Electrical Appliances Identification and Clustering using Novel Turn-on Transient Features

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Abstract: Due to the growing need for a detailed consumption information in the context of energy efficiency, different energy disaggregation, also called Non-Intrusive Load Monitoring (NILM), methods have been proposed. These methods may be subdivided into supervised and unsupervised approaches. Electrical appliance classification is one of the tasks a NILM system should perform. Depending on the chosen NILM approach, the classification task consists of either identifying the appliances or grouping them into clusters. In this paper, we present the results of appliance identification and clustering using the Controlled On/Off Loads Library (COOLL) dataset. We use novel features extracted from a recently proposed turn-on transient current model for both identification and clustering. The results show that the amplitude-related features of this model are the most suited for appliance identification (giving a classification rate (CR) of 98.57%) whereas the envelope-related features are the most adapted for appliance clustering.

1 INTRODUCTION

In the context of energy efficiency, Non-Intrusive Load Monitoring (NILM) approaches aim to provide, in a non-intrusive manner, detailed energy consumption. This detailed information helps increase the awareness about energy consumption behavior of consumers along with other benefits. The benefits of such consumption feedback were discussed in several previous works (Fischer, 2008) (Darby, 2010) (Hancke et al., 2012). The interest in this field pioneered by Hart's work during the mid-1980s (Hart, 1985) (Hart, 1989) (Hart, 1992) started to grow rapidly these past few years starting around the year 2010 (Parson, 2016).

Along with the appliance working periods and the consumed energy, appliance class is a very important output of a NILM system. NILM approaches may be classified using different criteria (Zeifman and Roth, 2011). One possible taxonomy is subdividing the approaches into supervised and unsupervised (Zoha et al., 2012) depending on the chosen strategy for appliance-related information inference.

Supervised NILM approaches are the most commonly found in the literature. These approaches need labeled data for the training of the appliance classifier. A major drawback of these approaches is the non robustness with respect to unseen appliances especially when the training dataset size is small.

To alleviate this problem, an alternative is the use of unsupervised NILM approaches (Bonfigli et al., 2015). These approaches try to solve the NILM problem (i.e. to obtain detailed consumption information) without *a priori* information (Zoha et al., 2012). Several challenges face theses approaches (Goncalves et al., 2011). Nevertheless, they are more adapted to solve the NILM problem in real case scenarios where unseen and different appliance types may be encountered.

A mid-way approach that is worth mentioning is the semi-supervised approach (Barsim and Yang, 2015) (Gillis and Morsi, 2016). This approach is a mix between both supervised and unsupervised approaches where a training step (supervised) helps in the prediction of the appliance type using a unsupervised approach.

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According to the above-mentioned approaches, electrical appliances classification problem can be subdivided into two sub-problems: identification and clustering. Identification is a *supervised* problem. Having a set of data (called training dataset), labeled with appliance type, the task is to *identify* the class (appliance type) to which a new appliance belongs. Clustering, on the other hand, is an *unsupervised* problem. Having an unlabeled set of data (the appliance types are unknown), the task is to find clusters, or groups, that define classes corresponding to appliances with common characteristics.

The aim of this paper is to present the results of both appliance identification and clustering using novel features extracted from a recently proposed turn-on transient current model (Nait Meziane et al., 2015). Conclusions on the usefulness of these features for both tasks are drawn.

The paper is organized as follows: section 2 describes the features used for appliance classification and the corresponding turn-on transient current model. This section also discusses the relevance of these features for the classification task and motivates the use of some chosen features instead of all the estimated ones. Section 3 presents the identification and clustering results. It also gives a brief description of the dataset used. The paper is concluded in section 4 where conclusions are drawn and some possible tracks for the improvement of the presented work are given.

2 TURN-ON TRANSIENT FEATURES

2.1 Turn-on Transient Model

The work presented in this paper is based on modeling the turn-on transient current signal using a recently proposed parametric mathematical model (Nait Meziane et al., 2015). The parameters of this model are then estimated and used as features for electrical appliances classification. One of the goals of this work is to assess the usefulness of these model parameters for classification. For simplicity, we suppose herein stationary amplitudes and phases in contrast to the more general model presented in (Nait Meziane et al., 2015).

According to this mathematical model, the turn-on transient current is an amplitude modulated sum-of-sinusoids that can be written as:

$$s(t) = e(t)s_s(t) + w(t), \tag{1}$$

where

$$s_s(t) = \sum_{i=1}^{d} A_i \cos(2\pi f_i t + \phi_i), \tag{2}$$

$$e(t) = \begin{cases} A_0 e^{\mathbf{b}^T \mathbf{t}} + 1 & \text{, if } t \geq 0 \\ 0 & \text{, otherwise} \end{cases} \tag{3}$$

and $w(t)$ is an additive white Gaussian noise (AWGN)[1]. $s_s(t)$ is a sum of undamped sinusoids such that A_i (≥ 0), $\phi_i \in [-\pi, \pi]$ and f_i are their amplitudes, phases and frequencies, respectively. The number of sinusoids d is supposed fixed and known *a priori*. The sinusoids frequencies are also known and are odd order-harmonics such that $f_i = (2i-1)f_0$, $i = 1, \ldots, d$ ($f_0 = 50$ Hz is the fundamental frequency also called mains frequency).

The amplitude modulation, or envelope, $e(t)$ describes the current amplitude variation from the turn-on until reaching the steady-state phase. $\mathbf{b} = [b_1, \ldots, b_n]^T$ is a vector of n polynomial coefficients and $\mathbf{t} = [t, \ldots, t^n]^T$ is a time vector such that $\mathbf{b}^T \mathbf{t}$ is a n^{th} degree polynomial allowing to tune the model amplitude variation to the real signal amplitude variation. A_0 is a parameter that specifies the initial amplitude of $e(t)$ i.e. when $t = 0$, $e(t = 0) = A_0 + 1$.

For the work presented in this paper, and after different tests on real signals, we chose $d = 5$ harmonics and a polynomial order $n = 3$. These values provide a good fit between the model and real signals.

All the model parameters can be put inside one vector $\boldsymbol{\theta} = [A_0, b_1, b_2, b_3, A_1, A_2, A_3, A_4, A_5, \phi_1, \phi_2, \phi_3, \phi_4, \phi_5]^T$. The used algorithm for the estimation of $\boldsymbol{\theta}$ is based on a nonlinear least-squares optimization algorithm called trust-region reflective (Coleman and Li, 1994). A detailed description of the model, the theoretical limits of the variance of the estimated parameters (Cramér-Rao Bounds) and the estimation algorithm will be considered in an upcoming work.

2.2 Relevance of the Turn-on Transient Features for Classification

In this sub-section we will analyze the features in order to select the most relevant ones for appliance classification amongst the elements of the $\boldsymbol{\theta}$ vector. First, we do a pre-analysis for these features to get an insight and conclude on their usefulness for appliance classification. Then, we compare the conclusions with the results of a feature selection algorithm.

[1]This assumption is verified for the measurements of the COOLL as shown in (Nait Meziane et al., 2016) where the measurement system used to create COOLL is described.

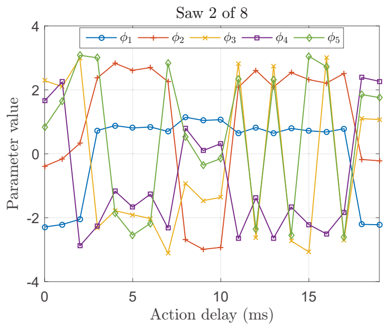


Figure 1: An example showing the instability of the estimated phase features ϕ_i from measurements of the same appliance: "an electric saw" from the COOLL dataset. The x-axis represent different action delays (0 to 19 ms) i.e. different measurements of the same appliance. Between action delays the mains frequency is likely to slightly vary which affects the phase estimates.

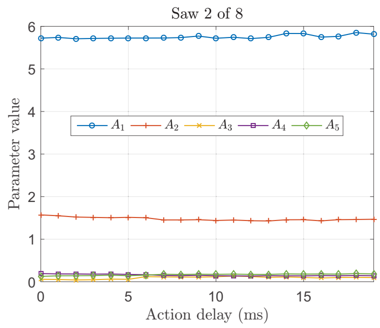


Figure 2: An example showing the stability of the estimated amplitude features A_i from measurements of the same appliance: "an electric saw" from the COOLL dataset. The x-axis represent different action delays (0 to 19 ms) i.e. different measurements of the same appliance.

Note that one of the main desired properties that define the usefulness for us is the low variability of the feature value for different measurement instances of the same appliance. Hence, we will give a special focus for this property in the sequel.

2.2.1 Pre-analysis of Features for Selection

Phase-related Features. The phase features $\phi_i, i = 1,\ldots,d$ specify the position (in radians) of the sinusoids $\cos(2\phi f_i t + \phi_i)$ at $t = 0$ with respect to the 2π time-cycle. These features are subject to an ambiguity in their definition. For example, the solution of $\cos(\phi_i) = 0$ is $\phi_i = 2\pi m$ with m being an integer number. This means that the solution is not unique and a set of solutions exists. This problem can be alleviated by only keeping the solutions that are in the range $[-\pi, \pi]$. Still, we will end up having two solutions to choose from (for example, the solutions of $\cos(\phi_i) = \frac{1}{2}$ are $\frac{\pi}{3}$ and $-\frac{\pi}{3}$).

Moreover, when working on real signals, the slightest nonstationarity encountered in real signals (especially the mains frequency very small variations that are usually less than 0.5 % of 50 Hz) seemed to affect negatively the estimated phase values (Figure 1).

For all the above-mentioned reasons, we chose not to use the phase features for the classification.

Amplitude-related Features. Unlike the phase features, the amplitude features $A_i, i = 1,\ldots,d$, representing the amplitudes of the sinusoids (Eq. (2)), are much more stable (Figure 2). The estimated valued also show a variability between the estimated amplitudes of different appliances, even for appliances of the same type. This suggests that these features are a good candidate for appliance identification instead of clustering.

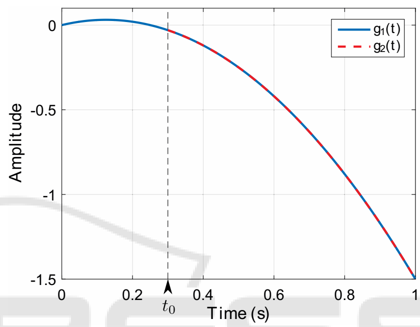


Figure 3: Functions $g_1(t)$ and $g_2(t)$.

In the sequel, these features are kept for use in appliance classification.

Envelope-related Features. The envelope features are A_0 and $b_j, j = 1,\ldots,n$. Whereas we, ideally, seek time-independent features for appliance classification, all b_j depend on the time reference t_0 except b_n. To illustrate this, we consider the following exponent of a simulated envelope with $n = 2$:

$$g_1(t) = b_1 t + b_2 t^2, \quad t \in [0,1]\ s \tag{4}$$

with $b_1 = 0.5$ and $b_2 = -2$ representing the polynomial coefficients. Our time reference is $t_0 = 0$ s. Suppose now that we shift our time reference from $t_0 = 0$ s to 0.3 s (i.e. we define a new time interval starting at 0.3 s). We then obtain the function $g_2(t) = g_1(t + t_0)$ which is the portion of $g_1(t)$ on the newly defined interval (Figure 3). Estimating the parameters b'_1 and b'_2 of $g_2(t)$, we find that $b'_1 = -0.7$ and $b'_2 = -2$. This corresponds to:

$$\begin{aligned} g_2(t) = \quad & = b_1(t+t_0) + b_2(t+t_0)^2 \\ & = (b_1 t_0 + b_2 t_0^2) + (b_1 + 2b_2 t_0)t + b_2 t^2 \\ & = b'_0 + b'_1 t + b'_2 t^2. \end{aligned} \tag{5}$$

The parameter that is not affected by the time reference shift is b_2. We show, using a similar reasoning for $n > 2$, that the only time reference-independent parameter is the last coefficient b_n adapted for use in appliance classification.

Note also that this time reference shift generates a new term b'_0 that we can pull out of the exponent and multiply by A_0 to get $A'_0 = A_0 e^{b'_0}$. Practically, we always take the time reference as the time where the current is at its extremum (max or min). Therefore, the estimated A_0 (or A'_0) specifies the highest amplitude the current can reach and is important to keep.

Finally, we *select* for the appliance classification A_0 and b_3 along with $A_i, i = 1, \ldots, 5$.

2.2.2 Feature Selection using a Wrapper Approach for Identification

Following the pre-analysis sub-section and in order to prove the soundness of the selected features, we propose hereafter to use a wrapper-based algorithm to perform the feature selection task.

The goal is to select the most relevant set of features from the set of all available features (in our case 14) for appliance identification. We propose to use the wrapper-based sequential forward search (SFS) algorithm (Kohavi and John, 1997). This latter, sequentially, adds at each selection step the "relevant" feature that gives the highest possible classification rate (CR). This selection procedure was used in (Hacine-Gharbi et al., 2015) and is summarized in Algorithm 1.

Algorithm 1: Wrapper-based sequential forward search (SFS) algorithm.

1. $\mathcal{F} = \{A_0, b_1, b_2, b_3, A_1, \ldots, A_5, \phi_1, \ldots, \phi_5\}$, $\mathcal{S} = \{\}$, $I = 14$ (initial number of parameters), $j = 1$ (iteration index).
2.
   - Evaluate the classification rate CR for each feature $f_l \in \mathcal{F}$.
   - Select the first feature $f_{\pi 1}$ such that: $f_{\pi 1} = \underset{f_l \in \mathcal{F}}{\arg\max}\,(CR(f_l))$.
   - $\mathcal{F} = \mathcal{F} - \{f_{\pi 1}\}$, $\mathcal{S} = \{f_{\pi 1}\}$.
3.
   - $j = j + 1$.
   - For each $f_l \in \mathcal{F}$, evaluate CR using $\mathcal{S} \cup \{f_l\}$.
   - Select the feature $f_{\pi j}$ such that: $f_{\pi j} = \underset{f_l \in \mathcal{F}}{\arg\max}\,(CR(\mathcal{S} \cup \{f_l\}))$.
   - $\mathcal{F} = \mathcal{F} - \{f_{\pi j}\}$, $\mathcal{S} = \mathcal{S} \cup \{f_{\pi j}\}$.
4. Repeat step 3 until $j = I$.
5. Give the output $\mathcal{S}$ that yields the maximum CR.

The chosen classifier is based on the k nearest neighbors (k-NN) algorithm. In order to study the effect of the value of k on the result, we propose to apply the selection procedure for $k = 1, 2, \ldots, 10$.

The feature selection procedure is conducted using the COOLL dataset (sub-section 3.1). COOLL was divided by keeping the first 10 measurement instances from each appliance for the training and the remaining 10 instances for the test (each appliance having 20 instances). This yielded 420 measurement instances for training and 420 measurement instances for the test.

Table 1 gives the corresponding indexes of the initial set of features that will be used to show the feature selection result.

Table 1: Initial set of features and corresponding indexes.

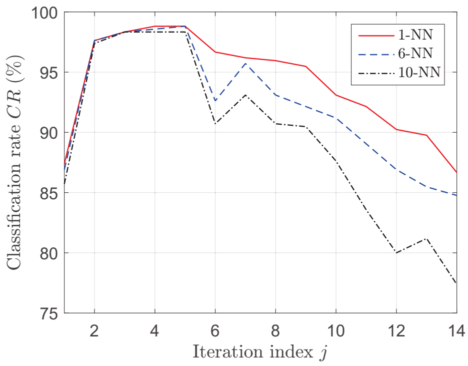
f_l	A_0	b_1	b_2	b_3	A_1	A_2	A_3
index	1	2	3	4	5	6	7
f_l	A_4	A_5	ϕ_1	ϕ_2	ϕ_3	ϕ_4	ϕ_5
index	8	9	10	11	12	13	14

The S matrix (Eq. (6)) gives the selection result where each row k corresponds to a specific k nearest neighbors choice and each column j corresponds to the set of selected features, by relevance, at each iteration j (Algorithm 1). The matrix elements are the indexes of the initial set of features (Table 1).

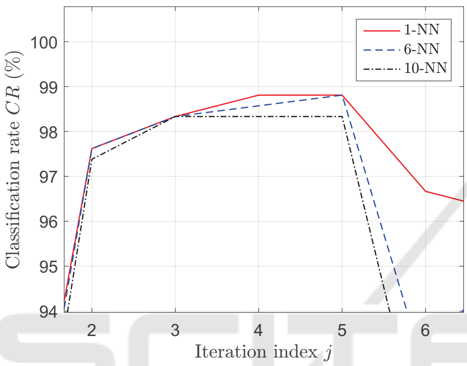
$$S = \begin{array}{cccccccccccccc}
5 & 6 & 7 & \boxed{8} & 9 & 1 & 2 & 4 & 3 & 10 & 11 & 13 & 12 & 14 \\
5 & 6 & 7 & \boxed{8} & 9 & 1 & 2 & 4 & 3 & 10 & 11 & 13 & 12 & 14 \\
5 & 6 & \boxed{7} & 8 & 9 & 1 & 2 & 4 & 3 & 10 & 11 & 14 & 12 & 13 \\
5 & 6 & \boxed{9} & 8 & 7 & 1 & 2 & 3 & 4 & 11 & 10 & 14 & 13 & 12 \\
5 & 6 & 7 & \boxed{8} & 9 & 1 & 2 & 4 & 3 & 11 & 10 & 13 & 14 & 12 \\
5 & 6 & 7 & 8 & \boxed{9} & 2 & 1 & 4 & 3 & 11 & 10 & 14 & 13 & 12 \\
5 & 6 & 7 & 8 & \boxed{9} & 2 & 1 & 4 & 3 & 13 & 10 & 12 & 11 & 14 \\
5 & 6 & \boxed{7} & 8 & 9 & 1 & 2 & 3 & 4 & 11 & 10 & 13 & 12 & 14 \\
5 & 6 & \boxed{7} & 8 & 9 & 1 & 2 & 3 & 4 & 11 & 14 & 12 & 10 & 13 \\
5 & 6 & \boxed{7} & 8 & 9 & 1 & 2 & 3 & 4 & 11 & 10 & 12 & 13 & 14
\end{array} \quad (6)$$

In Eq. (6), and for each row, the element that corresponds to the maximum CR is highlighted. The selected features are, then, the set that corresponds to this element (following Algorithm 1, for a specific row, each element represents the last added feature to $\mathcal{S}$). In the first row, for example, the highlighted element is the fourth element indexed 8. Hence, the selected features are A_1, A_2, A_3 and A_4 with corresponding indexes 5, 6, 7, and 8, respectively. To better illustrate this, Figure 4 gives the CR corresponding to rows 1, 6 and 10 of matrix S.

The selection results (see highlighted elements of matrix S) indicate that the algorithm selected the amplitude-related features as the most relevant for the identification. This is in agreement with the result of sub-section 2.2.1 where the amplitude-related fea-



(a) CR variation corresponding to rows $k = 1,6$ and 10 (representing also the number k of chosen nearest neighbors) of matrix S (Eq. (6)))



(b) Zoom of Figure 4a. The maximum values of CR for 1-NN, 6-NN and 10-NN are found, respectively, for $j = 4,5$ and 3.

Figure 4: Classification rate CR variation function of iteration index j (see Algorithm 1. j is also the column index of matrix S (Eq. (6))).

tures were suspected to be good candidates for appliance identification.

Note also that the phases are the least adapted for appliance identification which, again, is in agreement with the observations made in sub-section 2.2.1.

3 ELECTRICAL APPLIANCES IDENTIFICATION AND CLUSTERING

In this section we give the identification and clustering results right after giving a brief description of the used COOLL dataset.

In order to assess the usefulness of the model parameters for the classification, we do three tests for both the identification and the clustering. In the first test we only use the envelope-related features A_0 and b_3. In the second one, we use solely the amplitude-related features A_i and in the last one we use all seven features.

3.1 COOLL Dataset Description

Controlled On/Off Loads Library (COOLL) is a dataset of high-sampled electrical current and voltage measurements (840 current measurements and 840 voltage measurements) representing individual appliances consumption. The measurements were taken in June 2016 in the PRISME laboratory of the University of Orléans, France. The appliances are mainly controllable appliances (i.e. we can precisely control their turn-on/off time instants). 42 appliances of 12 types were measured at a 100 kHz sampling frequency (Table 2). A more detailed description of this dataset and its specificities can be found in (Picon et al., 2016).

Table 2: COOLL dataset summary. Source: (Picon et al., 2016).

N°	Appliance type	# of appliances	# of current signals (20 per appliance)
1	Drill	6	120
2	Fan	2	40
3	Grinder	2	40
4	Hair dryer	4	80
5	Hedge trimmer	3	60
6	Lamp	4	80
7	Paint stripper	1	20
8	Planer	1	20
9	Router	1	20
10	Sander	3	60
11	Saw	8	160
12	Vacuum cleaner	7	140
	Total	**42**	**840**

Note that we will use the current measurements for the classification. The voltage measurements (sampled at 100 kHz) presenting low variability from an appliance to another are, then, less adapted for classification and are discarded in this study.

The measurements of COOLL are 6 seconds long with a pre-turn-on duration of 0.5 second duration and post-turn-off duration of 1 second. Each appliance has 20 measurement instances. Each instance corresponds to specific *action delay* (a turn-on delay wrt the mains voltage time-cycle) ranging from 0 to 19 ms with a step of 1 ms (Picon et al., 2016).

3.2 Identification

For the appliance identification task presented hereafter, we use the supervised algorithm k-NN. This algorithm allows the prediction of the class of a new

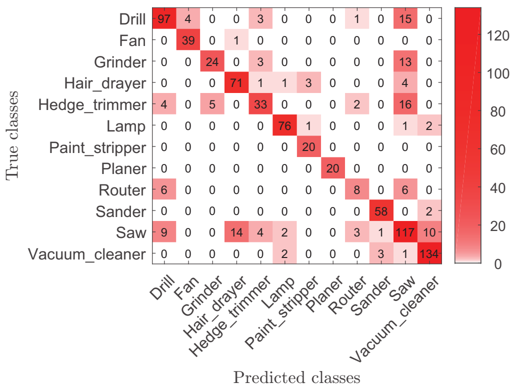


Figure 5: Confusion matrix for identification using A_0 and b_3. Classification rate CR = 82.98%.

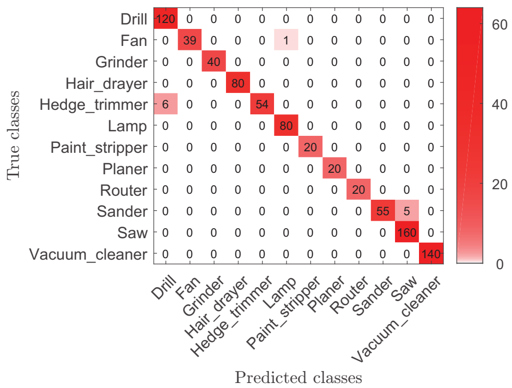


Figure 6: Confusion matrix for identification using A_i. Classification rate CR = 98.57%.

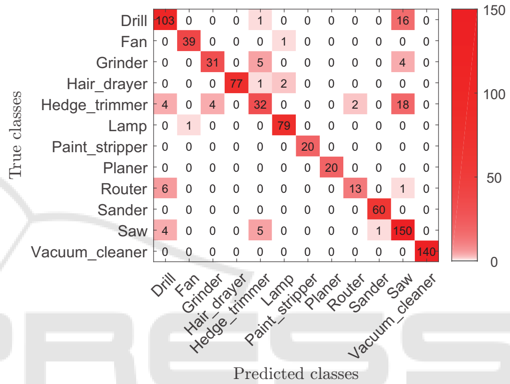


Figure 7: Confusion matrix for identification using A_0, b_3 and A_i. Classification rate CR = 90.95%.

point (in the feature space representing an appliance) by computing relative distances between this latter and points in its neighborhood. The appliance class is, then, decided with a majority vote between the classes of the k nearest neighbors.

The parameters to be fixed are the number k of nearest neighbors to consider and the distance metric. For our tests, we chose the Euclidean distance and $k = 10$. A low k value (< 5) may degrade the robustness of the classifier by increasing the risk of classifying using isolated points (the extreme case being $k = 1$). Since we already know, for our dataset, that a well-formed group should contain 20 points (the 20 measurement instances of the same appliance), we chose to compare each new point with half of the number of points we are supposed to find in its neighborhood. Hence the $k = 10$.

Since our dataset is not big enough to have a lot of measurement instances of all appliances in both the training and the test datasets, and in order to get more reliable test results, we chose to evaluate the identification performance using K-fold cross-validation with $K = 10$. The K-fold cross-validation consists of dividing the dataset, randomly, into K sets, doing K tests and averaging the results. For each test, we choose one *different* set from all the K sets for the test keeping the others for the training. We repeat this K times and we average the obtained results.

Figure 5 gives the confusion matrix for the identification using the parameters A_0 and b_3. With a classification rate (CR) of 82.98%, the identification gives several bad results which indicates that these features are not the most adapted for appliance identification.

Figure 6 gives the confusion matrix for the identification only using the features A_i. We note the (very) good CR value of 98.57%. This suggests that these features are more adapted to appliance identification than the envelope-related features.

Figure 7, on the other hand, shows the obtained identification confusion matrix obtained after using all the model parameters. With a CR of 90.95%, the use of all the features enhances the result of the envelope-related features but also deteriorates the result of the amplitude-related features.

As a conclusion, we can say that the identification results confirm the adaptability of the features A_i for the identification task and the nonadaptability of A_0 and b_3 for this task.

3.3 Clustering

For the clustering, we use one of the most known unsupervised algorithms i.e. the k-means. It requires the user to specify *a priori* the number of clusters needed to be formed. We chose $k = 12$ clusters based on the number of device types we have in the COOLL dataset.

Figure 8 shows the results as a confusion matrix using A_0 and b_3. The algorithm formed, especially, one big cluster (cluster 1) and different smaller clusters. The smaller clusters contain only lamps whereas the big cluster contains mostly motor-driven appli-

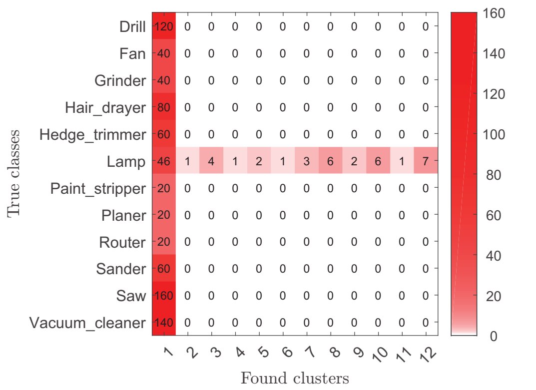


Figure 8: Confusion matrix for clustering using A_0 and b_3.

ances. This result is very interesting. The appliances of the COOLL dataset are mostly motor-driven appliances (i.e. appliances with a motor that is responsible for the main task the appliance is supposed to perform) that were gathered inside that big cluster. This indicates that the envelope-related features are suitable for distinguishing appliances having different working principles.

Lamps have a different working principle than the motor-driven loads. One of the reason that may explain the scatter of the rest of the appliances (not motor-driven) in different clusters is that the lamps are of different types that have different working principles. Actually, the four lamps of COOLL are, respectively, a 1.6 W light emitting diode (LED), a 15 W compact fluorescent lamp (CFL), a 105 W halogen lamp (HL) and 100 W halogen lamp (HL).

The tests we did show that the feature b_3 is related to the envelope amplitude decrease rate. Higher (negative) values indicate faster amplitude decrease.

Note also (Figures 8) that 46 lamps were grouped inside the big cluster. These lamps are seemingly lamps with no transient (Figure 9) (the current goes almost directly from zero to the steady-state and no transition is observed; they are most likely LED and CFL lamps) and, hence, are different from lamps with high amplitude variation transients (halogen lamps).

Figure 10 shows the clustering result using the A_i features. Clearly, these features are not adapted for the clustering since no link between the found clusters and the true classes is clear and apparently no deterministic pattern seems visible to distinguish well defined clusters.

The result of Figure 11 shows that the use of all available features still allows us to retrieve the motor-driven cluster even with the use of the A_i features in contrast to what happened with identification.

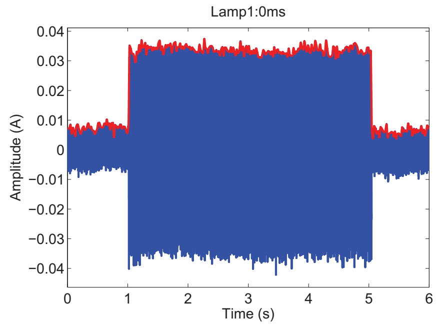


Figure 9: Turn-on transient current of a light emitting diode (LED). The interval $[0,1]$ s represents the pre-turn-on period whereas the interval $[5,6]$ s represents the post-turn-off period.

Figure 10: Confusion matrix for clustering using A_i.

Figure 11: Confusion matrix for clustering using A_0, b_3 and A_i.

4 CONCLUSIONS

In this paper, novel features extracted from a recently proposed mathematical model for modeling the turn-on transient current were presented and used in order to classify electrical appliances. These features were analyzed for the sake of selecting a set of features that is relevant for appliance classification. From a set of fourteen features seven were selected. A sequential forward search (SFS) wrapper-based selection algorithm was also used and its results validated the soundness of the previously selected features.

The Controlled On/Off Loads Library (COOLL) was used for the classification. A comparison between the appliance identification and clustering results using the turn-on transient features was conducted. The results indicate that the amplitude-based features $A_i, i = 1, \ldots, 5$ are the most relevant for appliance identification whereas the envelope-based features A_0 and b_3 are the most relevant for appliance clustering.

Future work may investigate further the robustness of the obtained results by testing the classification on other datasets with bigger sizes than COOLL and containing other families of appliance types (TV, washing machines, refrigerator, etc.). Other problems like model selection (parameters d and n) for the turn-on transient current model may also be addressed.

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