A phase diagram approach for transient events detection and classification in power distribution networks

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Résumé - Ce papier présente une solution d'un problème bien connu des réseaux de distribution d'énergie : la détection et la classification des événements transitoires précurseurs des défauts pouvant conduire à des pannes du réseau électrique. Nous montrons les inconvénients de certaines approches classiques (la transformée en ondelettes et l'analyse statistique) et nous présentons les résultats d'une nouvelle approche de classification, basée sur la dynamique de l'entropie de diagramme de phase et les caractéristiques de diagramme de phase.

Abstract - This paper presents a solution of a well-known problem in power distribution networks: the detection and classification of transient events that precede faults that can lead to power outages. We show the inconveniences of some classical approaches (wavelet transform and statistical features) and we present the results of a new classification approach, based on the dynamics of phase diagram entropy and the characteristics of phase diagram.

1 Introduction

The topic of fault detection in power system is of great interest in these days. One of the most common faults is represented by partial discharges (PDs). Most often these are caused by insulation defects and can occur in any phase of the production-transport-distribution chain. These are one of the main causes of breakdowns in power systems [1]. Therefore, partial discharges are a phenomenon that must be detected and monitored in order to analyze the state of the power system.

In most cases, in addition to the partial discharge signals, other signals corresponding to loads are transmitted through the power cables, often much stronger than the PD signals. This can lead to problems in the PD detection process. Thus, a high number of such signals in power networks is a major impediment in network analysis. The existence of these signals and the large spread of electrical infrastructures cause difficulties when it comes to predictive maintenance of power systems [2]. One of the main approaches in this situation is based on their classification in order to make correct decisions regarding the state of the power network.

In this context, the purpose of this paper has a double perspective. First, we propose a detection model free method derived from nonlinear dynamical systems, more precisely phase diagram-based entropy. This method eliminates the disadvantages of classical detection methods, such as those based on spectrogram or wavelet. Secondly, we propose a set of features extracted from the phase diagram in order to successfully characterize and classify all the transient activities detected in the power system.

The structure of the paper is as follows: Section 2 presents theoretical notions underlying the detection and characterization process derived from the phase diagram, as well as the presentation of the classification algorithm. Section 3 describes the results obtained by applying the method of analysis and classification algorithms on a real power distribution network and Section 4 presents the conclusions of this paper and future perspectives.

2 Theoretical aspects

This section presents the method used to detect transient signals, as well as the features extracted from the phase diagram representation and machine learning algorithms used in the classification part.

2.1 Phase diagram-based entropy

Phase diagram-based entropy method comes from the dynamic system theory. The emphasis of each transient event occurred in the power system can be done by transposing the analyzed signal in a multidimensional representation space, through the phase space vectors as in (1).

$$\overrightarrow{v_{[i]}} = \sum_{k=1}^{m} x[i+(k-1)d]\cdot\overrightarrow{e_k},\ i=1,2,...,M \qquad (1)$$

Changing the representation space and obtaining the phase diagram is done based on the delay d between samples and the encapsulation dimension m. The determination of these parameters is done using the mutual information and the false nearest neighbor method [3]. Also $\overrightarrow{e_k}$ are the axis unit vectors and $M = N-(m-1)d$, where N is the length of the time series. Each two vectors from the phase diagram will be evaluated in terms of similarity in order to highlight the changes that occur in the analyzed system with the help of (2):

$$C_i^m(r) = \frac{1}{N-(m-1)d} \sum_{j \neq i} \Theta\left\{ r - d\left[\overrightarrow{v_{[i]}}, \overrightarrow{v_{[j]}} \right] \right\} \quad (2)$$

where r is a tolerance threshold used to establish the range in which the data fluctuations are considered similar, $d[\cdot]$ is the operator of Euclidean distance and Θ is the Heaviside function. Analyzing all pairs of two vectors in the phase diagram we quantify the degree of similarity in a logarithmic manner, as in (3).

$$\Phi_m = \frac{1}{N-(m-1)d} \sum_{i=1}^{N-(m-1)d} \log\left(C_i^m\right) \quad (3)$$

Thus, in defining the phase diagram-based entropy [4], we measure the changes that occur in the system as an increase of the embedding dimension, as shown in (4).

$$PDEn = \Phi_m - \Phi_{m+1} \quad (4)$$

A higher value of this entropy highlights the less predictable character of the system and highlights irregular appearances.

2.2 Phase diagram features

The representation in the phase diagram has the potential to highlight the existence of important features capable of characterizing transient signals. More details can be found in [4]. Three signal classification features will be presented in this subsection. In defining them we start from a test signal and its representation in the phase diagram, both representations can be viewed in Figure 1. In the representation we considered $d=1$ and $m=2$. We chose this test signal because it fits best with the shape of the existing transient signals in real power networks.

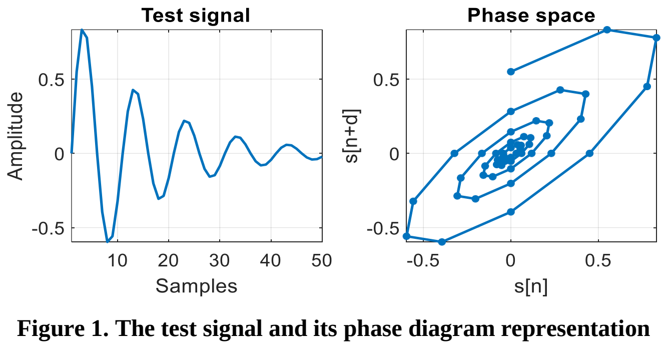

Figure 1. The test signal and its phase diagram representation

Figure 2 displays the features derived from the representation in the phase diagram. These will be used in classification algorithms.

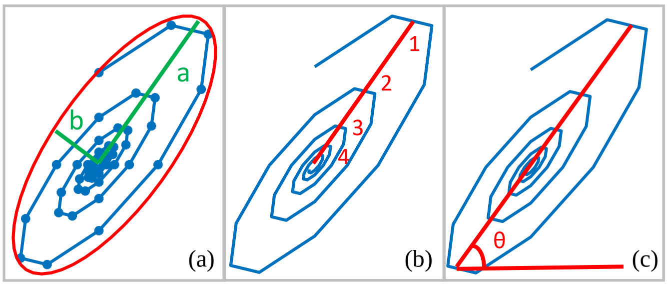

Figure 2. Phase diagram dispersion (a), the number of spirals (b) and orientation (c)

2.2.1 Phase diagram dispersion

As can be seen in Figure 2a, the representation in the phase diagram can be inscribed in an ellipse. Thus, the two semi-axes of the ellipse show us the degree of dispersion of the points of the trajectory. We can quantify this according to the two dispersions in the two directions with the help of (5).

$$PDD = \sqrt{ab} \quad (5)$$

This feature is related to the amplitude of the signal. If the signal is strong and its generating source is close to the sensing point, the dispersion will have a higher value.

2.2.2 The number of spirals

The representation of the test signal in the phase diagram consists of several spirals, as show in Figure 2b. It is possible to quantify the number of spirals of the representation as the number of vectors that intersect with the major semi-axis of the ellipse that contains the representation using (6) and (7).

$$P_i = \overrightarrow{v_{[i]}} \cap a, \ i = 1, 2, \ldots, M-1 \quad (6)$$

$$NS = size\ of\ P_i \quad (7)$$

This feature is related to the duration and shape of the signal. The more spirals there are, the longer the duration is and the amplitude of the signal decreases over time.

2.2.3 Orientation

As shown in Figure 3c, orientation gives the angle between the major axis, the line which best fits all the points of the representation of the ellipse and its projection on the OX axis. This can be quantify using (8).

$$\Theta = \arccos \frac{a}{X_a} \quad (8)$$

This feature is related to the signal symmetry in the time domain and the distribution of its samples. For example, the orientation of a sinusoidal signal is 45°.

In order to show the interest of the proposed features, in Section 3 we compare them with some classical features based on wavelet transform approach.

2.3 Machine learning algorithms

Support Vector Machine (SVM) is an algorithm which find an optimal hyperplane between the possible outputs, that distinctly classifies the data [5]. In multiclass classification task, we need a hyperplane to separate between every two classes, neglecting the points of other classes. The computations of data points separation depend on a kernel function. This function determines the smoothness and efficiency of class separation. In our paper, we use a second order polynomial kernel function.

Decision tree (DT) learning is a method for approximating discrete-valued functions, in which the learned function is represented by a decision tree. The aim of decision tree learning is recursively partition data into sub-groups [5]. In our study, the AdaBoostM2, a boosting algorithm designed for multiclass problems with weak base classifier is adopted. The algorithm is designed to minimize a loose bound on the training error.

Quadratic Discriminant Analysis (QDA) is a probabilistic parametric classification technique. QDA models the likelihood of each class as a Gaussian distribution, then uses the posterior distributions to estimate the class [5].

The performance metrics used to evaluate the classifiers are recall, specificity, precision and accuracy.

3 Experimental configuration and results

In this paper we have studied a real three-phase power distribution network. Through three high frequency current transformer sensors and one acquisition board we collected the electrical signals from the distribution cables. The acquisition system and the power distribution network diagram are shown in Figure 3.

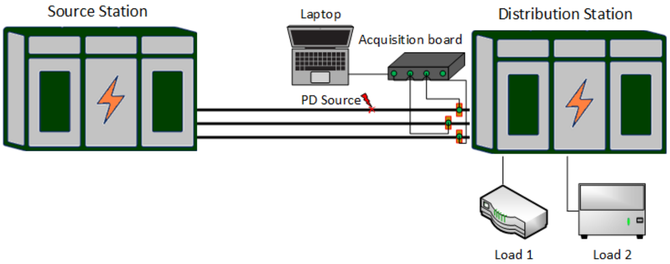

Figure 3. The power distribution network benchmark

Figure 4 shows one of the signals collected from the network. The signals were recorded at $f_s = 5\ MHz$ sample frequency. The analysis of the cables highlights several transient activities in the network. Three different types of transient events can be distinguished, specific to three generating sources.

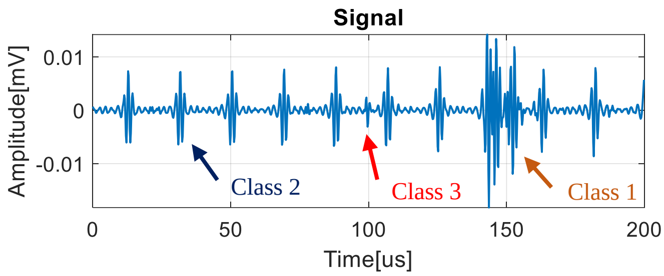

Figure 4. The signal collected distribution network

The choice of the classes is made based on the level of amplitude. To Class 1 we assign the strongest signal in terms of amplitude and with the longest duration. To Class 2 we assign the periodic signal, with a pulse repetition rate of $T = 19\ us$. To Class 3 we assign the signal specific to the partial discharge activity.

In order to evaluate the performance of the detection we compare our approach with one of the most used methods for the detection of transient signals, namely the wavelet transform. Figure 5 shows the results of the detection process using the two methods.

For the phase diagram-based entropy detection, a 10-sample window is slid over the entire duration of the signal to highlight entropy variations. For the tolerance threshold, the value of 0.5 is chosen from the standard deviation of the signal contained in the sliding window.

For the wavelet-based detection, the type of wavelet used in this paper is the Daubechies order 4 family. This family of wavelets corresponded to the best results obtained via many trials.

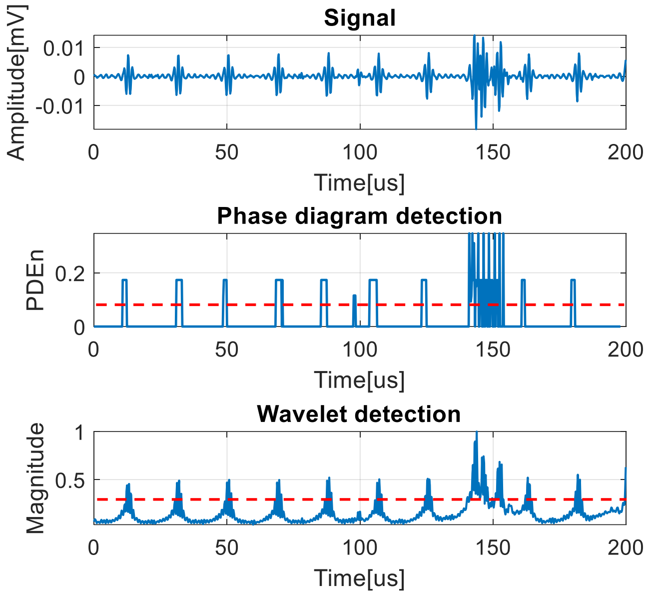

Figure 5. Transient detection results

As can be seen, only the phase diagram-based entropy method could detect the partial discharge signal. In the study of distribution networks, this type of signal is the most important, because it is an indicator of the cable degradation. Failure to detect this will lead to false information about the status of the system.

In Figure 6, we display a signal specific to each class form the created database. As it can be seen the three transient signals have a specific shape.

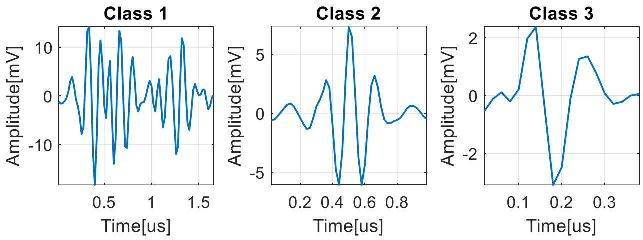

Figure 6. The three classes of transient signals

One of the classical approaches for feature extraction is based on the wavelet transform approach. In our case is a problematic approach, because the impossibility of identifying a suitable scale is a real impediment, as shown in Figure 7. We also encounter problems in choosing the type of wavelet which best corresponds to the analyzed signals.

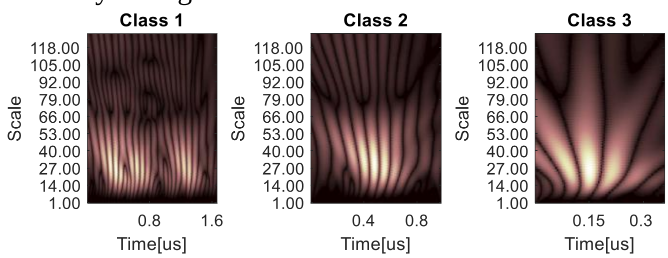

Figure 7. The scalograms of the three transient signals

However, in order to have a reference for the classification algorithm, we use a set of features widely used in such applications extracted based on wavelet transform [6]. We use wavelet decomposition of the transient signal and we extract the detail coefficients at the coarsest scale from the wavelet decomposition structure as shown in Figure 8.

From these coefficients, we extracted statistical information for each level: maximum values, minimum values, the mean values and the standard deviation of the coefficients in each sub-band.

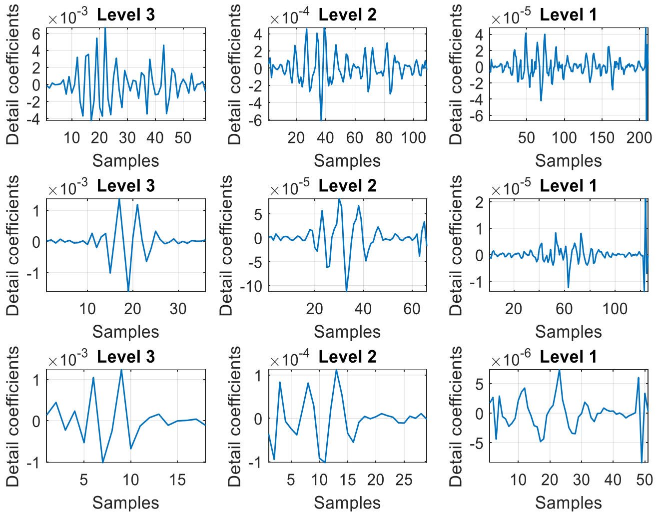

Figure 8. The detail coefficients for three levels for class 1 signal (up), class 2 signal (middle) and class 3 signal (down)

We created a database using several measurements at different times. In this sense, we gathered 750 signals specific to the three classes, each class consisting of 250 signals. Of these signals, 70% were used for training and 30% for the testing part of the classification algorithms. Figure 9-11 shows the performances obtained in the classification process using both approaches. The phase diagram approach results are shown in the left side of the figure and wavelet approach results in right side.

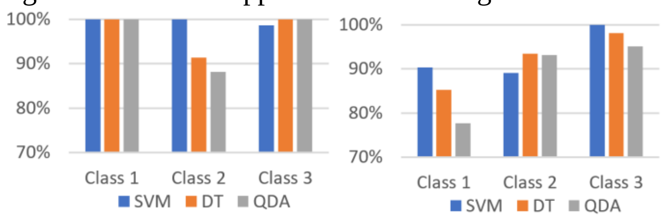

Figure 9. The recall performance

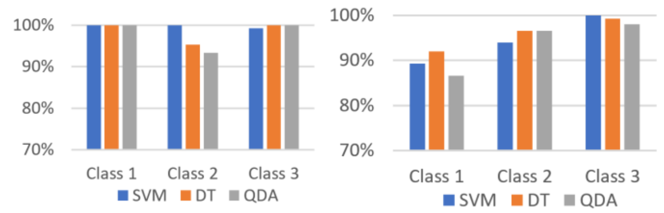

Figure 10. The specificity performance

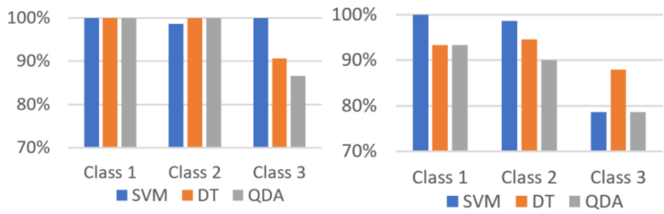

Figure 11. The precision performance

As we can see, all classifiers based on extracted features from phase diagram domain have very good results. In particular, the best performance is obtained by using the SVM classifier. The performance obtained with the phase diagram approach is superior when it comes to recall, specificity and precision. When it comes to the precision parameter, the wavelet approach has the worst results for the partial discharge class.

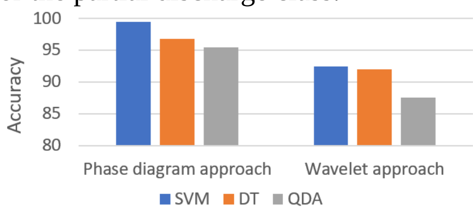

Figure 12. The accuracy performance

Figure 12 shows a comparison in terms of the accuracy of the classification process for the two approaches. The results obtained with our proposed set of features is superior to those obtained with the wavelet statistical features. The best result obtained is 99.5% for the phase diagram approach and the SVM. The worst result obtained is 87.5% for the wavelet approach and the QDA.

4 Conclusions

In this paper we present a new approach based on phase diagram analysis of a power distribution network in order to detect and classify all the transient events. Our approach was compared with an intensively used method, both in detection and classification.

The machine learning algorithms that classify power distribution network signals provide valuable decision support. The best one is SVM, which offers a high classification accuracy followed by the Decision Tree classifier and Quadratic Discriminant Analysis. Our approach brought an increase of up to 8% for the same classifier in the performance of the classification accuracy.

A future research direction will be based on extraction of the best combination of nonlinear features from the phase diagram and identification of new features in a multi-dimensional representation space.

5 References

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