An approximate probabilistic approach for event-based disaggregation

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ABSTRACT

We consider the problem of overlap in the power draw between different appliances in nonintrusive load monitoring. We complement the power features by time-on and time-off statistics and use approximate semi-Markov models for robust computationally-efficient disaggregation. The superior disaggregation accuracy of our algorithm is demonstrated on actual household data.

Keywords

Disaggregation algorithm, power draw, appliances, signal features, energy management.

1. INTRODUCTION

Numerous new nonintrusive load monitoring (NILM) methods have been proposed recently in both academic and industrial research [1], however, it appears that these methods are not yet applicable to computationally efficient disaggregation of data obtained with such ubiquitous devices as home energy displays (HED) or smart meters. In this paper, we explain a new algorithm for disaggregation of HED data. It uses a probabilistic framework to incorporate information beyond power draw that dramatically improves disaggregation accuracy.

2. ALGORITHM DESCRIPTION

The algorithm is explained in detail elsewhere [2]. Here, we provide a brief overview. In the current version, the algorithm is applicable to two-state appliances (i.e., to on/off appliances), but it can also be extended to incorporate multi-state and permanent-on devices.

The key idea is to decompose a system of appliance models such that only appliances overlapping in power draw with a given appliance are considered at a time. In this way, the complexity of the disaggregation algorithm is linearly proportional to the number of appliances whereas the complexity of other probabilistic methods exponentially grows with the number of appliances.

Suppose there are N on-off appliances ordered by their power draw. Consider appliance i, $1 < i < N$. The measured power draw of appliance i can overlap with the measured power draws of the "adjacent" appliances $(i - 1)$ and $(i + 1)$. It may also overlap with the measured power draws of more "distant" appliances, such as $(i \pm 2)$, $(i \pm 3)$, .., $(i \pm k)$, but the overlap degree becomes smaller with k. In the simplest case, the overlap with the distant appliances is negligible and only appliances $(i \pm 1)$ overlap with appliance i. The system of the three appliances can be modeled as a Markov Chain, and the system states can be optimally decoded using the Viterbi algorithm. However, this system could be "non-pristine" in the sense that fractions of the power draw populations corresponding to appliances $(i - 1)$ and $(i + 1)$ could be missing and "foreign" data from other appliances could be present in the system, as is shown in Fig. 1.

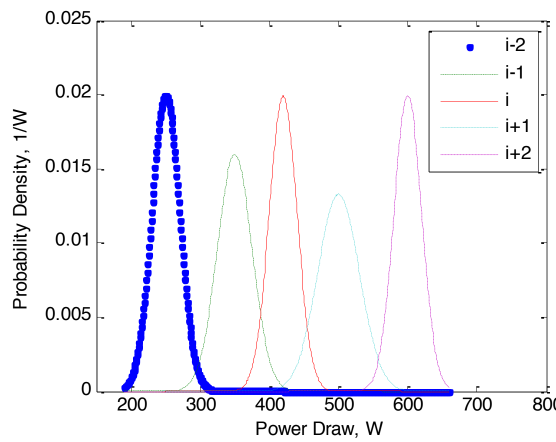

Fig. 1. Possible PDFs of power draw of appliances i and its neighbors.

The non-pristinity of the system suggests that the Markov chain needs to account for the missing and foreign data. Since the "pristine" part of the system is characterized by both power draw and time-on/off features, the resultant Markov chain that includes both pristine and non-pristine components will be approximated. Also, there will be 64 transitions within the triplet system $\{i, (i - 1) \text{ and } (i + 1)\}$, which may slow down the computations.

In this work, we implement an even more approximate approach, in which we consider appliance pairs. To this end, we further decompose the triple $\{(i - 1), i, (i + 1)\}$ into two pairs, $\{(i - 1), i\}$ and $\{i, (i + 1)\}$. Within each pair, there are only 16 transitions. The states of the system comprising appliances i and $(i + 1)$ are listed in Table I.

TABLE I
STATES OF TWO-APPLIANCE SYSTEM

State	Appliance i	Appliance $(i + 1)$
1	Off	Off
2	On	Off
3	Off	On
4	On	On

Table II presents possible events underlying transitions that correspond to an observed negative power change. Note that the events selected are the likeliest among other possible events. The probabilities of the events listed in Table II can be calculated using the statistical distributions of power- and time features. We assign a constant probability of a foreign datum and a constant probability of a missing datum, and their dependence on time is modeled also through a constant probability. Therefore, the proposed method is approximated in two ways (i) only likeliest events underlying each system transition are considered and (ii) constants are used to model missing and foreign data.

TABLE II
TRANSITION SCENARIOS FOR OBSERVED NEGATIVE CHANGE OF POWER

Transition between states	Underlying Event(s)
1,1	Is foreign datum
1,2	Was missing datum from state 2 and is foreign datum
1,3	Was missing datum from state 3 and is foreign datum
1,4	Were missing data from states 2 and 3 and is foreign datum
2,1	Appliance *i* is turning off but appliance (*i* + 1) has not turned on
2,2	Is foreign datum
2,3	Was missing datum from state 4 and is 4,3 transition
2,4	Was missing datum from state 4 and is external datum
3,1	Appliance (*i* + 1) is turning off but appliance *i* has not turned on
3,2	Was missing datum from state 4 and is 4,2 transition
3,3	Is foreign datum
3,4	Was missing datum from state 4 and is foreign datum
4,1	Was missing datum from either state 2 or 3 and is 2,1 or 3,1 transition
4,2	Appliance (*i* + 1) is turning off but appliance *i* has not turned off
4,3	Appliance *i* is turning off but appliance (*i* + 1) has not turned off
4,4	Is foreign datum

Table II suggests that the Markov chain, which approximately models the system of appliances *i* and (*i* + 1) is of the first order for each appliance, but is of a higher order for the entire system. This implies that the standard Viterbi algorithm that optimally decodes the states of a first-order Markov chain, needs to be modified. In the case of two on-off appliances comprising the system, we need to keep in memory the likelihood calculated at one step prior to either appliance status change. Even though the number of such previous steps is not known a priori, the computer implementation is straightforward.

After applying the algorithm to the overlapping pairs, the decoded information on the state of appliance *i* is fused from the two pairs using the maximum likelihood principle [2]. Thereafter, the results are updated to prevent overlaps in decoding. We fuse the information decoded for the individual appliances using the maximum likelihood approach.

3. RESULTS

We applied the algorithm to the data collected by Kolter and Johnson [3]. We selected data submetered on nine circuits in home 1 [3], because these data represented most of the common appliances collected over a prolonged period of time [2]. The data were artificially aggregated and then pre-processed. The pre-processing included clustering of the aggregated data and statistical characterization of the clusters (power draw and time on/off distributions). The disaggregation algorithm was then applied to better separate the clusters. Table III presents the disaggregation results in terms of the F-measure. For the sake of comparison, the estimates of a simple Bayesian classifier were also calculated.

TABLE III
DISAGGREGATION RESULTS

Circuit (usually appliance)	Bayesian classifier	Our algorithm
Refrigerator	0.859	0.831
Dishwasher	0.881	0.846
Kitchen 1	0.989	0.936
Microwave	0.775	0.899
Kitchen 2	0.409	0.840
Bathroom GFI	0.753	0.927
Oven 1	0.800	0.908
Oven 2	1.0	0.962
Kitchen 2	1.0	0.971

The disaggregation results for the non overlapping circuits (first three and last two circuits of Table III [2]) do not show any noticeable improvement by using the proposed method. At the same time, for the heavily overlapping circuits 4-7 the use of our method results in dramatic accuracy improvement.

4. REFERENCES

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About the author:

Michael Zeifman received his undergraduate degree in Engineering Physics from St. Petersburg State Polytechnic University, Russia, and a M.Sc. in Quality Control and a Ph.D. in Physical Reliability from Technion – Israeli Institute of Technology. Michael has developed physics-based methods for data analysis and signal processing that significantly improved accuracy and predictive capability. He is currently leading home energy monitoring and modeling work at the Fraunhofer Center for Sustainable Energy Systems.