An Experimental Study on Electrical Signature Identification of Non-Intrusive Load Monitoring (NILM) Systems

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Abstract. Electrical load disambiguation for end-use recognition in the residential sector has become an area of study of its own right. Several works have shown that individual loads can be detected (and separated) from sampling of the power at a single point (e.g. the electrical service entrance for the house) using a non-intrusive load monitoring (NILM) approach. This work presents the development of an algorithm for electrical feature extraction and pattern recognition, capable of determining the individual consumption of each device from the aggregate electric signal of the home. Namely, the idea consists of analyzing the electrical signal and identifying the unique patterns that occur whenever a device is turned on or off by applying signal processing techniques. We further describe our technique for distinguishing loads by matching different signal parameters (step-changes in active and reactive powers and power factor) to known patterns. Computational experiments show the effectiveness of the proposed approach.

Keywords: feature extraction and classification, k-nearest neighbors, non-intrusive load monitoring, steady-state signatures, support vector machines.

1 Introduction

"Your TV set has just been switched on." This may very well be a sms or email message received on your mobile phone in the near future. For energy monitoring, health care or home automation, concepts like Smart Grids or in-Home Activity Tracking are a recent and important trend. In that context, an accurate and inconspicuous identification and monitoring of electrical appliances consumptions are required. Moreover, such monitoring system should be inconspicuous.

Currently, the available solutions for load consumption monitoring are smart meters and individual meters. The first ones supply aggregated consumption information without identifying which devices are on. To overcome this limitation, to use an individual meter for each appliance in the house would be sufficient. However, this would turn out to be an expensive solution for a household.

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A non-intrusive load monitoring system (NILM) fulfills all the requirements imposed by the Smart Grids and in-Home Activity Tracking challenges at virtually no cost. NILM is a viable solution for monitoring individual electrical loads: a single device is used to monitor the electrical system and to identify the electric load related to each appliance, without increasing the marginal cost of electricity or needing extra sub-measurements. Nevertheless, only with the present low-cost sensing devices, its full potential could be achieved.

The central dominant goal of a NILM system is to identify which are the appliances switched on at a certain moment in time. The signals from the aggregate consumption of an electrical network are acquired and electrical features are extracted, in order to identify which devices are switched on. Each appliance has a particular electrical signature which must be recognized in order to perform an accurate identification. This paper presents a study for its electrical distinctive characterization. The proposed signature is based on the analysis and recognition of steady-states occurring in the active and reactive power signals and the power factor measurements. To evaluate this approach, data from a set of appliances were collected and classified using a Support Vector Machine (SVM) method and the K-Nearest Neighbors (K-NN) technique. The results of the computational experiments indicate that an accurate identification of the devices can be, in fact, accomplished.

This paper is organized as follows: the next section presents a brief overview of the related literature. Section 3 describes the concepts behind the NILM system and the electrical signature problem. It proceeds describing the developments associated to the step-changes analysis in an electrical signal and the features that can be used as distinctive marks, introducing a result that enables an algorithm for steady-state recognition. Finally, Section 4 describes the experimental setup, where the new algorithm for feature extraction was used followed by SVM and K-NN classification algorithms and the classification results. Conclusions and future work are addressed in Section 5.

2 Related Literature

To identify the devices switched on at a certain moment in time, a non-intrusive load monitoring system uses only the voltage and current signals of the aggregated electrical consumption using sampling of power at a single point. The concept was independently introduced by Hart [1] (then working at the Electric Power Research Institute) and by Sultamen (Electricité de France) [2]. Over the last decades, due to the pressing environmental and economic issues, the interest in this area has increased, being the focus of PhD theses as [3]. In 1996, the first NILM system was commercialized by the company Enetics, Inc..

The main steps in a non-intrusive load monitoring system are: a) the acquisition of electrical signals, b) extraction of the important events and/or characteristics and c) production of a classifier of electrical events (see Figure 1). To perform the identification, the definition of an electrical device ID is needed. Therefore, the electrical signatures are the basis of any NILM system [1]. These are defined as a set of parameters that can be measured from the total load. For

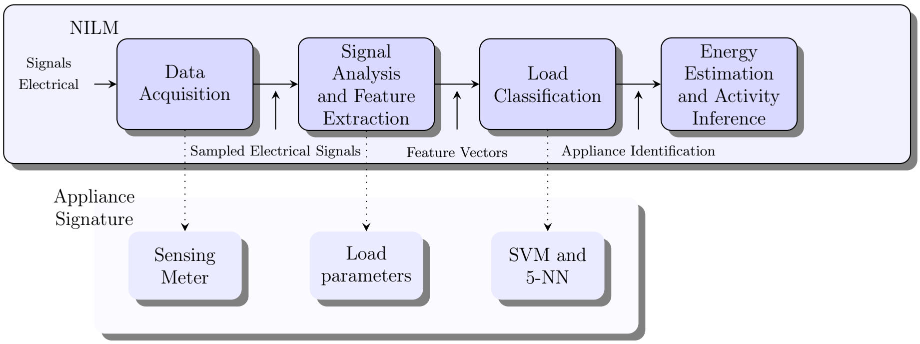

Fig. 1. A NILM high-level system and approach for the device signature study

a NILM system, usually these parameters result, either from signal steady-states or are obtained by sensing transients.

A steady-state signature is deduced from the difference between two steady-states in a signal consisting of a stable set of consecutive samples, whose values are within a given threshold. The basic steady-state identifies the turning on and off of an electrical device connected to the network. To achieve this steady-state detection is much less demanding that what is required for capture and analysis of the transients. Other advantages are the fact that we can recognize turning off states and when two appliances are on at the same time, it is possible to analyze its signature sum. Hence, they were used by Hart for the prototype presented in [1]. Since then, steady-state signatures were used by several authors, mainly for residential load monitoring systems. In [4,5,6] discrete changes on the active and reactive power are analyzed while [7] only uses the active power. Nevertheless, some limitations can be pointed out, as the impossibility to distinguish two different appliances with the same steady-state signature. The small sampling rate can be also considered a disadvantage: sequences of turning on loads during a period smaller than the sampling rate are not possible to identify. To overcome these limitations, the transient signatures, which result from the noise in the electrical signal caused by the switching on/off of an appliance, can be used. Yet, for transient identification a high sampling rate is needed.

Since both steady-state and transient signatures have their own limitations, considering both for a study of a joint ID is interesting. Such was considered by Chang *et al.* in [8], very recently. The following section describes our approach.

3 Steady-States (StS) Recognition: Proposed Approach

Electrical signatures are the main component of a NILM system. Usually individual load identification uses transients and steady-states (StS) signatures. Due to the high sampling frequency needed for the first, residential NILM systems typically use the latter. However, one of the drawbacks of StS is the fact that distinct appliances can present very similar signatures. In fact, using only the step-changes in the active power, little information is provided which may lead to an incorrect identification. This paper studies the incorporation of further signal information in order to enrich the electric profile of each appliance, namely from the reactive power signal and power factor measurements.

The first step in the definition of a StS is the recognition of a stable value sequence in the sampled signal. In [9] the authors presented a method for the identification of a steady-state signature based in ratios between rectangular areas defined by the successive states values. The method allows for the identification of a complete steady-state, i.e., when does the StS begin and when does it end. The approach is based on the difference between the rectangular area produced by aggregating a new sample and the one already defined by the previous values in the stable state. However, keeping only the extreme values already in the stable state and testing the new sample value against the previous ones can simplify this approach. This improvement is described in the following. The new result was implemented in order to extract features from power signals: the active, reactive power and power factor signals.

3.1 A Rule for Steady-States Recognition

A sequence of consecutive samples is regarded as a stable-state if the difference between any two samples of the sequence does not exceed a given tolerance value. The minimum number of consecutive samples needed to identify a stable state depends on the sampling frequency: when this is low, a small number of samples is enough, otherwise a bigger number is needed. For instance, with a sampling frequency of 1Hz, the minimum number of samples can be defined as three, which is the one used in [1], where other methods for steady-states recognition are proposed (namely, filtering, differentiating and peak detection).

Consider a sequence of n consecutive sampling values, $Y = \{y_i, i = 1, \ldots, n\}$ already identified as a steady-state. By definition, $|y_i - y_j| \leq \epsilon \ \ \forall i, j = 1, \ldots, n$ and $i \neq j$, where $\epsilon > 0$ is the defined tolerance. Let $y_M = \max\{y_i\}$ and $y_m = \min\{y_i\}, \forall i = l, \ldots, n$ be the maximum and minimum values, respectively, for Y, and that $y_r\,(r = n+1)$ is the next sample value. Next we prove that y_r maintains the stable behavior of Y only for a limited range of values.

Theorem 1. *In the conditions above, the* $n+1$ *consecutive values form a steady-state iff* $y_M - \epsilon \leq y_r \leq y_m + \epsilon$, *i.e.,*

$$|y_i - y_j| \leq \epsilon \ \ , \forall i, j = 1, \ldots, n+1 \ .$$

Proof. In fact, if $y_m \leq y_r \leq y_M$, then $|yi - yr| \leq |y_m - y_M| \leq \epsilon$, for all $i = 1, \ldots, n$.

Consider now that, $y_M < y_r \leq y_m + \epsilon$. For any $y_i \in [y_m, y_M]$, $i = 1, \ldots, n$, we have,

$$|y_i - y_r| \leq |y_m - y_r| \leq |y_m - y_m + \epsilon| = \epsilon.$$

Thus, the sequence of the $n+1$ values, $y_i, i = 1, \ldots, n+1$, forms a steady-state with a new maximum value: $y_M = y_{n+1} = y_r$.

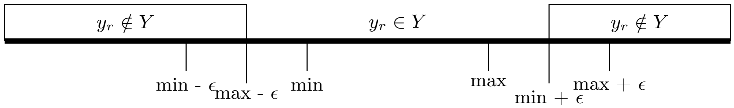

Fig. 2. Range of acceptable values for inserting y_r in a previous identified StS

If we assume that $y_M - \epsilon < y_r \leq y_m$, then, using a similar reasoning, we prove that $y_r = y_n + 1$ maintains the value stability of the state, and the steady sequence $y_i, i = 1, \ldots, n+1$ as a new minimum value: $y_m = y_{n+1} = y_r$.

In all other cases, that is, $y_r < y_M - \epsilon$ or $y_r > y_m + \epsilon$, y_r does not belong to the steady-state Y since it goes above the maximum tolerance value.

Let us consider $y_r < y_M - \epsilon$. Therefore, (Figure 2), $y_r < y_M - \epsilon \leq y_m \leq y_i \leq y_M$. Hence, $|y_r - y_M| > |y_M - \epsilon - y_M| = \epsilon$.

The remaining case can be proved similarly. □

In conclusion, a consecutive sample point y_r belongs to the steady-state immediately before if $y_M - \epsilon \leq y_r \leq y_m + \epsilon$ such that y_m and y_M are the minimum and the maximum values in the state. Otherwise, the previous sample is considered as the end of the steady-state. When all the samples of the signal have been tested for steady-states identification, the method ends by computing the differences between consecutive states and a feature vector is built.

3.2 Defining a Signature

As it was mentioned, the signature composed only by the changes in the active power provides little information for an accurate appliance recognition. The active power (also known as real power) represents the power that is being consumed by the appliances. However, two other electrical parameters can also be used: the apparent power and the reactive power.

In a simple alternating current circuit, current and voltage are sinusoidal waves that, according to the load in the circuit, can be in phase or not. For a resistive load the two curves will be in phase and multiplying their values, at each instant, produces a positive result. This indicates that only real power is transferred in the circuit. In case of a reactive load, current and voltage will be ninety degrees out of phase, which suggests that only reactive energy exists. In practice, resistance, inductance and capacitance loads will occur, so both real and reactive power will exist. At last, the product of the root-mean-square voltage values and current values represents the apparent power. The real, the reactive and the apparent powers are measured in Watts, volt-amperes reactive (VAR) and volt-ampere (VA), respectively. See an example for a LCD 20" in Figure 3.

The relation between the three parameters is given by $S = P^2 + Q^2$ where S, P and Q represent the apparent power, the active and the reactive powers, severally. The apparent and the real powers are also connected by the power factor. The latter constitutes an efficiency measure of a power distribution system and is computed as the ratio between real power and apparent power in a circuit. It varies between 0, for the purely reactive load, and 1, in case of resistive load.

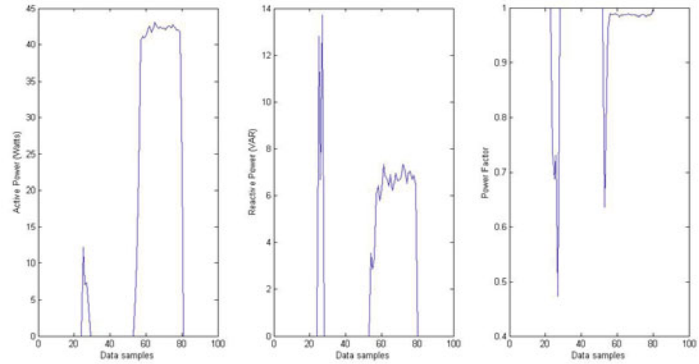

Fig. 3. Active, reactive power and power factor for a LCD of 20”

4 Computational Experiments

4.1 Data Collection and Feature Extraction

The data, namely, the active power, voltage, current and power factor signals were acquired using a sensing meter prototype provided by ISA-Intelligent Sensing Anywhere [10]. However, for monitoring several parameters this prototype has a severe limitation for monitoring several parameters: only one parameter value can be supplied at each point in time. This implies the existence of a delay between the values of different parameter types. Another shortcoming is related with the fact that errors in the measurements can eventually occur, resulting in the failure of deliverance of the expected value.

To evaluate the effectiveness of the composed signatures, data from several electrical appliances were acquired, presenting 100 milliseconds delay between the several parameters data samples. The parameter data types are: active power, current, voltage and power factor. Therefore, the frequency between each sample data type was of 400 milliseconds.

The data for each appliance is collected in four steps: a) during 10 to 15 seconds, signal samples are acquired without the appliance being plugged to the socket; b) the device is plugged in and samples are collected for 15 seconds; c) the apparatus is switched on and it runs for a period of 1 minute[1] and d) the appliance is switched off after, a 15 seconds sampling period occurs. For each one of the appliances the process was repeated fifty times. The devices chosen for the experiments were: a microwave, a coffee machine, a toaster, an incandescent lamp and two LCD’s (from the same manufacturer but different models).

In order to proceed with StS identification, Theorem 1 from Section 3 was implemented obtaining a recognition algorithm for processing the collected signals. For each one of the different appliances is possible to identify three steady

[1] For the coffee machine, the running time is less than a minute corresponding to the time needed for an expresso.

-states: a stable signal before the switch on of any of the devices; one other StS corresponding to the appliances' operation phase and a last one occurring after switching off. In fact, one LCD in particular presented four different states: it was possible to identify the steady-state related to the standby mode. For any of the four measured parameters, the difference between the identified steady-states was calculated such that a positive/negative value was associated to the switch on/off, respectively.

4.2 Feature Classification Methods and Multi-evaluation Metrics

To assess the performance of the composed signature, the features for the six class problem associated to the switch on were normalized. Classification was performed using Support Vector Machines (SVM) and 5-Nearest Neighbors (5-NN) methods. The SVM is developed for solving binary classification problems, nevertheless, in the related literature two main approaches to solve a multi-classification problem can be found: one-against-all and one-against-one [11]. In the first technique, a binary problem is defined by using each class against the remain ones. This implies that m binary classifiers are applied ($m > 2$, represents the number of different classes). In the other one, $\frac{m(m-1)}{2}$ binary classifiers are employed , comparing each pair of classes. For a given sample, a voting is carried out among the classifiers and the class obtaining the maximum number of votes is assigned to it. This last approach is supplied in LIBSVM [12], a package available to implement SVM classification. A similar package is SVMLight [13] whereas this uses the multi-class formulation described in [14] and the algorithm based on Structural SVMs [15] to perform multi-class classification.

To perform the classification of the composed electrical signatures the one-against-all tactic was implemented using SVM and 5-NN methods. For the SVM, the linear kernel and the radial basis function (RBF) with scaling factor $\sigma = 1$ were used. For the multi-class classification, the SVMLight available implementation was chosen. A 3-fold cross validation was employed to the data set in order to evaluate the tests performance. The results are reported in Table 1. To assess the tests performance accuracies, macro-average and micro-average were used. On the latter, the F-measure performance is calculated in two different ways: a) the mean value of every F-scores computed for each binary problem (macro-average); b) the global F-measure, calculated from a global confusion matrix computed from the sum of all the confusion matrices related to the binary problems (micro-average). The F-score is an evaluation of a test's accuracy which combines the recall (R) and the precision (P) values of a test. The general formula is $F_\beta = \left(1+\beta^2\right)\frac{P \cdot R}{\beta^2 \cdot (P+R)}$. In this paper $\beta = 1$ is used, i.e., F_β is the harmonic mean of the precision and recall. In order to evaluate a binary decision task, we first define a contingency matrix representing the possible outcomes of the classification, namely the true positives (TP - positive examples classified as positive), the True Negatives (TN - negative examples classified as negative), the False Positives (FP - negative examples classified as positive) and the False Negative (FN - positive samples classified as negative). The recall is defined as $\frac{TP}{TP+FN}$ and the precision is $\frac{TP}{TP+FP}$.

Table 1. The mean accuracies and F-scores values for the tests performed using one-against-all SVM (linear and RBF kernels) and one-against-all 5-NN

	SVM one-against-all				5-NN one-against-all	
	Linear		RBF			
	F1 (%)	Acc. (%)	F1 (%)	Acc.	F1(%)	Acc. (%)
Incandescent bulb	95.2 ± 1.7	98.1 ± 0.0	97.1 ± 2.8	98.5 ± 0.1	99.4 ± 1.1	99.7 ± 0.6
Lcd 22	*n.d.*	83.2 ± 0.1	49.1 ± 21.2	89.6 ± 1.2	99.4 ± 0.0	99.0 ± 0.0
Lcd 32	96.0 ± 0.0	99.3 ± 0.5	95.9 ± 1.9	98.4 ± 0.4	96.0 ± 4.6	97.9 ± 0.8
Microwave	96.7 ± 1.6	98.7 ± 0.3	97.9 ± 3.6	99.4 ± 0.5	96.8 ± 5.6	98.1 ± 1.0
Toaster	97.2 ± 2.8	99.2 ± 0.3	98.2 ± 3.2	99.8 ± 0.4	100.0 ± 0.0	100.0 ± 0.0
Coffee Machine	*n.d.*	99.2 ± 0.3	86.9 ± 4.9	99.8 ± 0.9	98.0 ± 1.2	100.0 ± 0.0
Average	*n.d.*	96.3 ± 6.4	87.5 ± 19.3	97.5 ± 4.1	98.3 ± 1.6	99.1 ± 0.9
Micro-average	76.8		90.0		98.9	

4.3 Evaluation Results

For each one of the tests one-against-all (SVM and 5-NN) the F-scores and mean accuracies are illustrated in Table 1. Towards a global evaluation, the macro-averages (mean values of the F-scores), micro-averages and mean accuracies are also presented.

As it can be observed, the one-against-all approaches performance is quite effective. In average, we have an accuracy around 96% for the Linear SVM, 97% for the RBF SVM and 99% for the 5-NN. Rather, the multi-class method presents very low accuracy values: around 40%. Micro and macro averages are measures only applied to binary problems. Therefore, in order to compare the SVMLight multi-class test results, micro-averages were computed for the obtained classifications. For that, the results of the six binary problems one-against-all were determined based on the multi-class classification results as well as the respective confusion matrices and F-measures. With respect to the accuracy, the results for the linear and RBF kernels were of $40.57 \pm 8.55\%$ and $40.57 \pm 8.55\%$, respectively. The micro average values were computed as previously described resulting in a value of 40.67% for both kernels.

Notice that accuracy values provide only global information: high accuracy is not necessarily related to a precise identification of true positives. In fact, micro-averages supply particular information related to the samples classified as true where the multi-class classification scored badly. This may result from the fact that, in the test data sets associated to binary problems used, the number of samples that belong to the class in test is smaller than the remaining ones. Therefore, the number for TN probably will be greater than the number of samples labeled as TP. Actually, cases were no TP are labelled may occur and then the F-score cannot be defined. In our case, for the multi-class SVM the accuracy is low following the respective micro-average while for the remaining tests, both performance metrics are high.

For both one-against-all methods, the good performance indicates that the composed signature can be an accurate description for each one of the appliances in the database. Nevertheless, these findings may be related to the fact that the number of electrical appliances used is still very small. Moreover, all of these appliances have distinct loads with the exception of the LCD devices. Taking a closer look to the multi-class classification tests, the incandescent bulb was misclassified as the toaster and the LCD's and the coffee machine as the microwave. To overcome this limitation, other methods for multi-class classification can be studied, like the neural networks, a hybrid approach or even more features can be added to signature, for instance, information related to the transient signals.

5 Conclusions and Future Work

The project for the deployment of Smart Energy Grids requires automatic solutions for the identification of electrical appliances. The issue of implementing in-home activity modeling and recognition relies in cheap and inconspicuous recognition systems. The most suitable solution for both problems is a system NILM. Moreover, such a scheme can also be used as a household electrical management system. For implementing a NILM system, based in the sampling of power at a single point, feature extraction techniques and classification methods are needed to detect and to separate individual loads. This can only be accomplished through the definition of an effective electrical signature.

This work begins by presenting an approach to perform the identification of the step-changes of the electrical signal. This strategy was applied to the analysis of the signals acquired for a given data set of appliances, in order to extract features for the definition of an electrical ID for each device. The features use the step-changes in active and reactive powers and power factor. In order to evaluate the proposed approach, we used SVM and 5-NN classification one-against-all tests as well as SVM multi-class classification tests. The results show that the simplest methods are able to accurately tackle the recognition issue.

This work constitutes an experimental test case study for a composed steady-state signature. Future work will acquire more steady-states IDs in order to increase the data set and perform more ambitious tests. The incorporation of the transient pattern associated with each appliance in the signature is under study. The first problem to overcome is the very high sampling frequency required to obtain transients, not easy to achieve unless a specific sensing device is developed. Another research question that needs to be answered addresses the consumption variations of a device operating in its intermediate state. The proper identification of this variation with the respective device can bring an added-valued for the analysis of the information provided by a NILM system.

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References

1. Hart, G.W.: Nonintrusive appliance load monitoring. Proc. of the IEEE 80, 1870–1891 (1992)
2. Sultanem, F.: Using appliance signatures for monitoring residential loads at meter panel level. IEEE Transactions on Power Delivery 6, 1380–1385 (1991)
3. Leeb, S.B.: A conjoint pattern recognition approach to nonintrusive load monitoring. PhD thesis, Massachusetts Institute of Technology (1993)
4. Cole, A., Albicki, A.: Data extraction for effective non-intrusive identification of residential power loads. In: Instrumentation and Measurement Technology Conf., IMTC 1998. Conf. Proc. IEEE, vol. 2, pp. 812–815 (1998)
5. Cole, A., Albicki, A.: Algorithm for non intrusive identification of residential appliances. In: Proc. of the 1998 IEEE Intl. Symposium on Circuits and Systems, ISCAS 1998, vol. 3, pp. 338–341 (1998)
6. Berges, M., Goldman, E., Matthews, H.S., Soibelman, L.: Learning systems for electric consumption of buildings. In: ASCE Intl. Workshop on Computing in Civil Engineering, Austin, Texas (2009)
7. Bijker, A., Xia, X., Zhang, J.: Active power residential non-intrusive appliance load monitoring system. In: AFRICON 2009, pp. 1–6 (2009)
8. Chang, H.H., Lin, C.L., Lee, J.K.: Load identification in nonintrusive load monitoring using steady-state and turn-on transient energy algorithms. In: 2010 14th Intl. Conf. on Computer Supported Cooperative Work in Design, pp. 27–32 (2010)
9. Figueiredo, M., de Almeida, A., Ribeiro, B., Martins, A.: Extracting features from an electrical signal of a non-intrusive load monitoring system. In: Fyfe, C., Tino, P., Charles, D., Garcia-Osorio, C., Yin, H. (eds.) IDEAL 2010. LNCS, vol. 6283, pp. 210–217. Springer, Heidelberg (2010)
10. ISA Intelligent Sensing Anywhere, S.: Isa intelligent sensing anywhere (2009), `http://www.isasensing.com/` [Online; accessed 18-October-2010].
11. Fauvel, M., Chanussot, J., Benediktsson, J.: Evaluation of kernels for multiclass classification of hyperspectral remote sensing data. In: Proc. of IEEE Intl. Conf. on Acoustics, Speech, and Signal Processing, vol. 2, pp. 813–816. IEEE, Los Alamitos (2006)
12. Chang, C.C., Lin, C.J.: LIBSVM: a library for support vector machines (2001), Software available at `http://www.csie.ntu.edu.tw/~cjlin/libsvm`
13. Joachims, T.: Making large-scale svm learning practical. In: Schölkopf, B., Burges, C., Smola, A. (eds.) Advances in Kernel Methods - Support Vector Learning. MIT-Press, Cambridge (1999)
14. Crammer, K., Singer, Y., Cristianini, N., Shawe-taylor, J., Williamson, B.: On the algorithmic implementation of multiclass kernel-based vector machines. Journal of Machine Learning Research 2, 265–292 (2001)
15. Tsochantaridis, I., Hofmann, T., Joachims, T., Altun, Y.: Support vector machine learning for interdependent and structured output spaces. In: ICML 2004: Proc. of the twenty-first Intl. Conf. on Machine learning, p. 104. ACM, New York (2004)