Wavelet Cepstral Coefficients for Electrical Appliances Identification using Hidden Markov Models

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Abstract: In previews work, a construction of electrical appliances identification system has been proposed using Hidden Markov Models combined with STFS (Short-Time Fourier Series) features extraction. This paper proposes many extensions: (i) a larger spectral band up to the maximum frequency value for the analysis of the data is investigated, but requiring a higher dimensionality of the STFS feature vector; (ii) a more compact representation than the SFTS vector is investigated with the wavelet based approaches; (iii) the relevance of the wavelet based features are investigated using feature selection procedure. The results show that increasing the number of harmonics in STFS from 50 to 249 does not necessarily improve the CR because of the peaking phenomenon observed with high dimensionality. The wavelet cepstral coefficients (WCC) descriptor with 8 cycle time analysis windows presents a higher performance comparing to the STFS, discrete wavelet energy (DWE) and log wavelet energy (LWE) descriptors. Recommendations are also given for selecting wavelet family, the mother wavelet order within the family and the decomposition depth. It turns out that the Daubechies wavelet of order 4 and decomposition depth 6 (or Coiflet wavelet with order 2 and depth 7) is recommended in order to achieve the better CR values.

1 INTRODUCTION

1.1 Motivation

For electricity providers, accessing to detailed energy consumption at the appliance level helps in regulating the electric power delivery / demand balance. Indeed, demand responses can be modulated by targeting specific user and appliance groups. For the customers, the energy disaggregation information helps improving their energy consumption efficiency.

This objective can be achieved in the frame of smart grids with the use of sensors, communications, computation abilities and control systems. In order to infer what appliances are operating in a home, home's power consumption must be disaggregated into individual appliances. An energy meter allows the access to the energy consumption information of the appliance or group of appliances. A disaggregated consumption thus necessitates the deployment of many meters at home. This solution is fastidious, not flexible and costly. Conversely, the non-intrusive appliance load monitoring (NIALM or NILM) solution necessitates the installation of a single device only at the house's power. NIALM techniques aim at disaggregating total electricity consumption to individual contributions of each load. Their design requires many stages: data acquisition, event detection, feature extraction, event classification and finally energy computation (Basu, 2014). The event classification quality highly depends on the relevance of the features extracted from the acquired data. We have investigated in a previous paper (Nait-Meziane, et al., 2016) the contribution of the transient part of the turn on currents to the appliance identification rate. A pattern recognition system was created considering short time Fourier series coefficients (STFS) at the input of a hidden Markov model (HMM) classifier. The study demonstrated an interest in considering the transient part in addition to the steady state part

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of the current signals for an improved identification rate.

The purpose now is to extent this study to (i) a larger analysis spectral band up to the maximum frequency value which requires a higher dimensionality of the STFS feature vector; (ii) a more compact representation than the STFS vector using other potentially interesting features such as wavelet based approaches; (iii) the investigation of the features relevance using feature selection procedure.

1.2 Related Work

In (Nait-Meziane, et al., 2016), the use of HMM models were introduced to solve the electrical appliance identification problem based on high-frequency sampled signals. The HMM classifier were designed using extracted features from the current signals.

The current signals remain periodic at the rate of the main power frequency with possible high distortions. These current signals can be analyzed with the coefficients of Discrete Fourier Series (DFS) decomposition. For a N samples periodic signal $s[n]$, $n \in \mathbb{Z}$ the DFS coefficients are expressed as

$$C[k] = \frac{1}{N} \sum_{n=-N/2}^{N/2-1} s[n] \exp\left(\frac{-j2\pi kn}{N}\right),$$

with $-\frac{N}{2} \leq k \leq \frac{N}{2} - 1$. In the steady state part of the active current signals, the magnitude of these coefficients should be constant whatever the location of the considered time period.

For transient electrical current signals, however, the periodicity property is lost and strictly speaking this formula is no more correct. Nevertheless, the DFS coefficients still catch the greatest part of the signal energy. Moreover, the design of a HMM system requires the definition of many states which input features must be time-varying. For most of the appliances, the DFS coefficients magnitude varies along the time because of transient turn-on part, appliance regime changes or power fluctuations. This is the reason why the current signals were segmented into overlapping successive windows with DFS coefficients computed on each window.

The resulting STFS coefficients are obtained as DFS coefficients computed around each time location n as:

$$C[n,k] = \frac{1}{N} \sum_{m=-N/2}^{N/2-1} s[n+m] \exp\left(\frac{-j2\pi km}{N}\right),$$

with $\frac{N}{2} \leq n \leq M - \frac{N}{2} - 1$ and M being the total number of samples of the current signal. For the tested PLAID dataset, the number N was 500 samples at 30 kHz frequency for the 60 Hz cycle-time and the overlapping was 50% of the window size, *i.e.* $n = jN/2$ where j is the segment number.

Different choices for the identification system were investigated: the use of transient vs. steady-state signals, the use of even vs. odd-order harmonics features, and the optimal feature vector size. The conclusion of this study was that the combined use of the transient part of the electrical current signals with only a few odd-order harmonics allows constructing an appliance identification system that is accurate, fast, and less complex in terms of memory occupancy and computations.

Another choice for the characterization of the transient electrical current signals has been proposed in (Nait Meziane, et al., 2017). Novel features extracted from a proposed mathematical model for modelling the turn-on transient current are introduced and used in order to classify electrical appliances. The model of the current is an amplitude modulated sum-of-sinusoids with additive white Gaussian noise (Naït Meziane, et al., 2015). The sinusoids frequencies are known and are odd order-harmonics of the fundamental frequency (the frequency of the main power). The amplitude modulation, or envelope, describes the current amplitude variation of the turn-on transient part as a time polynomial expression of an exponential function until reaching the steady-state part with a unity envelope.

The results showed that the amplitude-related features of this model are the most suited for appliance identification (giving a classification rate of 98.57% evaluated on COOLL database) whereas the envelope related features are the most adapted for appliance clustering.

Moreover, these features were analysed for the sake of selecting a set of features that is relevant for appliance classification. A feature selection procedure using a wrapper approach for identification was carried out corroborating the previous results.

2 WCC FEATURE EXTRACTION

We introduce in this section a new feature for NILM based on wavelet theory and cepstral calculus.

2.1 Wavelet Processing for NILM Feature Extraction

The features extracted from the electrical signals are expected to characterise the electrical appliances. More precisely for NILM, the features should be relevant for appliances identification, *i.e.* they should be able to explain the electrical appliances classes during their consumption periods. The role of features is to provide a compact representation of the data. They should be as relevant as possible and their number should be minimal. Classical features used in electrical engineering are the current and voltage root mean square values and the instantaneous power with the active and reactive parts. However, these averaged values partly hide the rich information contained in the frequency domain. Indeed, the measured voltage and current remain periodic at the period of the AC power main. The current signal in particular may have a lot of distortions which can be analyzed with the coefficients of DFS since the signal remains periodic as operated in (Nait-Meziane, et al., 2016). However, the period must be exactly known otherwise the computation may lack some information.

The nonstationarity of the data can otherwise be caught with the Short Time Fourier Transform (STFT). The differences with STFS rely on segment length and segment windowing choice possibilities. Actually, the STFT is a specific case of the Cohen's class time-frequency representations. Each case is defined by a specific kernel function giving rise many time-frequency methods like Wigner-Ville, Choï-Williams... Nevertheless all these approaches are not as appropriate as the time scale methods for the characterization of transient signals. Indeed, the multi-resolution and time-frequency localization properties of the time-scale methods are particularly suited for the simultaneous analysis of short time fast events and long time slow events. This is the case for electrical signals where the slow events are related to the steady state periodic behaviour of the AC power and the fast events are the electrical changes like impulses, transient phases between steady state phases or electrical discharges.

We thus propose to use wavelet-based signal decomposition instead of STFS or STFT for the feature extraction procedure. The scale effect of the wavelet transform is obtained by applying a scale factor to the time course of a mother analysing wavelet. The mother wavelet should also present oscillations in order to extract a spectral content around its rescaled central frequency. The time-varying spectral analysis is obtained just by applying a temporal shift factor to the mother wavelet before scaling. The wavelet transform was thus first expressed in the continuous domain as continuous wavelet transform (CWT). The discrete wavelet transform (DWT) was second elaborated in the mathematical frame of multi resolution analysis providing two digital filters $h[l]$ and $g[l]$. The first one is a low pass filter and the second one is a high pass filter.

The discrete wavelet coefficients $a_j[n]$ and $d_j[n]$ can be produced, at each level j, by the recursion formula:

$$a_j[n] = \sum_l a_{j-1}[l-2n]\, h[l]$$
$$d_j[n] = \sum_l a_{j-1}[l-2n]\, g[l]$$

Note that the mother wavelet does not directly appear in these recursive expressions but its continuous waveform can be retrieved from the $g[l]$ sequence. Similarly, another continuous waveform (the so-called scaling function) can be retrieved from the $h[l]$ sequence.

The algorithm is initialized at level 0 by setting $a_0[n] = x[n]$ defined on N samples. At each iteration, the filters split the full data bandwidth in low and high frequency bands (the result can therefore be down sampled by a factor 2 which is the dyadic scale factor in the discrete version, see the $2n$ term in the formula). Low frequency components are thus represented by the approximation coefficients $a_j[n]$ while high frequency components are represented by the detail coefficients $d_j[n]$. The DWT wavelet coefficients at the decomposition depth p can be put in a vector as the concatenation of the detail coefficients computed at all the scales plus the remaining approximation coefficients computed at scale p $\{d_1[n], d_2[n], \cdots, d_p[n], a_p[n]\}$. Because of the factor 2 down-sampling, the number of coefficients $d_j[n]$ at iteration j is $N_j = N/2^j$. This means that the number N of $x[n]$ samples is preserved in the DWT domain with N coefficients. The maximal decomposition depth can be $\log_2(N)$ but practically depends of the filters length.

A reduced dimensionality of the features can be obtained by computing any energy measure or information measure from the wavelet coefficients at each scale (Gray and Morsi, 2015).

2.2 Review of Wavelets in NILM

Wavelet processing was introduced in NILM at the beginning of the 2000s. The first works used the wavelet scale decomposition ability for electrical signal analysis. Indeed, the harmonic Fourier series expression can be decomposed in different scale components which permits to highlight some changes in harmonic components because of the filter bank effect of the wavelet decomposition (Cristaldi, Monti, and Ponci, 2003). This wavelet property also allows a precise detection of the beginning and the end of the turn-on transient parts of the electrical currents (Su, Lian, and Chang, 2011).

The work proposed in (Figueiredo, de Almeida, and Ribeiro, 2011) uses the reversibility property of the DWT for a denoising stage before NILM processing by selecting certain coefficients to retain, and discarding the others considered as noise.

The authors in (Duarte, Delmar, Goossen, Barner, and Gomez-Luna, 2012) are the only ones using the CWT in NILM for the characterization of switching voltage transients. The complex Morlet mother wavelet was applied at chosen decomposition scales. The scale values were experimentally found such that the 3dB bandwidths, obtained for each selected scale, cover the whole signal bandwidth without overlapping.

In (Gray and Morsi, 2015), the energy of the detail coefficients was used and their computation at each scale was used as the feature vector components for classification. The classification accuracy was also evaluated and compared using features obtained by various orders of Daubechies (Db) wavelets. They showed that higher order Db wavelets (and Db5 in particular) exhibit higher classification accuracy.

In (Tabatabaei, Dick, and Xu, 2017), the authors also calculate the energy of the wavelet coefficients at each scale using Haar wavelets and use them as the feature vector instead of the wavelet coefficients. Finally, an adapted wavelet specifically designed for NILM application was proposed by (Gilis, Alshareef, and Morsi, 2016) (Gillis and Morsi, 2017). The authors also applied the DWT on a derivative pre-processing of the data: for each N samples period, the difference signal between $x[n]$ and $x[n-N]$ was considered.

However, the improvement achieved by the newly designed filter is found to be small compared to Db wavelets.

2.3 Wavelet Cepstral Coefficients (WCC)

In the previous section, the authors took advantage of the wavelet transform for the electrical signals analysis in the NILM problem. Many of the authors reduced the dimensionality in the DWT domain by computing a discrete wavelet energy (DWE) features set composed of the wavelet coefficients energies evaluated on each scale as:

$$\begin{cases} E(d_j) = \sum_{n=0}^{N_j-1} \left|d_j[n]\right|^2 \quad \text{for } j = 1, \cdots, p \\ E(a_p) = \sum_{n=0}^{N_p-1} \left|a_j[n]\right|^2 \end{cases}$$

At this step, other measures on the wavelet coefficients have been proposed in the literature covering various application domains such that Teager-Kaiser energy, the log of the energy, the hierarchical energy (Didiot, Illina, Fohr, & Mella, 2010), or information measures like entropy. (El-Zonkoly and Desouki, 2011).

In the speech processing domain, the logarithm is often used in order to highlight the harmonic content and to separate transfer functions. For a speech-music discrimination application, the authors in (Didiot, Illina, Fohr, and Mella, 2010) introduced the log wavelet energy (LWE) computed on normalized energies:

$$\begin{cases} LE(d_j) = \log\left(\frac{1}{N_j}\sum_{n=0}^{N_j-1} \left|d_j[n]\right|^2\right) \; j = 1, \cdots, p \\ LE(a_p) = \log\left(\frac{1}{N_p}\sum_{n=0}^{N_p-1} \left|a_p[n]\right|^2\right) \end{cases}$$

In this speech domain, the classical features are the Mel Frequency Cepstral Coefficients (MFCC) and the authors compared the LWE-based discrimination approach with the MFCC-based one. The MFCC is a Fourier transform (FT) approach where the log of the energy is computed in different frequency bands (with a Mel filter applied). The inverse Discrete Cosinus Transform (DCT) is applied for the decorrelation of the coefficients. By replacing in this procedure the FT by the DWT, the Wavelet Cepstral Coefficients (WCC) can be obtained. This new typology of features has already been proposed in the speech (Lei and Kun, 2016). In a bat classification problem, the authors of (Gladrene, Juliet, and Jayapriya, 2015) go beyond by also proposing the Dual-Tree Complex WCC. Indeed, the DWT is based on real valued oscillating wavelets whereas the FT basically uses complex-valued oscillating sinusoids. So the Dual-Tree Complex Wavelet Transform has been proposed for enhancing the DWT because it answers to some shortcomings of the DWT as the oscillations, the shift variance, aliasing and lack of directionality.

In the NILM domain, (Kong, Kim, Ko, and Joo, 2015) partly investigated this idea using the quefrency position and amplitude of the dominant peaks in the smoothed cepstrum of the voltage signal as appliance features to distinguish ON/OFF appliances. But their work did not exploit the DWT.

We thus propose to use the WCC features for the NILM problem. The following experiments aim to identify the most suitable wavelet family as well as the optimal decomposition level. The second step will investigate the feature selection problem using DWE, LWE or WCC features.

3 EXPERIMENTS AND RESULTS

We present in this section a number of experiments we carried out to evaluate the performance of the WCC based feature extraction method for the task of appliance identification. In these experiments, the WCC coefficients are used as features to identify 11 electrical appliances of Plaid dataset using HMM classifier based identification system (Nait-Meziane, et al., 2016). Three experiments are conducted in order (i) to compare the performance of the WCC features to other features commonly used in the literature; (ii) to search for the optimal combination of mother wavelet and decomposition level; (iii) to analyze the WCC features relevance after feature selection procedure.

3.1 HMM based Identification System

The standard appliances identification system presented in (Nait-Meziane, et al., 2016) has been used in this work. The HMM based classifier system is composed of two principal phases, the training phase (learning) and the classification phase (testing) as presented in fig 1. Therefore, the database is divided into a training database and a testing database.

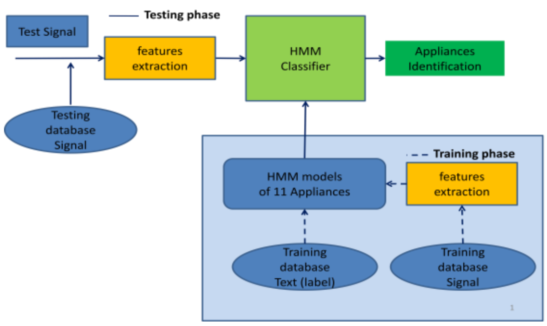

Figure 1: HMM-models-based electrical appliances identification.

Both phases need firstly a feature extraction step which consists in converting the temporal current waveforms signal into a sequence of features vectors (STFS coefficients). The total active current signals (transient and steady state phases) were considered because this repartition gives better CR results than those obtained with the steady state phase only as demonstrated in (Nait-Meziane, et al., 2016). This sequence is considered as input sequence of observations to the HMM classifier. In (Nait-Meziane, et al., 2016), STFS feature vectors are computed on 50% overlapping window, each of 16.7 ms duration (one 60 Hz cycle-time).

The training phase consists to model each appliance signature by HMM model of 3 states, each one being associated to GMM model of 3 Gaussians. In this phase, the system learns occurrences of the training database: the sequences of feature vectors of the training corpus are used for estimating the parameters of each HMM model using the embedded Baum-Welch reestimation algorithm performed by HEREST HTK command (Young, Kershaw, Odell, and Ollason, 1999).

In the classification phase, the classifier uses the trained HMM models for assigning each input feature vectors sequence to one of 11 appliances using the Viterbi algorithm (HVITE command). The testing dataset is used to evaluate the performance of the identification system. The performance evaluation is based on Classification Rate (CR) defined in (Nait-Meziane, et al., 2016).

In this paper, the STFS feature extraction process has been replaced by DWE / LWE / WCC features. This process is represented in fig.2.

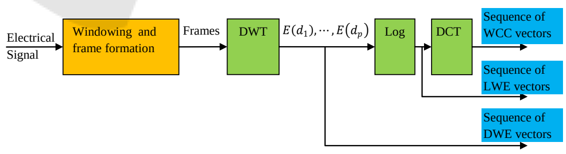

Figure 2: process of DWE / LWE / WCC feature extraction with Hamming windowing.

The PLAID dataset has been used for the experiments. PLAID is a public dataset of current and voltage measurements taken from 55 houses. This dataset contains electric signatures of 11 appliance types with a total of 1074 signals (current and voltage) sampled at a 30 kHz rate (Gao, Giri, Kara, and Bergès, 2014).

In this work, the dataset is divided into a training set and a testing set; each one is composed of 537 current signals with the consideration that all the houses (55 in total) have examples in the training and in the testing sets.

3.2 Comparative Study between STFS and DWE / LWE / WCC

This experiment allows evaluating the advantage of WCC compared to STFS coefficients and DWE (Discrete Wavelet decomposition based calculus Energy) descriptors for the task of electrical appliances identification. Another case of WCC descriptor consists to calculate only the log of energy at each decomposition level without DCT transform (Didiot, Illina, Fohr, and Mella, 2010) in order to keep the interpretation of coefficients as frequency band energies. We called the last descriptor as LWE (Log wavelet decomposition based energy).

Furthermore, this experiment allows extending the last work presented in (Nait-Meziane, et al., 2016) by using a larger spectral band of signal and considering descriptors up to the maximal frequency (Fs/2 = 15 kHz). Hence the STFS set is composed on 249 coefficients without taking the DC component (0 Hz).

In (Gray and Morsi, 2015), the authors used the DWT for the classification problem in NILM and concluded that the order 5 Daubechies wavelet Db5 gave the best performance in this family. For this reason, we firstly take the Db5 wavelet with maximum wavelet decomposition level of p=5 (the maximum depth obtained regarding the wavelet filter of Db5 and the number of samples N=500, using `wmaxlev` Matlab command). Thus, the DWE, LWE and WCC descriptors have a dimension of 6 (energies in 5 levels, plus energy of approximation).

3.2.1 HMM Number of States (NS)

In this experiment, we search for the optimal states number of models in different cases of descriptor. The component number of GMM model is fixed to three (Nait-Meziane, et al., 2016). Table 1 gives the CR values with optimal number of states (NS_{opt}) when varying NS from 1 to 8. From these results we can give the following points:

- enlarging the bandwidth from 50 to 249 harmonic features for the SFTS descriptor produces lower CR results probably because of the peaking phenomenon observed with high dimensionality (Jain, Duin, and Mao, 2000);
- the SFTS gives the best CR with a reduced 50-dimension feature vector with 4 HMM states;
- in the case of large bandwidth, the STFS and WCC descriptors give the best CR of 93.48% with respectively NS equal to 7 and 6. However the WCC descriptor is a very compact representation with a 6-dimension features vector compared to the STFS descriptor with a large 249-dimension features vector;
- taking only the wavelet energy as feature without the log gives the poorest performances as already noticed by (Gray and Morsi, 2015).

Hence, this result demonstrates the superiority of the WCC descriptor to the other full band descriptors regarding both CR and dimensionality.

Table 1: Performance Comparison of the CR (%) for STFS, DWE, LWE and WCC features using DB5 at level 5 for the HMM Optimal Number of States (NS_{OPT}).

	STFS (50 features)	STFS (249 features)	DWE	LWE	WCC
NS_{opt}	4	7	8	5	6
CR	94.41	93.48	77.65	93.30	93.48

3.2.2 Duration Window

This experiment allows investigating performance improvement taking into account the advantages of wavelet analysis in the case of non stationary signal segments compared to the STFS analysis. For this reason, we propose to increase the window analysis until 12 cycle time (200 ms). This experiment considers the identification system with Db5 wavelet and with a decomposition level equal to 5. Table 2 shows the accuracy for different values of window duration. The result shows that increasing the window duration until 8 cycles improves the CR achieving the 97.01% maximal value. Hence, for the next sections, we will consider window durations equal to 8 cycle time.

3.2.3 Choice of the Mother Wavelet and Decomposition Level

Many papers use the Haar wavelets which are rough and cannot smoothly follow a continuous signal, although this characteristic is beneficial when studying signals with sharp transitions. By considering successive convolution operations of the Haar scaling function (a rectangular function) with itself, many smoother wavelets can be obtained. These are the famous Daubechies wavelets where the number of convolutions defines the order of the Daubechies wavelet. So the purpose of this section is to evaluate the impact of the smoothness as well as the impact of the wavelet family on the CR. Other mother wavelet families which members are defined by an order also exist and can be used.

This experiment will permit to select the optimal wavelet mother within its family and the optimal decomposition level. In this work, we consider the following wavelet families:

- the Daubechies family with orders 1 to 8: Db1 or Haar, Db2, ... , Db8;

- the Coiflets family with orders 1 to 5: Coif1, Coif2,..., Coif5;

- the Symlets family with orders 1 to 8: Sym1, Sym2, ..., Sym8.

For the first experiment, we consider the HMM identification system with 6 states and a window duration of 8 cycle time, with 50% overlapping between successive windows.

Table 3 shows that the higher CR value of 97.01% is achieved with the Daubechies wavelet of order 5 with a decomposition level equal to 5. Table 4 presents the CR taking the same conditions as the last experiment but increasing the overlapping to 2/3 of the window duration (66.66%). The results show globally the improvement with last value of overlapping. The Daubechies wavelet of order 4 with a decomposition level equal to 6 gives the best performance with CR equal to 97.20%. This result demonstrates that the Daubechies wavelets family gives the best performance results in the case of high orders and high decomposition levels (in particular order 4, 5 and levels 6 and 7).

This latter experiment was also carried out using the Coiflets and the Symlets wavelet families previously cited. The Coiflets with order 2 with level 7 gives the best value of CR equal to 97.20%. Also, the Symlets wavelet with order 4 and level 6 gives the highest CR of 97.01% (table omitted).

We can conclude from these experiments that WCC descriptor based on Daubechies or Symlets wavelet families gives the highest performance results in the case of high order (4) and high level (6) values. In the case of Coiflets family, the best result is given taking order 2 and level 7.

Hence, whatever the wavelet family or order, the best performance results are obtained with high decomposition levels.

3.2.4 Feature Selection using a Wrapper Approach

In this experiment, we study the relevance of different descriptors by selecting the most relevant features explaining the appliances classes or types. In this work, we applied the wrapper-based sequential forward search (SFS) algorithm (Kohavi and John, 1997). This algorithm adds sequentially at each selection step the feature that gives the highest CR. This algorithm has been used in (Hacine-Gharbi, Petit, Ravier, and Nemo, 2015) (Nait Meziane, et al., 2017).

We consider the LWE and WCC descriptors taking into account the Daubechies wavelet of order 4 with level 6. Hence, 7 features are considered for each descriptor. Table 5 displays the CR as a function of the total number of selected features at iteration j. Also this figure gives the selected feature number (Sel#) at iteration j. Several remarks can be drawn from Table 5:

- the first selected feature in the case of LWE is feature # 7 which corresponds to the approximation spectral band;
- globally, the first four LWE features strongly explain the classes. Most of these features correspond to high decomposition levels (in particular levels 6 and 5 and approximation feature 7). Hence we can conclude that the most information quantity about appliances is localised in the low spectral bands and the higher spectral band corresponding to level 2.

4 CONCLUSIONS

In this paper, a novel wavelet based feature extraction approach has been presented for electrical appliance identification. The first goal was to investigate a larger spectral band analysis in STFS feature extraction step applied on a previous identification system based on HMM classifier and evaluated on PLAID database. This system requires a higher dimensionality of the STFS feature vector. The second goal is to search a more compact representation than the SFTS vector using wavelet based approaches such as DWE and LWE proposed in NILM domains. In this work, we have presented a novel features extraction approach for NILM domain that extracts features from the DCT of log energies computed at each detail scale and at the approximation level of the DWT. Through several experiments and a comparison study, we can draw the following conclusions:

- enlarging the bandwidth produces 249 features without improving the CR obtained with 50 features probably because of the peaking phenomenon observed with high dimensionality;
- the WCC descriptor with 8 cycle time analysis windows presents higher performance results

compared to the STFS, DWE and LWE descriptors;
- the Daubechies wavelet of order 4 and decomposition depth 6 (or Coiflet wavelet with order 2 and depth 7) is recommended in order to achieve the better CR values.

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Table 2: CR (%) obtained with respect to the duration of analysis window (expressed in number of cycles, one cycle is 16.67 MS long).

# cycles	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
WCC	93.48	94.41	94.97	95.71	95.34	96.46	95.15	97.01	96.46	96.46	96.27	96.46

Table 3: CR (%) obtained with respect to Order n of Daubechies mother wavelets and Decomposition level p. ovelapping between segments equals 50%

p DbN	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Db1	78.73	80.41	85.26	85.82	87.87	86.57	86.38	69.78	70.15	69.22	64.74
Db2	73.88	85.26	91.42	91.60	93.47	94.96	92.72	80.78	78.92	78.54	
Db3	73.13	88.43	90.11	94.59	96.08	96.08	94.03	84.51	82.09		
Db4	72.57	89.74	89.37	93.66	95.52	95.90	95.15	87.31	86.57		
Db5	71.46	89.74	89.93	93.84	97.01	95.90	94.40	86.57			
Db6	70.34	89.74	89.93	93.10	94.59	95.52	96.27	87.50			
Db7	68.84	89.18	90.30	92.16	95.15	94.96	94.96	85.82			
Db8	68.47	89.37	90.30	91.79	95.71	95.15	94.78	89.55			

Table 4: CR (%) obtained with respect to Order n of Daubechies mother wavelets and Decomposition level p. ovelapping between segments equals 66%

p DbN	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Db1	82.09	81.16	86.75	87.50	90.67	88.62	89.18	80.78	78.36	78.73	77.43
Db2	75.19	87.50	92.72	91.79	95.34	96.46	96.46	87.500	88.06	88.06	
Db3	73.69	89.18	93.10	94.59	95.15	95.52	95.34	91.04	88.81		
Db4	72.77	90.11	90.49	91.79	96.46	97.20	96.27	93.28	90.86		
Db5	71.64	90.11	92.16	93.10	94.96	96.64	96.83	94.96			
Db6	72.20	89.37	90.30	93.28	96.27	94.96	96.46	93.28			
Db7	71.08	89.18	89.93	94.03	95.15	96.46	96.64	93.47			
Db8	69.59	88.81	90.49	91.79	95.15	96.27	96.83	95.34			

Table 5: CR as a function of the number of selected features for descriptors: LWE and WCC; *j*is the iteration number; Sel#is the selected feature number, the lowest value represents the highest frequency band while the highest value represents the lowest frequency band; CR is considered taking all the features selected at iteration.*j*

j		**1**	**2**	**3**	**4**	**5**	**6**	**7**
LWE	Sel#	7	2	6	5	1	4	3
	CR	55.60	85.63	92.72	94.4	94.78	95.34	94.96
WCC	Sel#	3	2	6	4	1	7	5
	CR	58.77	82.65	91.98	94.78	96.64	96.46	97.20

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