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Building Simulation (Innovation, Rapid Design, Design Support) & ICT

Near Real-Time Appliance Recognition Using Low Frequency Monitoring and Active Learning Methods

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Abstract

Electricity load monitoring in residential buildings has become an important task allowing for energy consumption understanding, indirect human activity recognition and occupancy modelling. In this context, Non Intrusive Load Monitoring (NILM) is an approach based on the analysis of the global electricity consumption signal of the habitation. Current NILM solutions are reaching good precision for the identification of electrical devices but at the cost of difficult setups with expensive equipments typically working at high frequency. In this work we propose to use a low-cost and easy to install low frequency sensor for which we improve the performances with an active machine learning strategy. At setup, the system is able to identify some appliances with typical signatures such as a fridge. During usage, the system detects unknown signatures and provides a user-friendly procedure to include new appliances and to improve the identification precision over time.

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Keywords: NILM; Appliance recognition; active learning;

1. Introduction

Non Intrusive Load Monitoring (NILM) is the most prominent approach based on the analysis of the global electricity consumption signal of the habitation, typically using a smart meter. The qualification of non-intrusive means that no extra equipment is installed in the house. With NILM, the appliance signatures are superposed and, for comprehending the contribution of single appliances, they have to be separated through an operation called disaggregation [1]. In our case, the task consists in detecting appliance events and classifying the events into a dozen of categories such as fridge, dishwasher or microwave.

Many NILM strategies are relying on medium to high frequency sampling, with sometimes complex transient modelling [2–5]. Such systems have a good precision for appliance recognition but are using relatively expensive systems with a priori more difficult installation procedures and setup.

In our work, we explore another strategy based on low frequency analysis of the active and reactive power signal (at 1Hz) using a low cost sensor. We compensate the lower quality of the electric signatures by using data-driven approaches based on machine learning algorithms. Such algorithms are computing models from data, capturing signature patterns.

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The novelty of our approach is in the fact that a set of appliance models are initially obtained using an existing database and that this set is enriched using active learning approaches to improve the precision of the identification over time. Such procedure allows to train on-the-fly robust models for appliances that were unseen in the training set and also to fine-tune the existing pre-trained models on the specificities of the appliance under use.

This paper is organised as follows. Section 2 gives an overview of the related work. Section 3 gives details about the appliance recognition infrastructure. In Section 4, we present and discuss our classification results and our training process. Finally, In Section 5, we conclude and present potential future works.

2. Related work

From a research perspective, appliance load monitoring is an important task in the domain of electricity consumption understanding. The purpose of this monitoring is to detect and identify appliances in operation. Once this classification is correctly performed, some other system can use the information to perform reporting and/or triggering events such as alarms based on the operating time and on the observed consumption of the identified appliance. Different types of appliance can be defined as explained in [6] and [7].

Type I corresponds to ON/OFF appliances, i.e. appliances with only with 2 states such as lamps or toasters.

Type II is associated to appliances that operate according to a finite number of states, e.g. a fan with multiple speeds.

Type III corresponds to continuously variable devices, i.e. appliances that consumes power proportionally to another parameter such as a drill with continuously variable speed.

Type IV represents appliances that are constantly consuming power such as phones or smoke detectors.

Two approaches are existing for appliance load monitoring. The first one is the Intrusive load Monitoring (ILM) that relies on a set of sensors distributed in the habitation [6]. In its more granular and expensive setting, ILM would rely on dozens of sensors per habitation, ultimately equipping each power outlet. The electric signals then observed are corresponding to one or few appliances, making the detection and identification task easier. Different machine learning modelling strategies are used to capture the specificities of electric signature with ILM, such as the use of Gaussian Mixture Models or Hidden Markov Models that reported good identification accuracy up to 95% [8,9].

The other approach is called Non Intrusive Load Monitoring (NILM) that relies on a unique sensor typically placed in or beside the metering system [1]. With NILM, the qualification of non-intrusive comes from the unicity of the sensor located at the electricity entry point in the habitation. Further to the non-intrusiveness, an advantage of NILM approaches is that the installation cost is much lower. The disadvantage of NILM is that appliance signatures are superposed making the identification of single appliances more difficult [7]. If we define $P(t)$ the NILM power measured at a given time t, we may simply write $P(t) = P_1(t)+P_2(t)+...+P_n(t)$, where n is the number of appliance that drain power in the meter. In NILM, the separation of power for each appliance consists of computing the individual contributions $P_i(t)$ and is called the disaggregation. This can be done either by using a supervised or unsupervised machine learning approaches. The supervised learning method [10,11] shows good results in the disaggregation task. The main drawback is the need of a-priori information which can be solved using public databases like BLUED, REDD [12] or ACS-F2 [13]. The unsupervised learning method does not include this disadvantage. This kind of algorithm shows some good perspectives as they reduce the cost of installation and the a-priori informations needed by the algorithm. For example, some authors announce very good results using algorithm like Additive Factorial Approximated MAP and a Hierarchical Dirichlet Process Hidden Semi Markov Model [14,15].

For both ILM and NILM approaches, two operating modes are usually distinguished [6]. The first one is called *automatic setup* where the system is pre-trained (or pre-configured) with a finite set of known appliances. When turning on such system, it is supposed to recognise the different appliances without any intervention of the user. The other mode is called *manual setup* where the system will ask the user to actively switch on or off the different appliances in the setup of the system, and to provide the corresponding labels. Automatic setup is usually more user convenient but with less identification performance while the manual setup leads to better identification performance at the price of involving more user interventions. As explained in the next Section, the active learning strategy we propose corresponds to an operating mode that is in-between an automatic setup and a manual setup. The system actually starts operating in automatic setup and falls back to manual setup when its confidence is too low.

3. System description

Our system is based on a NILM approach and focuses on near real-time classification using low frequency sampling of the electricity consumption at 1Hz. We use a two steps procedure. In the first step we detect an appliance event as an abrupt change in the electricity consumption. In the second step, we use a classifier fed with the signal surrounding the event, able to classify the event into an activation or de-activation of an appliance. An overview of the system is given in Figure 1.

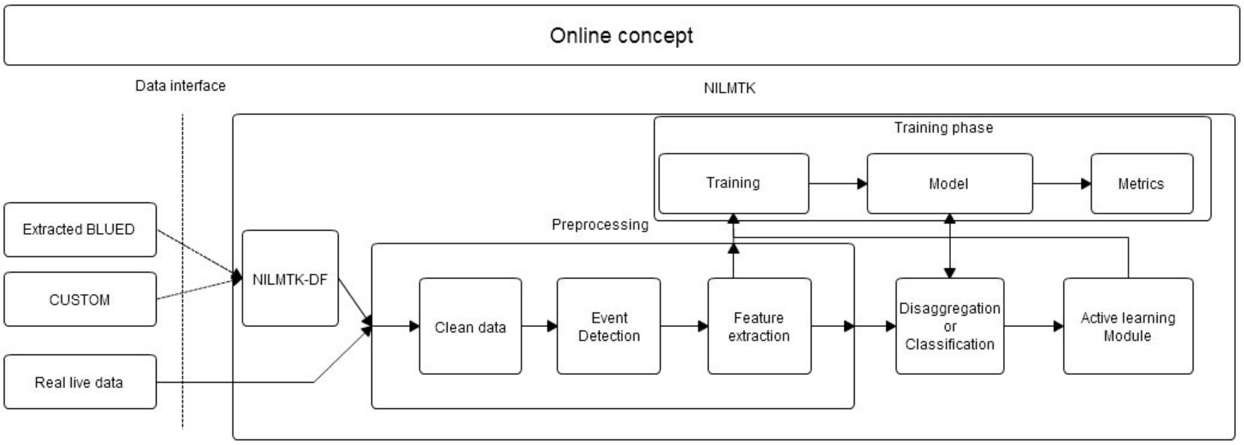

Fig. 1. Processing pipeline of the proposed system

We use the NILMTK-DF [16] to store and retrieve data from the different datasets used for training the system. The processing pipeline consists of a pre-processing part to clean data, detect event and extract features. If an event is detected, a classification is triggered using pre-trained models. The active learning module will be describe at the end of this section.

A research question was for us to find the best performing machine learning algorithm with a minimum of tuning. For that purpose, we used the Machine Learning toolkit (ML studio) provided on the Azure cloud by Microsoft. Keeping the remaining parts of the processing pipeline constant, this toolkit allowed us to spin through a wide range of classification algorithms, for which we report the performances in Section 4.

To train the models, we collected a data set in a residential setup and completed these signals with a subset of the BLUED public dataset [17]. Table 1 summarises the appliance categories present in each set. We had to re-sample the data of BLUED to make it fit with our 1Hz constraint. Each of these dataset have also been balanced to avoid difficulties occuring with some discriminant machine learning algorithms when trained on unbalanced categories.

Dataset	#Class	Appliances
BLUED-subset	11	Air compressor, Basement, Computer, Garage door, Iron, Kitchen light, Laptop, LCD Monitor, Monitor, Refrigerator, TV
CUSTOM	10	Phone Charger, Laptop, Iron, Coffee Machine, Desktop Lamp, Fan, Fridge, Hair Dryer, Humidifer, Tea Machine, TV

Table 1. Datasets description

We attempted to use different feature extraction to augment the raw power signal, such as its first and second derivatives (velocity and acceleration), as well as min-max difference in the considered analysis window. The best performing feature was identified as the min-max difference of the raw signal.

The principle of the active learning strategy we have put into place is to trigger a re-training of the models with new inputs validated by the user. The machine learning algorithms are actually able to compute a confidence level when emitting an class hypothesis on a given input. When this confidence level is too low, the system switches to a manual mode and relay a question to the user to validate the recognition hypothesis. If the user validate the hypothesis, the new data is added to the previously available data for that category. If the user invalidate the hypothesis, the user can specify the correct category or a new category label corresponding to a potential new device unseen from the system. The system then launch a model re-training when enough additional data is collected.

4. Results and discussions

We designed our tests protocols to match automatic setup and manual setup. An automatic setup would correspond to a train-validation-test process on a single dataset using cross-validation to maximize the performance accuracy during the training-validation process. An automatic setup would correspond to a train-validation process on a dataset and test on another dataset unseen from the train-validation procedure. The results reported below corresponds to a fully manual setup since the results on the automatic setup are rather low. Some appliances that have well-characterised loads such as for the fridge category were correctly classified using the automatic setup. This actually motivated us to include such appliances in the initial knowledge base of the live system and go for an active learning strategy.

	CUSTOM		BLUED	
	Precision	Recall	Precision	Recall
SVM	0.88	0.85	0.40	0.47
Multi-Class Neural Network	0.80	0.84	0.53	0.50
Multi-Class Decision Jungle	0.97	0.96	0.77	0.77
Multi-Class Decision Forest	0.96	0.96	0.77	0.77
Multi-Class Logistic Regression	0.87	0.84	0.43	0.48
Averaged Perceptron	0.87	0.82	0.45	0.49
Bayes Points Machine	0.89	0.85	0.44	0.47
Boosted Decision Tree	0.92	0.88	0.72	0.73
Decision Forest	0.96	0.96	0.77	0.77
Decision Jungle	0.96	0.96	0.79	0.79
LD-SVM 0.880618 0.865909	0.88	0.86	0.56	0.56
Logistic Regression	0.88	0.85	0.43	0.49

Table 2. Algorithm comparison over the custom and BLUED dataset. Performances a reported in terms of precision and recall expressed as percentages.

We used a rather large panel of different classification algorithms for which the hyper parameters were tuned using a basic grid search procedure. As reported in Table 2, the selected algorithms are the SVM, Multi-class Neural Networks, Multi-class Decision Jungle, Multi-class Decision Forest, Multi-Class Logistic Regression, Averaged Perceptrons, Bayes Points Machine, Boosted Decision Tree, Decision Forest, Decision Jungle, LD-SVM and Logistic Regression. Some of the algorithms, like Decision Forest and Decision Jungle have been tested as-is, using the implemented multi-class options available on Azure ML Studio or manually implementing the multi-class using a one-versus-all procedure. We observe that the Decision Jungle and Decision Tree systematically outperform the other algorithms.

The confusion matrices for the Decision Jungle algorithm are reported in Tables 3 and 4 for the custom and BLUED datasets.

	Phone charger	Laptop	Iron	Coffee Machine	Lamp	Fan	Fridge	Hair dryer	Humidifier	Tea machine	TV
Phone charger	1										
Laptop		1									
Iron			1								
Coffee Machine				1							
Lamp					.99						.01
Fan						1					
Fridge							1				
Hair dryer								1			
Humidifier									1		
Tea machine		.08								.92	
TV					.28						.72

Table 3. Confusion matrix for the custom dataset, reporting accuracy per category in percentage.

	Air Compressor	Light	Computer	Garage door	Iron	Kitchen aids	Laptop	LCD Monitor	Monitor	Fridge	TV
Air Compressor	.96				.04						
Light		.85		.03							.12
Computer		.03	.80				0.11		.03		.03
Garage door	.03	.08		.84					.02		.02
Iron					1						
Kitchen aids						1					
Laptop		.05	.09				.68		.14	.04	
LCD Monitor		.02	.26				.06	.41	.25		
Monitor		.03	.03	.03			.13	.06	.59	.06	.07
Fridge							.04		.04	.92	
TV		.22		.03							.75

Table 4. Confusion matrix on the BLUED dataset, reporting accuracy per category in percentage.

5. Conclusions

In this work we analyzed the pertinence to use a low frequency sensor in a NILM approach for which we improve the performances with an active machine learning strategy. With this strategy, the system is able to a priori identify some appliances with typical signatures and to improve its performance by requesting the help of the user when the classification confidence is low. The operating mode of our system is therefore in between an automatic setup and a manual setup.

We also evaluated the proposed system using a subset of the signals available in the BLUED public dataset and by collecting a custom dataset in a residential setup. We demonstrates through the evaluation that the appliance identification achieves good results (95%) when the appliances are a priori known, i.e. when identical appliance with same brands and models are observed and labelled in the training set. When the task consists of classifying unseen appliances, the recognition performance is significantly worse (below 80%). A reason for this is in the inherent variability of the functioning of electric appliances when observing different brands and models. Another source of variability in also in the user when involved in the appliance functioning. These results were actually the motivation for us to propose an active learning procedure.

We also observed that classification algorithms taken from the family of decision trees (random forests, decision jungles) are leading to efficient systems with relatively few tunings compared to other algorithms.

Conceptually, we can conclude that a fully automatic setup of such system is probably very difficult to reach as the brands and models of appliance are very volatile and constantly changing. The approach we propose is leveraging on a continuous enrichment of the knowledge base by the user.

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