Unsupervised Disaggregation of Low-Frequency Smart Meter Data

Nonintrusive load monitoring (NILM) estimates appliance-specific energy usage from a building's aggregate energy consumption reading (Faustine, Mvungi, Kaijage, & Michael, 2017). NILM solutions with high accuracy already exist but require additional hardware in the home. Utilities desire a cost-effective way to disaggregate low-frequency, whole-house data produced from their existing infrastructure. In 2008 the United States government provided stimulus funding to deploy smart meters on residential and commercial buildings. Smart meters report the aggregate electric consumption at low-frequencies, typically no more than 1Hz. The simple hardware of current smart meters complicates disaggregation, but studies suggest that the highest consuming appliances can still be detected with reasonable accuracy. Appliance-specific disaggregation is a promising field, however most work revolves around whole-house disaggregation. The wide-spread deployment of smart meters renewed interest in the disaggregation problem because current NILM approaches are not effective at low frequencies.

Non-Intrusive Load Monitoring

Initial approaches to load monitoring involved installing sensors at each plug to record individual appliances. This intrusive load monitoring (ILM) monitored each appliance with a sensor at the plugin and reported to central hub. ILM fell out of favor with the development of more cost-effective nonintrusive approaches. NILM happens in three major steps: the system acquires electrical signals from a central point in the building, extracts features from the samples, and classifies the appliances with a disaggregation algorithm. Appliances are described by a set of features that characterizes its behavior, otherwise known as appliance signatures. There are two main kinds of electronic features to describe appliances: transient features and stable-state features. Transient features are high-frequency fluctuations generated when an appliance switches on or off. They are desirable for disaggregation because the fluctuations are closely tied to the appliance's electric circuits (Wong, Sekercioglu, Drummond, & Wong, 2013). Stable state features are the sustained changes in load characteristics when an appliance changes state. They do not require high sample rates and thus are the focus of low-frequency NILM. The last two decades of NILM algorithmic work achieved better results due to exploiting advances in high-frequency sensor technology. Modern NILM work that uses transient features can disaggregate most appliances with high accuracy but requires specialized high-frequency sensors. The wide deployment of smart meters has renewed interest in low-frequency disaggregation (Faustine, Mvungi, Kaijage, & Michael, 2017).

Identifying Individual Appliances

The two main classes of appliance signatures are changes in real power and reactive power. A real load acts like a resistor: it dissipates current and produces a voltage drop. A reactive load acts like a capacitor: it produces a voltage drop but dissipates very little current (Kuphaldt, 2007). Both signatures are useful for distinguishing appliances, however ambiguities can still occur. For example, a refrigerator and laptop charger appear similar when measuring both real and reactive power. The inability to discern between appliances is known as aliasing and suggests the need for additional signature dimensions (Wong, Sekercioglu, Drummond, & Wong, 2013). To avoid aliasing, most low-frequency NILM algorithms require both real and reactive power measurements. Because smart meters only report real power, most of the recent NILM work is not applicable to smart meters. Birt, et al. (2012) proposed disaggregating into five load categories for low sample rates. Temporal information can provide insight into appliance state but requires probabilities of the distribution of appliances and their state from external data sources. Some approaches can disaggregate the highest usage appliances at 15-

minute sample rate, but disaggregating using only real power measurements, with high accuracy, and at low sample rates, remains an open issue (Liao, Elafoudi, Stankovic, & Stankovic, 2014).

Disaggregation with Low Sampling Rates

Efforts to disaggregate appliances using temporal information go back to the field's inception by George Hart. Hart's landmark paper, "Nonintrusive Appliance Load Monitoring," published in 1992, was the first to describe a cost-effective disaggregation method based on two stable-state measures, current and voltage. Hart used an edge detection algorithm on real power data sampled at 1Hz to detect appliance state changes (like ON/OFF). Appliances were modeled as finite state machines (FSM). This is known event-based NILM because it relies on detection of the appliance state transition (Lu, Xu, & Huang, 2017). These transitions are less detectible at low frequencies (< 1Hz) due to odds of multiple appliance state transitions occurring between measurements (Kim, Marwah, Arlitt, Lyon, & Han, 2011). Non-event-based methods identify the most probable set of appliance states for each sample. They are computationally expensive and could result in false detections but perform better than approaches requiring edge detection at lower frequencies (Wong, Sekercioglu, Drummond, & Wong, 2013). The lowest frequency event-based approach provides 80% accuracy at 1/10Hz. Most work does not reveal how their algorithm scales with different frequencies because the disparity between datasets discourages training on multiple datasets. It is known that disaggregation algorithms that rely solely on temporal features tend to predict fewer appliances at lower frequencies. Therefore, non-event-based are likely more performant at low frequencies.

Hidden markov models (HMM) are the most popular non-event-based disaggregation algorithm. HMM improves upon FSM with a stochastic model describing a sequence of possible events in which the probability of each event depends only on the state of the previous event, otherwise known as a Markov chain. HMM-based approaches find the most likely combination of appliance states at each sample. HMM requires knowledge of each appliance and their associated transition probabilities prior to coming online. A training stage can identify the appliances prior to HMM, or other external data like appliance distribution from a survey company can supplement the training stage. Although HMM-based approaches can be unsupervised, all HMM-based approaches require relatively large training sets to establish transition probabilities and initial appliance states. HMM-based approaches are less sensitive to lower sample rates compared to traditional FSM but are sensitive to training. HMM has not been shown to perform well in the ultra-low frequency domain (<1/60Hz) because, “the benefits of exploiting temporal correlation are negligible due to stochastic human behavior” (Liao, Elafoudi, Stankovic, & Stankovic, 2014). Because HMM retains the underlying FSM model of appliances, it struggles to find accurate models for continuously-variable appliances (Wong, Sekercioglu, Drummond, & Wong, 2013). As household appliances become complex, continuously variable devices, current HMM approaches will become less accurate.

Choice of Learning Algorithm

Any NILM approach that is compatible with current smart meters must operate on low-frequency sample rates using only real power measurements. Liao, et al. (2014) proposed simple supervised and unsupervised NILM algorithms that could disaggregate the highest consuming appliances with good accuracy at sample rates of 1Hz to 1/10Hz. This paper’s focus is unsupervised disaggregation because they are more deployable. Unlike supervised approaches like HMM, they not require an intrusive dataset, which can cause poor translation to real-world environments (Wong, Sekercioglu, Drummond, & Wong, 2013). Old wiring, improper wiring architecture, and poor grounding cause a high variation in appliance signatures (Zoha, Gluhak, Imran, & Rajasegarar, 2012). Supervised NILM algorithms can suffer up to a 25% drop of accuracy when implemented in real-world environments (Liao, Elafoudi, Stankovic, & Stankovic, 2014). Although unsupervised approaches collect appliance signatures when the system goes online, they cannot provide meaningful appliance names without expert information.

Unsupervised Disaggregation with Dynamic Time Warping

The unsupervised approach by Liao, et al. consists of three steps: 1) detect events that occur due to one or more appliance state changes, 2) extract feature windows with an edge detection algorithm, and 3) classify extracted feature windows with dynamic time warping (DTW). DTW is a pattern matching algorithm for time-series data. Like HMM, it is a very popular algorithm in speech recognition (Liao, Elafoudi, Stankovic, & Stankovic, 2014). DTW produces a nonlinear measure of similarity between vectors, possibly of different lengths. A training stage consisting of the first two steps captures, encodes, and stores appliance signature vectors in the appliance database. The algorithm uses DTW to compare a feature window to every appliance in the database. DTW is tolerant to stretching and compressing within the signature. This improves accuracy when classifying appliances whose runtime may be long and variable, such as televisions. This approach scales to low frequencies better than HMM, but its reliance on edge detection means that it will not scale well to ultra-low frequencies (Liao, Elafoudi, Stankovic, & Stankovic, 2014).

Study Bias

Liao, et al. (2014) compared the performance their DTW-based approach to a modern HMM-based approach designed for low frequencies. The authors evaluated the algorithms with a relatively small one-week dataset, using 20% to train and 80% to test. DTW accurately classified 85-90% of the high-usage appliances while HMM only classified 66% (Liao, Elafoudi, Stankovic, & Stankovic, 2014). This small training set limited the performance of HMM, which are known to require larger training sets. However, the DTW-based approach discarded much of the training set to limit the size of its appliance database because its complexity is driven by the number of signatures (Liao, Elafoudi, Stankovic, & Stankovic, 2014). Once trained, the runtime complexity of HMM does not depend on the training set. The size of the training set is not a limiting factor for the deployability of NILM, thus, this study is biased towards algorithms that perform better with smaller training sets.

Future Work

Liao, et al. (2014) proposed a relatively simple DTW-based approach to unsupervised low-frequency disaggregation. Although limited by the size of the training set, DTW requires less training data to match the performance of HMM-based approaches. DTW also scales to 1/10Hz sample rate better than HMM (Liao, Elafoudi, Stankovic, & Stankovic, 2014). DTW struggled to recognize low-load appliances because their state transitions were not detected during training. Generally, such appliances are not recognizable at low-frequencies, so this may not be a shortcoming of the approach. Other approaches incorporated external survey data about appliance distribution to improve appliance detection. For example, a survey company revealed that a game console is unlikely to be on unless a television is also on. Incorporating this and other information, such as the weather, improved the performance of various HMM-based approaches (Kim, Marwah, Arlitt, Lyon, & Han, 2011). Another shortcoming is the DTW-based approach compared an unknown signature to every signature in the database. A threshold algorithm discarded most of the training data to provide acceptable runtime performance. Future work should explore ways to improve the search complexity. Search and sorting algorithms may be applicable. A search that prioritizes the breadth of appliances could avoid comparing multiple signatures for an appliance that is unlikely. Because accuracy and performance are limited by the size of the appliance database, any improvement in complexity will likely provide higher accuracy.

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