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A Hybrid Signature-based Iterative Disaggregation algorithm for Non-Intrusive Load Monitoring

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HIGHLIGHTS

- The hybrid, efficient, algorithm "HSID" for Non-Intrusive Load Monitoring is proposed.
- HSID outperforms benchmark techniques for residential power load disaggregation.
- HSID is robust to signal noise and high number of appliances, and can be used in semi-supervised applications.

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ABSTRACT

Information on residential power consumption patterns disaggregated at the single-appliance level is an essential requirement for energy utilities and managers to design customized energy demand management strategies. Non-Intrusive Load Monitoring (NILM) techniques provide this information by decomposing the aggregated electric load measured at the household level by a single-point smart meter into the individual contribution of each end-use. Despite being defined *non-intrusive*, NILM methods often require an intrusive data sampling process for training purpose. This calibration intrusiveness hampers NILM methods large-scale applications. Other NILM challenges are the limited accuracy in reproducing the end-use consumption patterns and their trajectories in time, which are key to characterize consumers' behaviors and appliances efficiency, and the poor performance when multiple appliances are simultaneously operated. In this paper we contribute a hybrid, computationally efficient, algorithm for NILM, called Hybrid Signature-based Iterative Disaggregation (HSID), based on the combination of Factorial Hidden Markov Models, which provide an initial approximation of the end-use trajectories, and Iterative Subsequence Dynamic Time Warping, which processes the end-use trajectories in order to match the typical power consumption pattern of each appliance. In order to deal with the challenges posed by intrusive training, a supervised version of the algorithm, requiring appliance-level measurements for calibration, and a semi-supervised version, retrieving appliance-level information from the aggregate smart-metered signal, are proposed. Both versions are demonstrated onto a real-world power consumption dataset comprising five different appliances potentially operated simultaneously. Results show that HSID is able to accurately disaggregate the power consumption measured from a single-point smart meter, thus providing a detailed characterization of the consumers' behavior in terms of power consumption. Numerical results also demonstrate that HSID is robust with respect to noisy signals and scalable to dataset including a large set of appliances. Finally, the algorithm can be successfully used in non-intrusive experiments without requiring appliance-level measurements, ultimately opening up new opportunities to foster the deployment of large-scale smart metering networks, as well as the design and practical implementation of personalized demand management strategies.

1. Introduction

The effectiveness of customized energy consumption feedbacks and, broadly, demand management strategies in the energy sector, such as economic incentives to upgrade poorly efficient energy

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consuming devices [1], hourly dynamic energy pricing to reduce demand in peak hours [2], and awareness campaigns to inform energy consumers about their broken-down consumption and savings [3], has been demonstrated to benefit from appliance-specific information [4,5]. The knowledge of timings, peak-hours, and frequencies of use of electric devices is key to understand consumers' behaviors, identify consumption anomalies, and, ultimately, design personalized demand management strategies (e.g., deferring the use of some appliances to peak-off hours). Appliance-specific personalized recommendations are potentially worth more than 12% reduction in annual domestic consumption and can bring multiple benefits to energy consumers, utilities, and research and development centres [6]. In the last two decades, this has been prompting big investments for the deployment of smart metering networks [7–9], along with the development of *Non-Intrusive Load Monitoring* (NILM) techniques. The main advantage of NILM [10] is that it allows decomposing the aggregated electric load measured at the household level by a single smart, high-frequency, meter into the individual contribution by each appliance, the so-called end-uses. Despite alternative options do exist for monitoring residential energy consumption at the appliance level (e.g., smart appliances, distributed sensing networks for direct measurement and smart plugs [11,12]), NILM methods, coupled with single-point sensors, are so far the most promising decomposition approach as they reduce hardware costs (sensor cost and related costs for installation, maintenance, battery and sensors replacement) as well as intrusiveness into users' houses, even though many require an intrusive calibration phase. Also, installing a unique high-resolution sensor per house significantly reduces the amount of data to manage, rather than collecting records from multiple sensors. Another reason promoting the suitability of NILM methods for large-scale energy disaggregation applications and market penetration consists in the overall economic advantages of disaggregation software technologies: a business case by Carrie Armel et al. [6] shows that the benefits per kW h in terms of potentially avoided energy generation and distribution outweigh the costs of disaggregation technologies by a factor of four. This is further demonstrated by the fact that NILM methods are currently used in domains other than energy consumption, including water and gas, and many companies such as General Electric, Opower and Belkin are working on their development closely with smart meter producers [13,6]. Yet, the problem of disaggregating an electric signal into its sub-components places a twofold challenge. On the one hand, disaggregation techniques should be able to maximize the appliance-specific information extracted from the aggregate signal. On the other hand, the algorithms should allow for scalability, while minimizing economic and privacy costs related to disaggregation activities (i.e., sensors installation, data collection, and data analysis).

Several NILM algorithms have been proposed in the literature (see Zoha et al. [13] and Zeifman et al. [14] and references therein for a review). Yet, a number of research and operational challenges are under debate and emerged in recent works. The first, most important issue is related to the rate of intrusiveness of the data sampling process [15]. In fact, after the seminal work by Hart [10], a first class of supervised algorithms has been developed, which requires large appliance-level data sets for the initial off-line training phase (e.g., Singh et al. [16], Elhamifar and Sastry [17], Kolter et al. [18]). Despite a certain level of intrusiveness is unavoidable to ensure accuracy in the subsequent stages of data disaggregation, the challenge is to keep it at a minimum. This challenge has been motivating the recent emergence of a second class of unsupervised algorithms, which generally avoid collecting appliance-level data (see Bonfigli et al. [19] and references therein).

Second, the definition of consistent accuracy metrics against which NILM algorithms can be evaluated and compared is another domain challenge. According to Butner et al. [20], Barker et al. [21] and Batra et al. [22], no consistent conventions and standards are currently in place for measuring the accuracy of NILM technologies. Many algorithms tend to focus only on accurately detecting the *on/off* status of each appliance (e.g., [23–25]) and their accuracy is hence evaluated using metrics accounting for *on/off* detection, such as the F-score [22]. Only few studies also consider the accuracy in reproducing the consumption patterns of single end-uses in time, which is evaluated either by visual inspection or by means of specific quantitative metrics [26–29,19,30,31]. While limiting the extent of NILM algorithms to only the detection of *on/off* events allows retrieving information on appliances time and frequencies of use, a correct reproduction of end-use patterns would support water utilities and demand management with more exhaustive information regarding consumers' behavior and energy usage efficiency. Accurate estimates of appliances power consumption patterns enables a better identification of peak-hours, a more accurate quantification of the power load contributed by each appliance during peak and off-peak hours, as well as assessments on the efficiency levels of different appliances. These are key information to understand consumers' behavior and, ultimately, design personalized demand management strategies targeted at improving power consumption efficiency and reducing costs, for instance through demand peak-shifting and retrofitting of low-efficiency devices.

Finally, a third challenge to energy disaggregation algorithms consists in the number of simultaneously operating appliances that can be identified by NILM algorithms [32,20,21]. This is a double challenge because an increasing number of simultaneously operating appliances not only raises the variety of appliance-specific consumption patterns to be identified, but also increases the combinations of overlapping uses, and, consequently, signal distortion [33].

In this work, we address these three challenges by contributing a novel Hybrid Signature-based Iterative Disaggregation (HSID) algorithm for NILM. A supervised and a semi-supervised versions of the algorithm are proposed, in order to deal both with applications involving intrusive measurements at single-appliance level, as well as non-intrusive ones. Both versions combine Factorial Hidden Markov Models (FHMMs) and Iterative Subsequence Dynamic Time Warping (ISDTW) to accurately characterize end-use trajectories for a number of simultaneously operating appliances and reduce the intrusiveness of the off-line training. More precisely, the FHMM module of the algorithm initially disaggregates the total power consumption signal into 2-state single-appliance piece-wise constant trajectories. Thus, FHMM provides a rough approximation of the end-use trajectories. ISDTW is then applied, in order to reshape them according to the typical power consumption pattern of each specific end-use, and include the intrinsic variability of the latter in terms of power range and appliance usage duration. After being processed through ISDTW, the estimated end-use trajectories describe more accurately and realistically the power consumption time series of each appliance. The two versions of HSID are independent and differentiate with respect to the information needed for algorithm training: the supervised version of HSID requires appliance-level load measurements, while the semi-supervised version exploits aggregate measurements from the smart meter to retrieve appliance-level information.

The paper is organized as follows. We formalize the disaggregation problem in Section 2 and describe the two versions of the new HSID algorithm in Section 3. In Sections 4 and 5, we comparatively analyze through a diverse set of metrics the performance of HSID against a state-of-the-art benchmark on real world power consumption data and test the sensitivity of the results with respect to the level of noise in the metered consumption, as well as the number of metered appliances. In the final semi-supervised experiment,