AUTOMATIC CLASSIFICATION OF VOLTAGE EVENTS USING THE SUPPORT VECTOR MACHINE METHOD

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ABSTRACT

Recorded disturbances are often evaluated manually by specialists. However, a lot of time could be saved if a majority of the recorded information could be classified automatically. This paper proposes a novel classification system based on the Support Vector Machine method for automatic classification of seven types of voltage disturbances. The performance of the classification system was investigated using synthetically generated training data and the test data originated from real disturbances recorded in two different power networks. The conducted classification tests showed an overall detection rate of 81.6%, 91.9% and 99.5% respectively.

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INTRODUCTION

The deregulation of the energy market, increasing energy prices and more demanding customers has forced utilities to become even more customer-oriented. As a consequence, high network reliability and good power quality have been increasingly important to keep customers satisfied. Translated into the field of power network monitoring this means an increased demand for more automatic monitoring systems. Today most of the data recorded by monitoring equipment like power quality instruments, protection relays and digital fault recorders, is analyzed manually by specialists. However a lot of time could be saved if common types of events could be classified automatically. Thereby, the specialists could focus on solving more sophisticated power quality problems. This requires the development of robust and reliable classification systems. A number of works based on different methods for detection and classification of voltage events and other power quality disturbances have been published over the past years. Theoretical foundations of voltage events are for example described in [1]. Classification systems based on wavelets are given in [2] and [3] and a statistical maximum-likelihood based method is described in [4]. A comprehensive approach including the description of an expert-system for automatic classification of voltage events is given in [5]. During the past five years another classification method – the Support Vector Machine (SVM) method – has become increasingly popular due to its powerful theoretical and practical characteristics. The SVM method is based on the statistical learning theory and its theoretical foundations – which are beyond the scope of this paper – are described in detail in [6] and [7]. Different applications using the SVM method within the field of power delivery and power systems are for example reported in [8] –[10]. The SVM method is based on supervised training, which means that the SVM classifier must be trained before it is able to classify unseen events. This is achieved by feeding the SVM with a large number of already classified events in terms of extracted features that characterize each event type. From these feature data the SVM calculates the most optimal decision boundary (hyperplane) that separates the classes. Then, if the statistical properties of features extracted from unseen data are similar to the properties of the training data we can expect high accuracy in the classification of unseen data. However, before a classification system based on the SVM method becomes attractive to implement in a commercial system, it must be able to be pre-trained from factory and fed with parameter settings valid globally. It is not realistic that the customer itself is responsible for training of the SVM.

Motivated by this, the aim of this work was i) to propose a classification system using SVMs which are trained on synthetic data and ii) investigate the performance of such a system. Synthetic training data from seven types of voltage events were generated by the power network simulation toolbox SimPowerSystems in Matlab. The test data originated both from real events recorded in two different power networks and from synthetically generated data.

The next section of this paper describes segmentation and feature extraction philosophies. The paper continues with the proposed classification system followed by the results of conducted experiments.

SEGMENTATION AND FEATURE EXTRACTION

A voltage event is a sudden change in the waveform caused by short circuits, overloads or starting of heavy motors etc. [1], [5], [11]. Fig. 1 represents a typical voltage event with its waveform representation and rms signature.

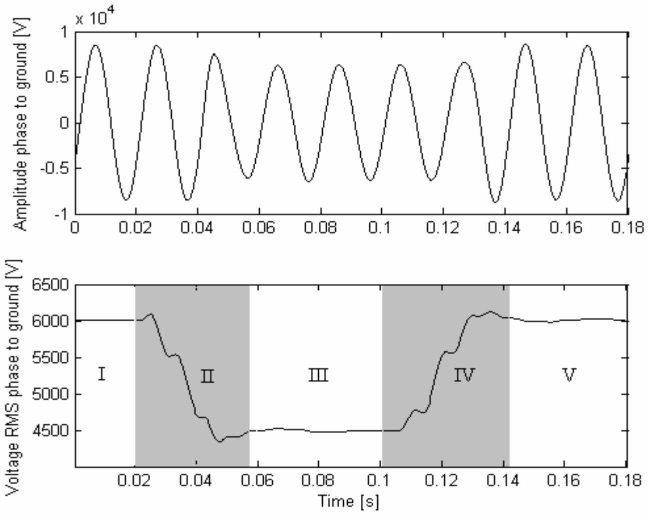

Fig. 1. Voltage event with its waveform (top) and rms signature (bottom). Shadowed areas indicate transition segments.

Different types of events give different patterns in the time- and frequency domain. This implies that a classification system can be achieved if robust features can be identified that describe a particular event.
A voltage event can also be divided into a number of transition segments (shadowed areas in Fig. 1) and event segments. Transition segments correspond to large and sudden changes in the signal and the event segments are the segments in between the transition segments.
The voltage event in Fig. 1 can be divided into five segments. Segments I and V are pre- and post-event segments. Segments II and IV are transition segments and segment III is the event segment. In segment II and IV the signal is non-stationary and hence no robust and reliable features can be extracted from these segments. Also the pre- and post event segments are of limited interest for feature extraction since the event has not started or has passed. Hence the remaining used for feature extraction is segment III where the event is in its most stationary phase. This segment contains information that is normally unique enough to distinguish between different event types. Examples of features used for classification purposes are: rms voltage; harmonic spectrum; symmetrical components and duration [11].

PROPOSED CLASSIFICATION SYSTEM

The proposed system is based on classification in two steps; detection of transition segments in the first step followed by the classification itself in the second step by using individually trained SVMs connected in a binary decision tree configuration. A complete block diagram of the proposed classification system is given in Fig. 2. First, the waveform of the disturbance is fed to pre-processing block (Fig. 2 block (a)) which normalizes the signal to a common format in order to make the information fit to the remaining blocks.

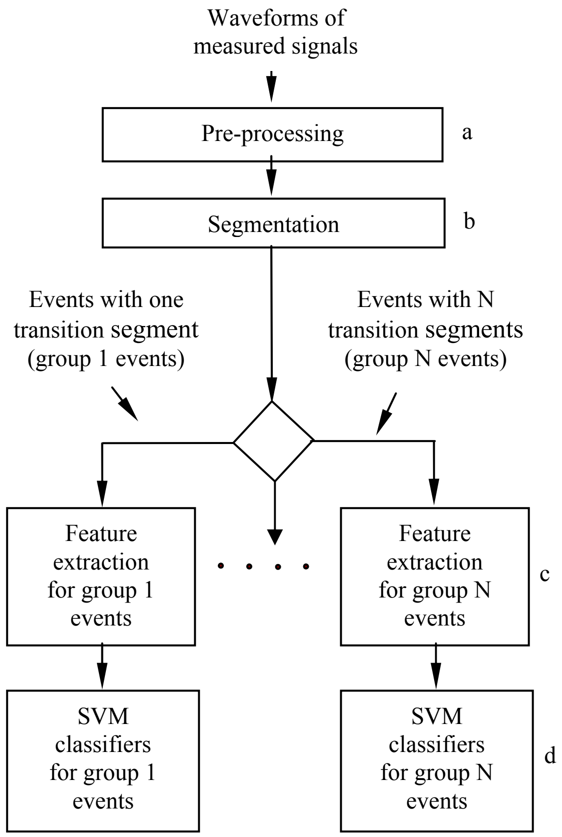

Fig. 2. Block diagram of the proposed classification system

Segmentation
Next (Fig. 2 block (b)) is the segmentation block. As mentioned before, different types of disturbances will cause different number of transition segments. Since the information suitable as a feature is mainly calculated in between the transition segments we need a mechanism that identifies the starting point of each transition segment. Furthermore, as the event types to be classified become more complicated the number of transition segments will increase and the optimal features to be extracted will also probably differ. Dividing the event types into different groups depending on the number of transition segments opens up for flexibility in terms of feature extraction since different feature sets can be defined for each group. Another advantage with grouping the events is that the classification system can easily be extended with new groups without interfering with already existing groups.
A transition segment detector can be designed in different ways; however from an implementation point of view it should be both accurate and fast. A block diagram the detector implemented in the proposed classification system is given in Fig. 3. The input signal to the detector is the three phase rms signature of the disturbance based on one cycle integration time with no overlap. First (Fig. 3 block (a)) the absolute values of the input signal are calculated in order to prepare for the threshold detection. Then (Fig. 3

block (b)) the derivative of the absolute values is calculated in order to identify sudden changes in the signal. Finally, a pre-set threshold level is used for decision whether a sudden change is the starting point of a transition segment or not (Fig. 3 block (c)). Starting points are at those sampling points where the output signal of block (b) crosses the threshold level with positive derivative.

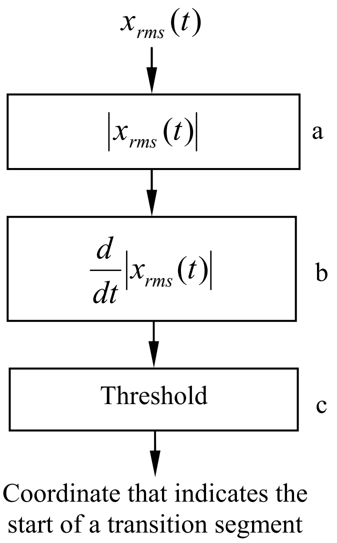

Fig. 3. Block diagram of the transition segment detector.

The output of the threshold block is the coordinates of the detected transition segments in terms of sample points. Finally, the transition segment detector used in this work was designed to identify one- and two transition segments events. However to extend the detector to detect more groups is an easy task (Fig. 2 block (b)). Furthermore, conducted performance tests showed an overall detection rate of 96.8% for the detector.

Feature extraction and classification

Next are the feature extraction and the classification itself (Fig. 2 blocks (c) and (d)). All features are extracted with the beginning immediately after the first transition segment and the following features are extracted: i) 11 rms values per phase equally spread in time. The rms calculation is based on one cycle integration time; ii) The fundamental, second, third, fifth and ninth harmonic voltage magnitude and the THD per phase; (iii) The symmetrical components; (iv) The time duration of the event. This results in a feature vector of 55 components. The feature vector is then fed to trained SVMs which are connected in a binary decision tree configuration. This means the first SVM_1 is trained to classify event type D1, SVM_2 is trained to classify D2 etc. and works as follows: A feature vector from an arbitrary event type enters the classifier (Figure 2 block (d)) related to the group that the disturbance belong to. First, the classifier checks whether the event characterized by the feature vector is of type D1 or not. If it is, the classifier indicates that type D1 is recognized and stops. If not the classifier continues to check against the remaining event types until success. If no match was found the classification failed and the system indicates 'not classified (NC)'.

EXPERIMENTAL TESTS AND RESULTS

Three experiments were obtained in order to investigate the performance of the classification system. In all three experiments were the classifier system trained on 200 synthetic data per event type. All synthetic data were generated from a power network model built in SimPowerSystems toolbox for Matlab. The test data originated from both real data and synthetic data. Table 1 shows the type of events classified by the proposed classification system. In the same table is also the number of available test data that originate from different sources (i.e. from power network A, power network B and from synthetically generated data).

Event type	Event	# of events from Power network A	# of events from Power network B	# of events from synthetic data
D1	Single phase dip	116	418	-
D2	Two phase dip	152	92	-
D3	Three phase dip	113	142	-
D4	Step-change (positive)	-	-	100
D5	Step-change (negative)	-	-	100
D6	Interruption	-	-	100
D7	Transformer energizing	158	-	-

Table 1. Type of events that are classified by the classification system together with the number of available test data per event type.

Event types D1-D3 belong to group 2 events (i.e. two transition segments) and the remaining ones belong to group 1 since they have one transition segment. More detailed information regarding characteristics of events is given in [5]. The first experiment was carried out on test data with two transition segments (i.e. D1-D3) originated from power network A. The second experiment classified the same type of events as in the first experiment but the test data originated from power network B. Finally the third experiment classified event types with one transition segment (i.e. D4-D7). The classification results are given in Tables 2-4.

	D1	D2	D3	NC	Detection rate
D1	93	0	14	9	80.2%
D2	6	133	0	13	87.5%
D3	4	0	85	24	75.2%
Overall detection rate					81.6%

Table 2. Classification results from experiment 1. The voltage events have two transition segments and originate from power network A.

	D1	D2	D3	NC	Detection rate
D1	393	0	2	23	94.0%
D2	3	80	0	9	87.0%
D3	2	0	126	14	88.7%
Overall detection rate					91.9%

Table 3. Classification results from experiment 1. The voltage events have two transition segments and originate from power network B.

	D4	D5	D6	D7	NC	Detection rate
D4	100	0	0	0	0	100%
D5	0	100	0	0	0	100%
D6	0	0	100	0	0	100%
D7	0	0	0	156	2	98.7
Overall detection rate						99.5%

Table 4. Classification result for voltage events with one transition segment and originating from power network A (D7) and from synthetic data (D4-D6).

Each row in Table 2-4 is an event type and the column gives the number of classifications per event type. The number of correct classifications are thus in the diagonal of the tables. The column NC indicates that the classifier failed to classify to any appropriate class.

Analysis of the results

We observe from the test results that the overall detection rates were high for experiment 2 (Table 3) and experiment 3 (Table 4) and slightly lower for experiment 1 (Table 2). The detection rates (100%) for event types D4-D5 was because the testing data and training data originated from the same source (synthetically generated data) and had therefore identical statistical characteristics. For all other event types training data and test data originated from different sources and therefore the detection rates became slightly lower. One way to increase the detection rates could be to refine the model that generates the synthetic data as well as fine-tune the SVM classifier in order to determine more optimal parameter settings. However, fine-tuning the SVM must be taken with care since it is a risk of overfitting resulting in a decreased generalization capability if tuning parameters become 'over-optimized'. Finally we can conclude from the results that chosen features characterize the event types quite accurately.

CONCLUSION

This paper proposes a system for automatic classification of seven common types of voltage events. The system is based on classification in two steps; detection of transition segments in the first step followed by the classification itself in the second step by using individually trained SVMs connected in a binary decision tree configuration. Furthermore the SVMs were trained on pure synthetic data and test data was from real voltage events recorded from two different power networks and from synthetic data. The performance tests showed that such classification structure offers both flexibility and high overall detection rates. It is also easy to maintain and is flexible in terms of adding new event types to the classification system. A further work is to refine the model used for generation of synthetic data in order to include more event types as well as an investigation whether other types of feature can be extracted that characterizes event types even better than the ones proposed in this work.

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