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Detection of unidentified appliances in non-intrusive load monitoring using siamese neural networks

Leen De Baets*, Chris Develder, Tom Dhaene, Dirk Deschrijver

IDLab, Department of Information Technology, Ghent University – imec, Technologiepark-Zwijnaarde 15, 9052 Ghent, Belgium

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ABSTRACT

Non-intrusive load monitoring methods aim to disaggregate the total power consumption of a household into individual appliances by analyzing changes in the voltage and current measured at the grid connection point of the household. The goal is to identify the active appliances, based on their unique fingerprint. Most state-of-the-art classification algorithms rely on the assumption that all events in the data stream are triggered by known appliances, which is often not the case. This paper proposes a method capable of detecting previously unidentified appliances in an automated way. For this, appliances represented by their VI trajectory are mapped to a newly learned feature space created by a siamese neural network such that samples of the same appliance form tight clusters. Then, clustering is performed by DBSCAN allowing the method to assign appliance samples to clusters or label them as 'unidentified'. Benchmarking on PLAID and WHITED shows that an $F_{1,macro}$-measure of respectively 0.90 and 0.85 can be obtained for classifying the unidentified appliances as 'unidentified'.

1. Introduction

In October 2014, EU leaders agreed upon three key targets for the year 2030 [1]: (1) a reduction of at least 40% cuts in greenhouse gas emissions, (2) a save of at least 27% share for renewable energy, and (3) at least 27% improvement in energy efficiency. Energy monitoring proves a useful aid to reach these targets by providing an accurate, detailed view of energy consumption. It helps because: (1) if this information is given to households, studies have shown that they could save up to 12% of electrical energy and thereby reduce the emissions [2] (also useful for non-residential buildings [3]), (2) this information allows us to assess and exploit the flexibility of power consumption, which in turn is important for demand response systems that are responsible for an increased penetration of distributed renewable energy sources, (3) energy monitoring is one major prerequisite for energy efficiency measures [4].

In order to achieve the required energy monitoring cost-effectively, i.e., without relying on per-device monitoring equipment, non-intrusive load monitoring (NILM) provides an elegant solution [5]. NILM identifies the per-appliance energy consumption by first measuring the aggregated energy trace at a single, centralized point in the home using a sensor and then disaggregating this power consumption for individual devices, using machine learning techniques.

Several supervised and unsupervised methods have been developed to recognise the appliances and to compute the total power consumption [6,7,5]. However, to our knowledge, most classification algorithms described in the literature can not handle unidentified appliances. These will be assigned a label and power consumption that corresponds to the appliance having the most similar features. This paper suggest a method that is capable of detecting unidentified appliances, which are labeled as 'unidentified'. When such an appliance is detected, the user can be queried for information about the appliance (i.e., the class label). In this paper, appliances are characterised by their binary VI trajectory image [8,9], although other representations can also be considered.

The proposed method has a training and a test phase, as shown in Fig. 1. In the training phase, a new, lower dimensional feature space where samples of the same appliance are clustered, is computed from the VI trajectory images by training a siamese neural network. The VI trajectory images must be paired and labelled respectively as must- or cannot-links, depending if the images belong to the same class or not. The transformation does not depend on the appliance label. On the transformed input, DBSCAN is performed to group samples with similar feature vectors in the new space. DBSCAN is a state-of-the-art clustering method that does not require prior knowledge about the amount of clusters and that is capable of detecting outliers. In the test phase, a VI trajectory image is transformed to the new feature space. If this point does not belong to a cluster, it is labelled as 'unidentified'.

The outline of the paper is as follows: Section 2 describes the related

* Corresponding author.
E-mail address: leen.debaets@ugent.be (L. De Baets).

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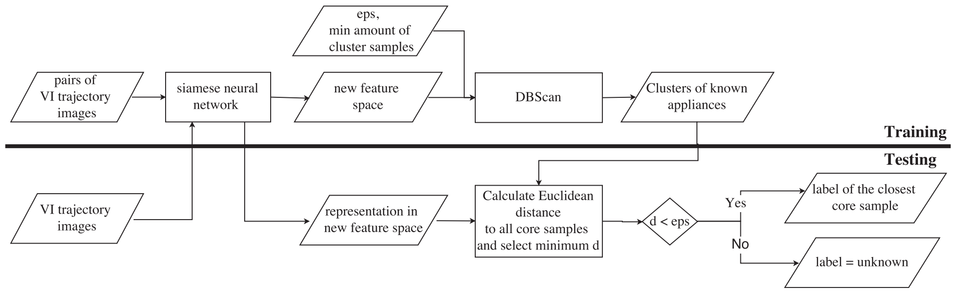

Fig. 1. The work flow of the proposed method that is able to detect unidentified appliances.

work concerning NILM classification algorithms. Section 3 explains the concept of siamese neural networks and how they can be used to learn a new feature space. Section 4 explains the DBSCAN clustering algorithm. Section 5 benchmarks the quality of the clustering, the capability of detecting unidentified appliances and the generalization property of the method. Additionally, it also discusses how this method can be used in a quasi real-time solution. Finally, Section 6 concludes this paper.

2. Related work

A specific application of NILM is appliance detection. Hart [10] was the first to describe the several steps in this process: (1) measuring the aggregated power consumption with a sensor attached to the main power cable, (2) detecting state-transitions of appliances (events) from the captured data using a robust statistical test [11], (3) describing transitions using a well-chosen feature vector, e.g., VI trajectories, (4) recognizing and monitoring each appliance using supervised and unsupervised methods. It must be noted that for some NILM algorithms, the event detection is a side effect of the approach, and not a separate module in the algorithm itself.

Feature definition. After detecting state-transitions of appliances, these must be described by a well-chosen feature vector. The type of features depends strongly on the sampling rate of the measurements. When using low frequency data (⩽1 Hz), the most common features are the power levels and the ON/OFF durations [12]. A drawback of this approach is that only energy-intensive appliances can be detected. When using higher frequency data, it is possible to calculate features like the harmonics [13] and the frequency components [14] from the steady-state and transient behaviour of the current and voltage signal, enabling the algorithm to also detect non energy-intensive appliances. More recently, the possibility to consider voltage-current (VI) trajectories has also been considered [8,9,15].

The VI trajectory of an appliance is obtained by plotting the voltage against the current for a defined time period when the appliance is turned on, see Fig. 2a. It is shown in [15] that manually extracting features from the VI trajectory can be informative to classify the appliances. Nevertheless, this is not straightforward. As an alternative, the VI trajectory can be converted into a binary VI image ($n \times n$ matrix) by meshing the VI trajectory, see Fig. 2b. In [8,9], each cell of the mesh is assigned a binary value that denotes whether or not it is traversed by the trajectory. Based on this binary VI image, several features can be extracted to classify different power loads [9]. Even the binary VI image itself can be used as input for a classifier [8], as will also be the case in this paper.

In order to distinguish appliances based on their VI trajectories, measurement devices must be used that are able to sample high frequency data.

Recognizing appliances and monitoring power consumption. Once the features are extracted, they can be fed into different classification methods, like support vector machines (SVM) [16,17], neural networks [18], decision trees [19], or nearest neighbours [20]. For these methods, labelled training data is necessary. If labels are not present, unsupervised methods can be used. An overview of these methods is given in [21].

The majority of the NILM approaches, supervised or unsupervised, are sensitive to appliance changes in the house, thus require regular retraining. In this paper, the focus lies on creating a classification algorithm that is able to detect unidentified appliances and is thus resilient against appliance changes in the house. If an unidentified appliance is detected, labeling and retraining is requested.

Clustering. In order to detect unidentified appliances, clustering must be performed. The idea is that samples originating from the same appliances will appear as clusters in the feature space and samples originating from unidentified appliances will appear as outliers indicating the need to create a new cluster. The use of clustering methods has previously been explored in non-intrusive load monitoring. In [10], a simple clustering algorithm was mentioned where the appliances are grouped using the active – reactive power (P-Q) plane as feature

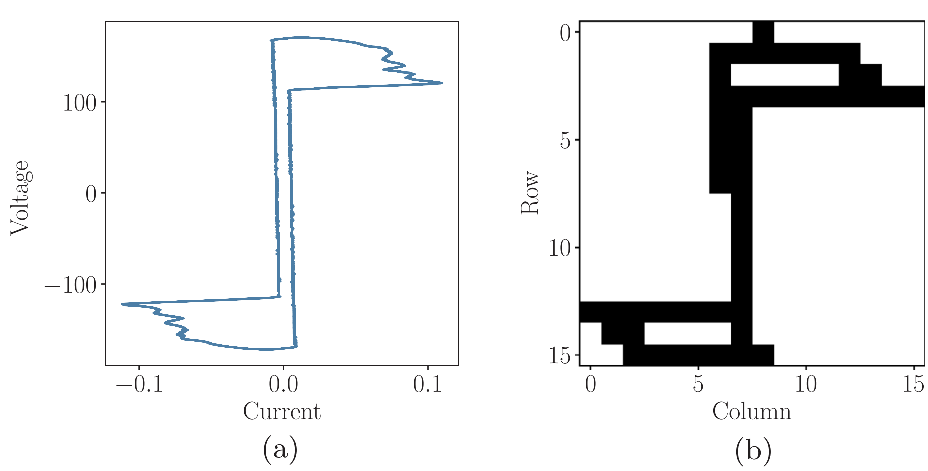

Fig. 2. The original VI trajectory (left) and the corresponding binary VI image (right).