Unsupervised Energy Disaggregation of Home Appliances

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Abstract. Energy management is a growing concern especially with the increasing growth of smart appliances within the home. Energy disaggregation is an ongoing challenge to discover the appliance usage by examining the energy output of a household or building. Unsupervised NILM presents the additional challenge of energy disaggregation without any reliance on training data. A key issue to address in Unsupervised NILM is the discovery of appliances without a priori information. In this paper we present a new approach based on Competitive Agglomeration (CA) which incorporates the good qualities of both hierarchical and partitional clustering. Our proposed energy disaggregation algorithm makes use of CA in order to discover appliances without prior information about the number of appliances. Validation with experimental data from the Reference Energy Disaggregation Dataset (REDD), and comparison with recent state of the art Unsupervised NILM indicates that our proposed algorithm is effective.

Keywords: Home energy management · Unsupervised energy disaggregation · Unsupervised non-intrusive load monitoring

1 Introduction

The growth of devices has increased the energy consumption of households as shown in [1], and placed a greater stress on energy demand [2]. This situation can be partially attributed to the advent of the Internet of Things and the increasing number of smart devices in homes. Given this, there is greater importance on the efficiency of energy usage, especially within the home. To this end there has been ongoing work to enable people to be better informed about their household energy usage. Feedback has been shown to have a positive impact on the livelihood of a household as shown in [3, 4], and a study [5] has presented findings that indicate that people are showing greater concern towards their energy consumption and protecting the environment.

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The first works on NILM were conducted by Hart in the 1980s and 1990s, and presented in [6]. In his work Hart defined the total load model as follows:

$$P(t) = \sum\nolimits_{\mathrm{i}=1}^{\mathrm{n}} P_i + e(t) \tag{1}$$

where $P(t)$ is the total power load as seen at time t, and $e(t)$ is a small noise or error term. This model is used as the basis for the energy disaggregation problem.

NILM classifies appliances as either Type I ON/OFF, Type II Finite State Machines (FSMs), or Type III Continuously Variable Devices (CVDs). Uncovering the composition of a total load is done through the use of appliance signatures, with steady-state signatures being preferred since they don't require complex extraction methods. Work in NILM typically involves extracting the data from the source and transforming it into an appropriate format for analysis. Events or changes in energy usage are then detected and then clustered placing similar events together. The next steps are then to build models of the appliances and track the energy usage through the models, and lastly provide feedback through the appliance models and their corresponding usage. There has been a wide range of approaches to the Unsupervised NILM problem, but practical solutions that can be applied in real world situations are of greater value. We aim to introduce one such practical approach with the research work presented in this paper.

2 Related Works

One of the most recent works in Unsupervised NILM is [7] which builds on the emerging Graph Signal Processing (GSP) concepts to develop a novel, blind, unsupervised low-rate NALM approach. Based on the results from disaggregating aggregate loads measured from 4 real houses, they show that their training-less GSP-based NALM approach has comparable performance with the supervised GSP-based NALM approach. [8] presents a Bayesian approach to obtain the disaggregation of the loads where only active power measurements are available at a sampling rate of a few seconds. The proposed method requires the prior availability of appliance information which are obtained using unsupervised learning. The results indicated that the appliances are disaggregated with a greater accuracy when the appliance ratings are distinct and those appliances with closely placed ratings have a poorer results. Also the possibility of some load combination power matching another appliance also affects the disaggregation results. Henao et al. [9] use transformed active power transitions as features. The proposed approach is based on the Subtractive Clustering and the Maximum Likelihood Classifier. The validation results with six commonly found ON/OFF residential appliances indicate that the proposed approach is effective. In addition, the obtained results from a Monte Carlo simulation suggest that this approach is less sensitive to power grid noise than a K-mean-based NIALM method. An unsupervised load disaggregation approach is proposed in [10] that works without a priori knowledge about appliances. The proposed algorithm works autonomously in real time. The number of used appliances and the corresponding appliance models are learned in operation and are progressively updated. The proposed algorithm considers each useful and suitable detected power state, and tries to detect power states corresponding to ON/OFF appliances as well as to multi-state appliances based on active power measurements in 1 s resolution. In [11] Jia et all present a fully unsupervised NILM framework based on Nonparametric Factorial Hidden Markov Models. They also propose a criterion, Generalized State Prediction Accuracy, to properly evaluate the overall performance for methods targeting at both appliance number detection and load disaggregation. Using low frequency power measurements from real world, they have showed that their framework outperforms the other Factorial Hidden Markov Model (FHMM) approaches, and is very computationally efficient. The aforementioned works show that the active power signature can be effectively used for unsupervised energy disaggregation.

Various approaches have also been used to address the challenge of discovering the number of appliances present in the load. [12] focuses on Stochastic Modeling and energy disaggregation based on Conditional Random Fields (CRFs) using real-world energy consumption data. The proposed disaggregation method uses a clustering method and histogram analysis to detect the ON/OFF states of selected types of energy-using devices in the home. Long spans of data from 21 households were used in a binary classification experiment, in which an 86.1% average classification accuracy was achieved. The proposed method was also evaluated using Hidden Markov models (HMMs), but significantly higher accuracy was obtained when CRFs were applied. In [13] a Heuristic Unsupervised Clustering algorithm is presented and evaluated to enable autonomous partitioning of appliances signature space (i.e. feature space) for applications in electricity consumption disaggregation. The algorithm is based on Hierarchical Clustering and uses the characteristics of a cluster binary tree to determine the distance threshold for pruning the tree without a priori information. The algorithm determines the partition of a feature space recursively to account for multi-scale nature of the binary cluster tree. [14] presents research on an unsupervised NILM system which consists of the typical stages of an event-based NILM system with the difference that only unsupervised algorithms are utilized in each stage eliminating the need for a pre-training process and providing wider applicability. They make use of Grid-Based Clustering algorithm for the event detection and Mean-Shift Clustering algorithm on the features extracted from the detected events. The system is tested on the publicly available Building-Level Fully Labeled Electricity Disaggregation Dataset (BLUED) and shows event detection and clustering accuracy more than 98%. The system also shows possible disaggregation up to 92% of the energy of phase A of the BLUED dataset. From our research work, there is no unsupervised NILM literature that makes use of our proposed approach for feature clustering, so we are justified in stating that our algorithm uses a new approach to energy disaggregation.

Additional literature on Unsupervised NILM algorithms including a listing of summary of the state of the art contribution performance can be found in [15].

The work presented in [16] first introduced a new clustering algorithm called Competitive Agglomeration (CA). CA minimizes an objective function that incorporates the advantages of both hierarchical and partitional clustering. The objective function has two components. The first component, is the sum of squared distances to the prototypes weighted by constrained memberships. This component allows for control of the shapes and sizes of the clusters and to obtain compact clusters. The second component is the sum of squares of the cardinalities of the clusters which allows us to control the number of clusters. When both components are combined and α is chosen properly, the final partition will minimize the sum of intra-cluster distances, while partitioning the data set into the smallest possible number of clusters. The clusters which are depleted as the algorithm proceeds will be discarded. The objective function of the CA algorithm is defined as follows:

$$\mathrm{J(B, U, X)} = \sum_{i=1}^{C} \sum_{j=1}^{N} \left(u_{ij}\right)^2 d^2\left(x_j, \beta_i\right) - \alpha \sum_{i=1}^{C} \left[\sum_{j=1}^{N} u_{ij}\right]^2 \tag{2}$$

Subject to

$$\sum_{i=1}^{C} u_{ij} = 1, \; for\, j \in \{1, \ldots, N\} \tag{3}$$

where $X = \left\{x_j | j = 1, \ldots, N\right\}$ is a set of N vectors in an n-dimensional feature space with coordinate axis labels $\left(x_1, \ldots, x_n\right)$, and $\mathrm{B} = \{\beta_1, \ldots, \beta_c)$ represents a C-tuple of prototypes each of which characterizes one of the clusters. $d^2\left(x_j, \beta_i\right)$ represents the distance from feature vector x_j to the prototype β_i, u_{ij} represents the degree of membership of feature point x_j in cluster β_i, and $\mathrm{U} = [U_{ij}]$ is a C x N matrix called a constrained fuzzy C-partition matrix. Equation 2 is constrained to Eq. 3, which states that the total membership for each cluster must be equal to 1.

3 Algorithm Design

3.1 Problem Definition

The NILM problem can be defined using Eq. (1). The goal is to find each individual appliance usage $P_i(t)$ that the total load is comprised of. The additional challenge of Unsupervised NILM is that we solve Eq. (1) without reliance on training data. Our algorithm makes use of active power as features, and thus the problem we aim to address can be stated as follows

$$P_{t_i} = \sum_{j=1}^{n} P_{jt_i} + e_{t_i} \tag{4}$$

where P_{t_i} is the total active power as seen at time t_i, P_{jt_i} is an individual appliance's active power contribution to the total active power, and e_{t_i} is a small noise or error term.

3.2 Goal and Objectives

The goals of the algorithm can be stated as follows:

1. Given a total load at time t decompose it into the individual energy usage events using the active power feature
2. Group similar features together and use these groups to build appliance models

3. Recognize the presence of appliances using the appliance models
4. Reconstruct the total load at time t by matching it with a set of appliances models.

The assumptions made with this algorithm are that:

1. the total load is sampled at a low-rate
2. only one device will change within the given window of time t.

3.3 Algorithm Overview

Our proposed algorithm is comprised of five modules: Feature Extraction, Feature Clustering, Appliance Modeling, Appliance Recognition, and Load Reconstruction.

Feature Extraction

Given a total load, the variations of the active power between given time windows can indicate the presence of an event, which would represent some form of change of state of an appliance. In order to determine appliance usage, we need to find the significant events that would indicate that an appliance could be in use. To do this we define a threshold value and make use of Eq. (5).

$$\Delta P_{t_i} = \left(P_{t_{i+1}} - P_{t_i}\right) > 0\,\mathrm{W} \tag{5}$$

where ΔP_{t_i} is a significant change in active power between two event windows.

Once all the significant events have been detected and the features extracted, they are then passed on to the Feature Clustering module.

Feature Clustering

Each feature is placed in a cluster that has features similar in value to itself magnitude-wise, resulting in a set of positive and negative clusters. The feature clustering module is based on the CA algorithm. We provide the CA algorithm with the extracted features and initialize the initial overspecified clusters (Cmax) to a fixed value. The CA algorithm iteratively groups similar features together. Once the algorithm has stabilized or run the maximum number of iterations, it outputs a set of feature clusters. The final number of clusters is determined automatically which is in line with our requirement of not depending on knowledge of the number or types of appliances in use.

The next step is to define appliance models which will serve as representations of actual appliances.

Appliance Modeling

Due to the simplicity of modeling transitions for Type I appliances, we make use of them here. In order to perform the modeling the set of positive and negative clusters will be split into two groups, one containing the positive clusters (C_P), and the other containing the negative clusters (C_N). The appliance models will be defined by first examining the set of positive clusters and doing the following:

1. given a positive cluster search the set of negative clusters for a cluster that is similar
2. if there is a match then the two clusters form a pair representing a cycle of state changes, and the clusters will be removed from their respective sets

We make use of the following equation for the appliance modeling:

$$M_i = \left\{ C_{P_i}, min\left(\left\| C_{p_i} - C_{N_j} \right\|^2 \right) \right\} \tag{6}$$

where M_i is the appliance model, C_{P_i} is the positive cluster,C_{N_j} is the negative cluster, $min\left(\left\| C_{p_i} - C_{N_j} \right\|^2 \right)$ is the negative cluster with the smallest Euclidean distance to the positive cluster, for $i = 1, \ldots, C_{p_n}$, and $j = 1, \ldots, C_{N_n}$.

The process stated above will be run until all the positive clusters have been examined and the result will be a set of paired clusters that each represent a cycle of events. Any unmatched positive and/or negative clusters will be discarded as we only consider matched pairs of clusters for Type I appliance models. This set of paired clusters will form the basis for determining the appliance usage and reconstructing the load.

Appliance Recognition

With the appliance models defined the next part is to use them to recognize their presence as part of the total load. The appliance recognition steps are as follows

1. given ΔP_{t_i} check if there is an appliance model that matches it, and record a value of true if there is a match
2. otherwise record a value of false

The appliance recognition can be defined as in Eq. (7) for step-up transitions and Eq. (8) for step-down transitions.

$$Match\ if\ rnd\left(\Delta P_{t_i}\right) = rnd\left(M_{j_P}\right) \tag{7}$$

$$Match\ if\ rnd\left(\Delta P_{t_i}\right) = rnd\left(M_{j_N}\right) \tag{8}$$

where M_{j_P} is the ON value of the appliance model, and M_{j_N} is the OFF value of the appliance model, for $i = 1, \ldots, n$, and $j = 1, \ldots, M_n$. If there is no close matching appliance model then the ΔP_{t_i} will be recorded as not being recognized.

Load Reconstruction

The Load Reconstruction module pieces together the appliance usage into an aggregate load. In order to do this we first examine the total load and for each time window t we take the following steps:

1. if there is a significant change, and if this significant change was detected, then we take note of the appliance usage
2. if there is a significant change, but the change wasn't detected then we don't take note of the appliance usage

The significant events that were matched will be used to reconstruct the signal. This is done by connecting the detected significant events together into one whole signal. The output will be a time series indicating the usage of appliances.

4 Validation with Experimental Data from REDD Database

In order to validate our proposed algorithm we make use of energy data from Reference Energy Disaggregation Dataset (REDD) [17], which is a commonly cited open access data set for energy data.

4.1 Validation Context and Scenario

To enable for a like-for-like comparison with the state of art FHMM approach [18] and the latest GSP-based approach [7] we made use of energy data from Houses 1, 2, and 6 of the REDD. We considered a three day period for each of the houses, from 28 to 30 April 2011 for Houses 1 and 2, and 28 to 30 May 2011 for House 6 (Fig. 1).

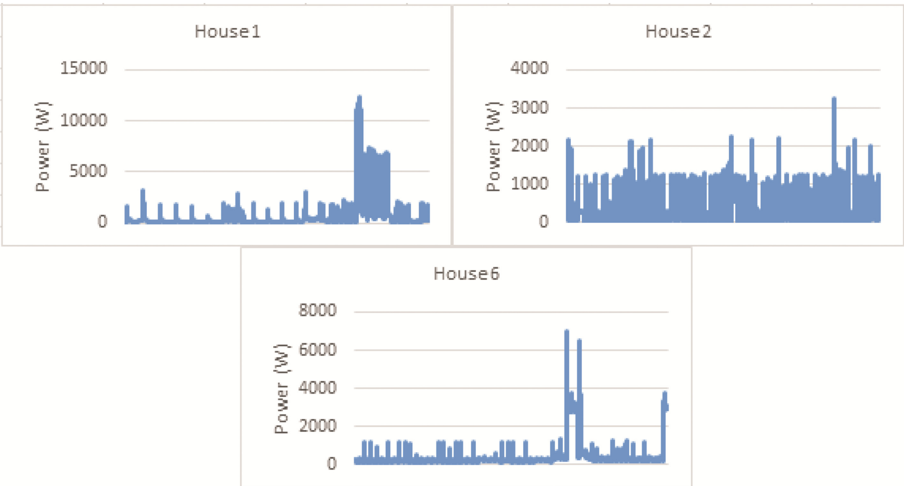

Fig. 1. Aggregate loads for REDD Houses 1, 2, and 6

4.2 Evaluation Metrics

In this paper we make use of Precision (P), Recall (R), and F-measure (f_1) NILM metrics, which are defined as:

$$\mathrm{P} = \frac{TP}{TP + FP} \tag{9}$$

$$R = \frac{TP}{TP + FN} \tag{10}$$

$$f_1 = \frac{2 \cdot P \cdot R}{P + R} \tag{11}$$

where the true positive (TP) presents the correct claim that the appliance was used, false positive (FP) represents an incorrect claim that an appliance was used, and false negative (FN) indicates that the correct appliance was not identified.

We also make use of the Disaggregation Accuracy metric for the household which is defined as:

$$\text{DAcc.} = 1 - \frac{\sum_{i=1}^{n} \sum_{m \in M} \left| \widehat{P}_{m_{t_i}} - P_{mt_i} \right|}{2 \sum_{i=1}^{n} \overline{P}_{t_i}} \tag{12}$$

4.3 Results and Discussion

We evaluated our proposed algorithm using the energy data from each of the aforementioned houses. We extracted features from each of the loads, shown in Fig. 2.

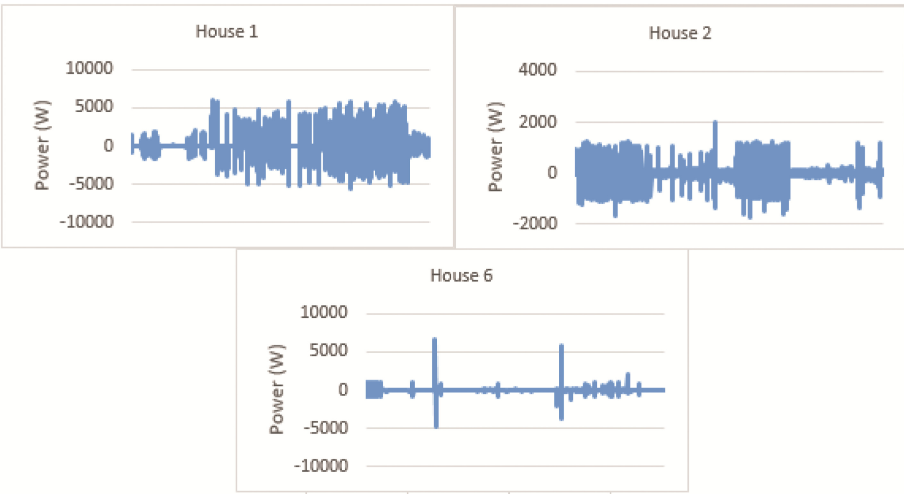

Fig. 2. Extracted features for REDD Houses 1, 2, and 6

The extracted features were then grouped together using the Feature Clustering module and the resulting clusters were used for Type I appliance modeling. The models are shown in Fig. 3.

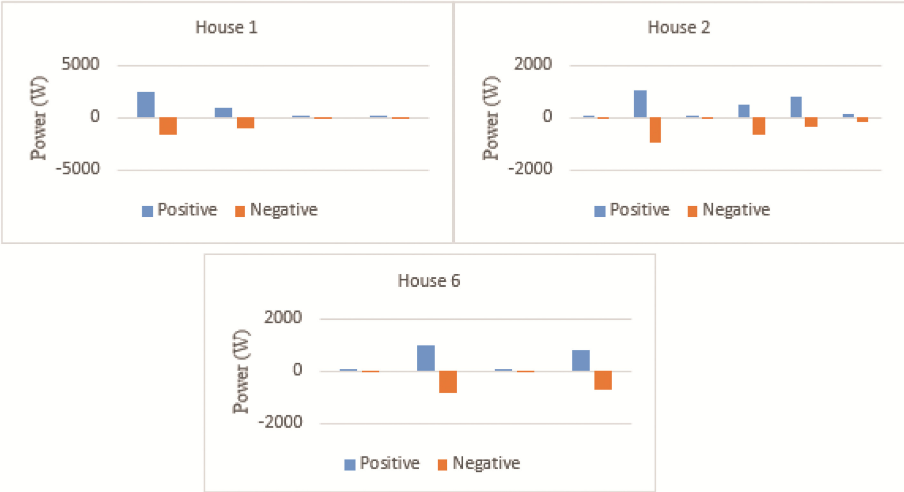

Fig. 3. Appliance models for REDD Houses 1, 2, and 6

The appliance models were then used for appliance recognition and load reconstruction. Appliance recognition is used to determine algorithm performance, and we discuss the results here. In Table 1 we have a comparison of our algorithm with the state of the art FHMM [18] and DTW [19] approaches for Precision, Recall and F-measure.

Table 1. Comparison of Precision, Recall, F-measure with FHMM and DTW

Approach	P (%)	R (%)	f_1 (%)
FHMM [18]	82.70	60.30	71.29
DTW [19]	91.24	81.77	86.16
Proposed approach (House 1)	100.00	78.15	87.74
Proposed approach (House 2)	100.00	83.86	91.22
Proposed approach (House 6)	100.00	68.58	81.36

From Table 1 we can see that our Precision is above the state of the art FHMM approach and DTW approach. It should be noted that our approach had no false positives hence the values for Precision. Our results for Recall were all above that of the FHMM approach and comparable with the performance of the DTW approach. Our F-measure results show that our algorithm performed better than the FHMM approach, and similarly with Recall it was comparable with the performance of the DTW approach.

Table 2 shows the disaggregation accuracies for the GSP-based approach and its benchmarks, alongside our proposed approach. It should be noted that the Expectation Maximization FHMM (EM-FHMM), Factorial Hierarchical Dirichlet Process HMM (F-HDP-HMM), and F-HDP Hidden Semi-Markov Model (F-HDP-HSMM) approaches [20] only considered the 5 top consuming appliances when performing the disaggregation. Additionally the GSP-based approach also used a pre-processing step to denoise the energy data which we did not do in this work.

Table 2. Disaggregation accuracy comparison with GSP-based and benchmarks

Approach	DAcc. (%)
Proposed approach	71.00
GSP-based [7]	77.20
EM FHMM [20]	50.80
F-HDP-HMM [20]	70.70
F-HDP-HSMM [20]	84.80
FHMM (without interaction) [21]	65.80
FHMM (with interaction) [21]	66.50

Table 2 shows that our algorithm outperforms the EM-FHMM, FHMM (without interaction), and FHMM (with interaction) approaches. It has similar performance with the F-HDP-HMM approach, and is slightly worse than the GSP-based and F-HDP-HSMM approaches. The result of F-HDP-HSMM approach could be due to the fact that it only considered the 5 top consuming appliances, whereas our approach, the GSP-based approach, and the two FHMM-based approaches used 7 appliances.

From the validation we saw that our theoretical framework for the proposed unsupervised energy disaggregation is justified to a certain extent. Our algorithm provides a means to disaggregate energy data without prior knowledge of the number or types of appliances. We were able to extract features from an aggregate load, group similar features together without knowledge of the actual clusters, and define appliance models that were used to recognize appliance usage in the aggregate load.

Our approach has some limitations. Due to the fact that we model Type I appliances it means that we cannot provide information regarding the actual appliances that the aggregate load is comprised off. We also made use of fixed values for the threshold for denoting significant events and the Cmax value in the feature clustering process. These limitations will serve as part of future work for this algorithm.

5 Conclusion

5.1 Conclusion and Future Works

In this paper we introduced a new approach to unsupervised energy disaggregation based on Competitive Agglomeration (CA) and the active power signature. Our proposed algorithm incorporates the goals of NILM and is able to disaggregate energy data, all without knowledge of the number of actual appliances in use. We validated the design of our algorithm with experimental data from the Reference Energy Disaggregation Data Set (REDD), and the results of this validation indicates that our unsupervised energy disaggregation algorithm is indeed effective. Additionally comparison of our algorithm with recent state of the art Unsupervised NILM algorithms shows that our work outperforms some of these works but also has slightly worse performance for others. Overall the comparison indicates that our algorithm has good performance.

In our future work we aim to overcome the identified limitations of the algorithm, and will focus on improvements to the appliance modeling and appliance recognition modules in order to gain better disaggregation performance.

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