenomena, some inherent to the operation of the system, such as voltage variations due to the connection or disconnection of large loads and others produced by them in particular, those that have electronic components that introduce harmonics to the network, which distorts the wave. Each of these phenomena has different ways of being quantified which makes it difficult to compare one and one to identify which one affects the signal the most.

Some studies mentioned that the appearance of active loads is characterized by their dynamic functioning and that this could lead to variable alterations in time that propagate along the distribution networks [1-3]. In order to address this problem, an analysis is presented from the perspective of wavelet transform analysis, to measure the reactive power of three phases, taking into account the new operating environment variable with time in three-phase systems. The wavelet-based approach to the measurement of reactive power was developed and tested under different time-varying power quality perturbations, including balanced and unbalanced systems that contemplate other basic small-wave functions of the Daubechies family.

Some works has been carried out in which indices have been proposed that allow classification and quantification of the effects caused by some phenomena that affect the quality of energy [4,5], for example, [6] proposes an index that quantifies the deviation between the control voltage or current and the ideal or current tension. This index can also be used for the detection, quantification, and classification of the severity of any disturbance. The index can be applied to steady state variations, as well as to transient events. In the first case, the index is used to quantify the severity of the variation. In the other case, the index can be used for the activation and detection of events but also to quantify its severity.

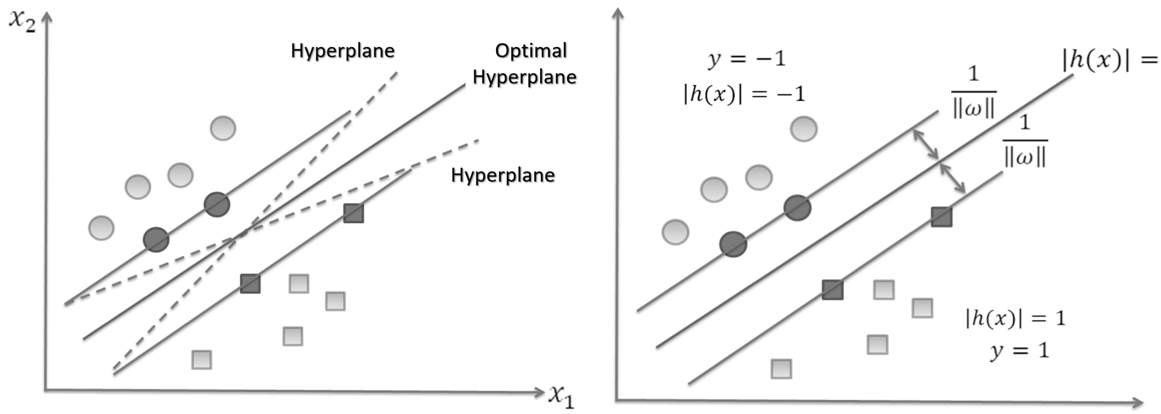
Support vector machine have been used as classifiers in different studies and for different variables such as magnetic resonance brain image [7], gene expression data [8], American football head impacts [9], as well as electrical variables for fault diagnosis [10-12], real time health monitoring of industrial machine [13] and power quality disturbances [14-17].

2. Support vector machine

Support vectors machine (SVM) are a set of learning algorithms based on the theory of statistical learning. This technique was initially a bi-class linear classifier for separable data and allows to find a linear model that separates the elements of both classes; later this technique was adapted to classification problems with non-separable data and even to solve regression problems [18].

2.1. Linear separation

SVM look for a line in such a way that the elements of each class are on each side of the line, which is called the optimal hyperplane since it must provide the maximum separation between classes, as shown in Figure 1(a), the optimal hyperplane can be defined as the geometric place that is equidistant from the lines defined by the training samples (solid color), which are the closest between the classes and are the only ones necessary to obtain the optimal hyperplane and they are called support vectors and are always the most difficult samples to classify. Similarly, the problem with its characteristic elements is presented in Figure 1(b), the two classes (equal to those in Figure 1(a)), the optimal hyperplane and the maximum margin between it and the classes.



(a) (b)

Figure 1. Class separation by (a) hyperplanes and (b) optimal hyperplane.

SVM classifier can be represented as the linear combination of the attributes of the applicants represented by x, multiplied by specific weights ω, as is shown in Equation (1):

$$h(x) = \omega^T x + b = 0, \tag{1}$$

where ω and $x \in \mathbb{R}^{\mathbf{d}}$ and d is the size of the entrance space, b is a noise term and ω^T is represented as column vectors.

The solution for the case will be meet, depending on the side where the samples are located with respect to the hyperplane [19]. Equation (2) and Equation (3) define the two classes present in the problem.

$$\omega^T x_i + b > 0, \text{ for } y_i = 1, i = 1, \ldots, n \tag{2}$$

$$\omega^T x_i + b < 0, \text{ for } y_i = -1, i = 1, \ldots, n \tag{3}$$

To solve the problem of classification, it should be considered that the support vectors, that is, the solid color elements in Figure 1(a). By definition, there can be no elements of the learning set within the margin range, therefore, Equation (1) is reduced to Equation (4).

$$y_i(\omega^T x + b) \geq 1, \text{ for } i = 1, \dots, n \tag{4}$$

For the points closest to the hyperplane meet that $|h(x)| = 1$, then, the distance of these to the hyperplane is presented in Equation (5).

$$\mathrm{dist}(h, x) = \frac{1}{||\omega||} \tag{5}$$

To find the values of ω and b, $\mathrm{dist}(h, x)$ it must be maximized between the hyperplane and the closest training point, fulfilling the condition expressed in Equation (5).

Minimizing the above expression is a nonlinear programming problem that can be solved using the Lagrange multipliers and the Karush-Kuhn-Tucker conditions. According to this, in the case where the data are not support vectors, the following solution is obtained from Equation (6) to Equation (8), they correspond to the optimal hyperplane with its respective decision boundary:

$$\omega = \sum_{i=1}^{n} \alpha_i y_i x_i \tag{6}$$

$$h(x) = \omega^T x + b = \sum_{i=1}^{n} y_i \alpha_i x_i^T x + b \tag{7}$$

$$b = -\frac{1}{2}\left(\max_{y_i=-1}\{\omega^T x_j\} + \min_{y_i=1}\{\omega^T x_j\}\right) \tag{8}$$

2.2. Non-linear separation

When there is no optimal hyperplane that allows the classes to be separated from any sample, the transformation of the input vector to a space with a greater dimension $\mathbb{R}^c$ that is called space must be considered [20].

2.3. Multiclass problems

In order for the SVMs to solve the problem of more than two classes, Weston and Watkins proposed a modification of the optimization function that takes all classes into account [20].

- One-versus-all: the problem of Nc classes are broken down into so many other binary problems, in which each of the classes faces the rest. Thus Nc classifiers are constructed that define other so many hyperplanes that separate class i from the remaining $\mathrm{Nc} - 1$.
- One-versus-one: The problem of Nc lases is broken down into $\mathrm{Nc}(\mathrm{Nc} - 1)/2$ binary problems, where all the possible one-on-one clashes between classes are created.

3. Results

3.1. Bi-class

For this case, which is the simplest in terms of classification with SVM, we proceeded to compare each of the classes with the other three. For each of the tests, 200 samples were used per class, as shown in Table 1. In this sense, the column successful predictions show how many samples were correctly identified from the initial 200. In that sense, having 200 as a result indicates that the SVM was able to identify all the samples without any error.

Table 1. Results for bi-class classification.

Classes		Successful predictions		% Error	
Class 1	Class 2	Class 1	Class 2	Class 1	Class 2
Harmonics	Swell	189	192	5.5	4.0
	Sags	187	197	6.5	1.5
	Flicker	192	189	4.0	5.5
Swell	Harmonics	192	189	4.0	5.5
	Sags	198	200	1.0	0.0
	Flicker	194	185	3.0	7.5
Sags	Harmonics	197	187	1.5	6.5
	Swell	200	198	0	1.0
	Flicker	195	161	2.5	19.5
Flicker	Harmonics	189	192	5.5	4.0
	Swell	200	194	0.0	3.0
	Sags	161	195	19.5	2.5

3.2. Multiclass

3.2.1. Minimum output coding. For this classifier, the minimum number of bits n_b is used to encode n_c as shown Equation (9):

$$n_b = \log_2 n_c \tag{9}$$

3.2.2. Error correcting output. This coding scheme uses redundant bits. Typically, the limit of binary classifiers n_b is given by Equation (10):

$$n_b \leq 15\lceil \log_2 n_c \rceil \tag{10}$$

However, it is not guaranteed to have a n_b valid representations of the n_c classes for all combinations. This routine takes longer execution time and takes more space in memory.

Table 2. Results for SVM types.

	Training				Validation				Evaluation			
	Harm	Swell	Sags	Flicker	Harm	Swell	Sags	Flicker	Harm	Swell	Sags	Flicker
One versus all	5.2	0.2	4.8	12.2	3.5	0.5	4.5	16.5	5.9	0.5	4.4	14.1
Error correcting output	5.0	0.2	2.6	12.0	3.5	0.5	2.5	17.5	5.7	0.3	2.4	13.8
Minimum output coding	3.6	0.2	2.2	10.0	3.5	0.5	2.5	11.0	4.4	0.3	2.3	12.4

3.2.3. One versus all. In this case, each of the n_c binary classifiers are trained to identify the combination of each of the n_c classes with the union of the others.

In Table 2 the results for all different types of SVM used in this work are shown. These results are presented as percentage for each simulation: Training (200 samples), validation (100 samples) and evaluation (500 samples). In the same way, is possible to observe that the signals with flicker have the highest errors, of the order of 10%, followed by the signals with harmonics, whose errors are between 3% and 5%. On the other hand, swells present the smallest errors in the order of 0.5% above sags with 2.6% errors.

Another relevant aspect that can be obtained from Table 2 is that the one versus all configuration is the one that presents the biggest errors in the three moments (training, evaluation and validation) with an error weighted by the number of samples at each stage of 6.4%.

4. Conclusions

The problem of classifying the four power quality disturbances analyzed (harmonics, sag, swell and flicker) was addressed in two different ways, the first one with the SVM bi-class, which consisted in making a comparison of the class 1 (any one is selected) versus class 2 (the other three different signals than the one selected for class 1). The second way was to use three different mechanisms available to convert the problem into a multiclass.

Analyzing each class individually in the support vector machine bi-class, signals with sags are those that present the best result, with a percentage of error of 1.33% while the flicker have the highest error with 9.6%, in the same sense, for this classifier the overall error of the signals with harmonics is 5.3% and that of the swells is 2.6%.

For the multiclass classification, is important to highlight that the class 4, corresponding to flicker is the one that presents the greatest errors compared to the other classes (higher than 10% in all cases), this possibly occurs because the pattern that identifies it is the most complex of those delivered to the SVM classifier. On the other hand, swells represent the class with the lowest classification error, having 0.2%, 0.5% and 0.3% as an error for training, validation and evaluation, respectively.

When analyzing the results of the three configurations of the support vector machine multiclass, minimum output coding is the one with the best results, with errors of 4.0%, 4.3% and 4.6% for training, validation and evaluation respectively. Thus, the overall error weighted by the number of samples is 4.6%.

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