Acoustic Based Appliance State Identifications for Fine-Grained Energy Analytics

Nilavra Pathak, Md Abdullah Al Hafiz Khan, and Nirmalya Roy
Information Systems, The University of Maryland Baltimore County, Baltimore, MD–21250
{nilavra1, mdkhan1, nroy}@umbc.edu

Abstract*— Fine-grained monitoring of everyday appliances can provide better feedback to the consumers and motivate them to change behavior in order to reduce their energy usage. It also helps to detect abnormal power consumption events, long-term appliance malfunctions and potential safety concerns. Commercially available plug meters can be used for individual appliance monitoring but for an entire house, each such individual plug meters are expensive and tedious to setup. Alternative methods relying on Non-Intrusive Load Monitoring techniques help disaggregate electricity consumption data and learn about the individual appliance's power states and signatures. However fine-grained events (e.g., appliance malfunctions, abnormal power consumption, etc.) remain undetected and thus inferred contexts (such as safety hazards etc.) become invisible. In this work, we correlate an appliance's inherent acoustic noise with its energy consumption pattern individually and in presence of multiple appliances. We initially investigate classification techniques to establish the relationship between appliance power and acoustic states for efficient energy disaggregation and abnormal events detection. While promising, this approach fails when there are multiple appliances simultaneously in 'ON' state. To further improve the accuracy of our energy disaggregation algorithm, we propose a probabilistic graphical model, based on a variation of Factorial Hidden Markov Model (FHMM) for multiple appliances energy disaggregation. We combine our probabilistic model with the appliances acoustic analytics and postulate a hybrid model for energy disaggregation. Our approach helps to improve the performance of energy disaggregation algorithms and provide critical insights on appliance longevity, abnormal power consumption, consumer behavior and their everyday lifestyle activities. We evaluate the performance of our proposed algorithms on real data traces and show that the fusion of acoustic and power signatures can successfully detect a number of appliances with 95% accuracy.

I. Introduction

Research on Non-Intrusive Load Monitoring (NILM) algorithms for metering the power consumption of everyday appliances has mostly focused on two different egresses:

- Smart-meters: In the green building computing paradigm smart meters provide the aggregate power consumption of the entire house.
- Smart plugs: In this alternate approach fine-grained energy consumption is enumerated at the room level or even at specific appliance level using smart plugs.

Unfortunately each of these approaches has its own operational, deployment and research challenges. In smart-meter assisted NILM techniques the deployment cost is minimal but disaggregating the energy consumption of 'low-load' appliances (e.g., microwave, coffee maker etc.) from the *total sum* is challenging. On the other hand, wireless smart plugs provide power measurements at much finer granularity but they have their own operational, deployment and monitoring costs. Again detecting outliers in power consumption, and appliance malfunctions and potential hazards require microscopic analysis of detailed energy footprints and state of the household appliances. Motivated by these shortcomings, we propose to augment the appliances' ambient signatures with their power consumption patterns to correctly identify the appliances' states and relate them with their power consumption behavior. Specifically, in this work we augment the appliances' acoustic signatures with its power consumption pattern to infer the individual usage, waste and safety.

While the idea of combining the appliances' ambient acoustic signature and power sensing is certainly not new [8], [16], [19]; our differentiator is unique because we explicitly consider fine-grained state of appliances based on acoustic and power signatures and augment both to reciprocate each other. This improves the effectiveness of energy disaggregation algorithms and appliances life cycle management system. In this case, the key challenge is to effectively identify the acoustic signatures of multiple appliances when they are concurrently in operating mode and correlate them with their power consumption behavior.

In this paper, we consider the challenge of discerning such hidden or ambiguous appliances power states through the appropriate combination of observations obtained from both acoustic and metering contexts in a multi-appliance environment. We first classify and correlate acoustic signatures of each appliance with its power consumption states individually to model the *intra-appliance* state evolution. We then consider multi-appliance, overlapped on their operation and model the *inter-appliance* state evolution. The unique innovation in our approach is to then model the appliances power state evolution as a Conditional Factorial Hidden Markov Model, with the individual appliance power state being condition together by a set of constraints that are obtained from *intra* and *inter* appliance acoustic enabled power state classification model. We then perform experiments on real life power and acoustic data traces from a variety of household appliances which attest that such a hybrid acoustic-augmented energy disaggregation model can significantly improve the performance of low-level appliance state identifications and non-intrusive load monitoring algorithms.

Key Contributions: We believe that our innovations and results provide strong preliminary evidence that such a hybrid model, where power sensing is augmented with ambient signature from cheap everyday sensors, can prove to be an attractive and practically viable alternative. The key contributions of our work are as follows.

978-1-4799-8033-8/15/$31.00 ©2015 IEEE

1) We propose a multi-layer fine-grained energy monitoring framework for appliance identification and energy disaggregation. We leverage the acoustic based sensing and correlate the appliance power states with its acoustic signatures.
2) We propose a hybrid model combining an energy disaggregation algorithm based on factorial hidden Markov model with the appliance state information obtained from the acoustic sensing model. We provide results that show that this approach is promising when the number of overlapped appliances is relatively small.
3) We evaluate the performance of our algorithms on real life data traces collected from the home environment. Our study shows that non-overlapped appliances can be recognized on average with an accuracy of 99% whereas the overlapped appliances and their finer state of operation can be detected on average with $\approx 70\%$ accuracy.

II. Related Work

The concept of Non-Intrusive Load Monitoring (NILM) was first introduced by Hart [6] where a single source energy consumption data is used to perform the load disaggregation. Since then there has been a lot of advances in the development of load disaggregation algorithms based on signal processing, but a majority of the work focus on high frequency energy consumption data and power features which are difficult to obtain from the meters used in homes [2]. We discuss some of the work related with our focus in this paper.

Smart Plugs for Energy: With the availability of smart meters we can access the sub-metering data but mostly these data has low frequency and is measured at an interval of few seconds or minutes unlike other high frequency metering devices like the ACme [1] which has a sampling rate of 16 kHz. With a very high sampling rate various properties of energy analytic of the devices can be obtained like the transients and higher harmonics etc [2]. But such measuring devices are not provided by the utility providers and also the cost of such a device is expensive and returns on investment based on its usability is not justified.

Graphical model based NILM: The task of load disaggregation is investigated for the low frequency energy measurement using variants of Factorial Hidden Markov Model [4]. An initial benchmark disaggregation results using FHMM model has been presented in [3]. In [20] a combined framework for the FHMM and a Difference FHMM has been used which takes into account both the total and difference in energy consumption to frame a time-series based optimization problem and solve it using Quadratic programming. Other than graphical models, matrix decomposition approaches like the Non-Negative Matrix Factorization or Sparse Coding techniques have been proposed to perform disaggregation but the dataset has higher granularity to the extent of an hour to days [5]. Since our objective is to focus on fine-grained energy analytics to the extent of a second to minutes, we focus on the probabilistic graphical models.

Acoustic Sensing: In Soundsense [10], a mobile phone app is used to detect the various sounds of daily living and an unsupervised technique is being used where a user feedback is later needed to label the data. In [9] the activities of the smart home inhabitants in a bathroom is predetermined by collecting acoustic data from the participants for future prediction. In case of appliance state identification and energy prediction we collect some of the appliances' acoustic footprint based on their regular usage in the home environment and label them with their energy consumption. A system to detect the energy consumption incurred by users' action based on audio recordings using smartphones has been proposed in Sensimate [16]. Users' ambient sounds are captured and suitable filtering steps and classification techniques are applied for learning the users' current activity. 16 typical household activities at an accuracy of 92% have been detected. Thus by annotating the detectable household activities with information about typical energy consumption, a good estimate of the energy intensity of the users lifestyles can be made. Knowing about the energy consumption is useful but their association with abnormal power consumption events and appliance safety and life cycle management are also impactful. Therefore to visualize more detailed energy analytics we need to consider the ambient context and its inter relationship with the appliance usage.

Indirect Energy Sensing: Digressions from the direct sensing approaches have also been investigated where the context and the ambient factors are taken into consideration for indirect sensing. ViridiScope [7], is an indirect sensing based power signatures detection framework where sensors like magnetometers, microphone, and light sensors are used to detect events. In Supero [8] multi-sensor fusion and unsupervised machine learning algorithms have been proposed. It can classify the appliance events of interest and autonomously associate measured power usage with the respective appliances. Unlike ViridiScope which proposes an ad-hoc and appliance specific sensor deployment, Supero proposes a systematic approach for monitoring a range of acoustic appliances which jointly processes the data from light and acoustic sensors to detect the appliance's working states. Our approach is synergistic with Supero, which employed acoustic classification, principally using the acoustic sensors to estimate the residential power usage. In contrast, we focus on augmenting the fine-grained acoustic signature based appliances states obtained from both overlapped and non-overlapped classification models with the energy disaggregation algorithm to identify and detect the appliance power consumption behavior and individual energy consumption at a finer level.

III. Overall Framework

We introduce the overview of our framework, whose logical steps are illustrated in Figure 1. Our framework assumes the presence of a recording device which records the data for appliances' acoustic noise and they have been placed appropriately so that most informative audio data can be collected. We maintain one recording device per room to capture the room's acoustic footprint related with a set of appliances. We also separately collect the acoustic data of the individual appliance and label them for the base case. Real data traces has also been collected in case of intra- and inter-appliances for testing purpose. The energy consumption data has been metered using Enmetric smart plugs [11] over a period of time and each individual appliance energy consumption distribution has been enumerated. The top level of the block diagram is the acoustic based appliance detection logic where we classify and detect the power consumption states of either individual or multiple appliance from the acoustic test data. We also enumerate the states of the various appliances from the acoustic data which further help to narrow down the search space when energy disaggregation algorithm is employed. The next step consists

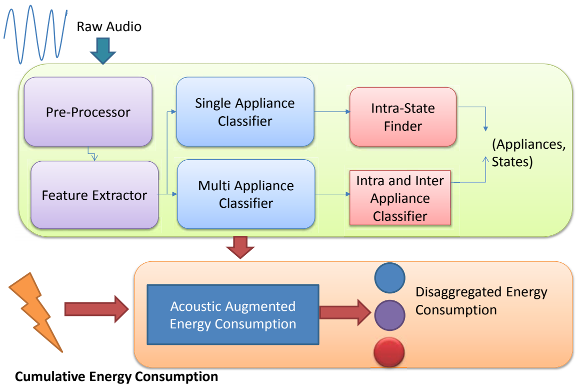

Fig. 1. Functional Overview of Our Approach

of metering the aggregated energy consumption, computing the appliance energy distribution, and inferring the individual appliance energy footprint. We devise a probabilistic graphical based model, more specifically a Factorial Hidden Markov Model (FHMM) where the hidden states estimation utilizes acoustic inference as condition. Subsequently, we also posit a computationally cheap heuristic algorithm based on our proposed model where the acoustic signatures are directly fed into to detect the specific appliances being used and the states they are operating in. This is utilized directly to look up, in particular, the individual appliance's probability distribution and name the dominating appliance. This not only increases the accuracy of prediction but also reduces the search space of the contributing appliances in our probabilistic energy disaggregation model.

IV. Acoustic Characteristics of Appliances

Acoustic noise carries versatile information of daily life [10]. All activities, appliance usage and human communication has some kind of sound associated with it. We first exploit their relationship with acoustic nature of the different appliance states and associate a direct link with the energy consumption, and latter use that to infer the energy consumption with the help of acoustic characteristics of the appliances. We use this acoustic enabled power states as a conditional factor to design our context-aware probabilistic energy disaggregation algorithm.

Our objective is not just a robust acoustic algorithm that can differentiate all sounds but a specific one which identifies the appliances which are 'ON' and the states they are running in, indeed we propose to augment the acoustic signatures of appliances along with its power states to disaggregate the total power consumption. The fact that most of the household appliances (e.g., washer, dryer, refrigerator, heater, humidifier, exhaust fan, blender, vacuum cleaner etc.) contain a motor or noise generating components, which suggests that it is possible to recognize them and infer their states based on their acoustic signatures. To validate the viability of acoustic sensing in case of power disaggregation we staged several isolated experiments. As the acoustic characteristics have much lesser variation from the nature of human speech we chose to collect the data samples at 8 kHz using a Google Nexus 4 kept in close proximity to the operating appliances/devices. To capture the most informative acoustic data from the individual appliance we placed the smartphone on top of the appliances inclining against it and in case of multiple appliances we placed it at a distance. We captured sound clips of the devices for different range of time as needed for experimental evaluation. The energy consumption was also monitored in parallel using Enmetric smart plugs [11] to collect ground truth and for some appliances with fairly similar number of states we used the REDD dataset [3] to relate energy consumption and their acoustic signatures.

Deducing the device states from the energy consumption is a subjective task. For example, the Washer has several cycles, like water-filling, spinning, flushing of dirty water, refilling and so on. However if we compare the states in terms of energy consumption the appliances may have the different steady states that are occurring in between. In case of other appliances like that of the refrigerator in the 'ON' phase, when there is a similar and constant sound, the energy consumption has a characteristic that starts with a spike and then takes the shape of a decreasing ramp. Our initial analysis thus is based on those appliances which maintain a steady energy curve when they are in a particular state. We consider the Humidifier, Heater, Dryer, Washer etc., to draw the initial insights on how an acoustic signature other than the power consumption behavior of appliances can play an important role in designing fine-grained appliance state classification model.

Feature Extraction: We captured the sound clips from several appliances and then stored each clip into a 1, 3, 5 and 7 minutes sound segment for faster processing using the Audacity tool [15]. Next we divided each of these 1, 3, 5 and 7 minutes segments into frames of 0.5 seconds with 50% overlap and applied a Hamming window to reduce spectral leakage. We generated Mel Frequency Cepstral Coefficient (MFCC) [10] [15] of those frames for acoustic classification. We chose 13 coefficients as feature vectors and ran multiple classification algorithms to establish the correlation between *intra-* and *inter-appliances* power states and acoustic signatures. We have constructed a training database where the individual appliance sound-streams have been divided into 1, 3, 5 and 7 mins. This database has been used later to find the segments that are representatives of each of the appliances' microscopic states.

Appliance State Identification: An initial one time analysis has been performed to find out the subset of appliances associated with the acoustic fingerprinting of a room in a house. Assume D is the total set of appliances in the house, $\hat{D}$ is the subset of appliances along with $\hat{N}$ as the affiliated acoustic sensors in each room. We compared the captured acoustic signatures from each of the individual rooms with the acoustic signature of all the appliances in the appliance set D to dedicate the appliances to the noise sensor in the room to which it belongs. This concept of defragmentation of acoustic noise based on the external structure of premises is similar to the concept of electrical circuit breaker. A circuit breaker taps into the different circuits of a house which can be used to perform circuit level disaggregation [23] which reduces the complexity of the problem. Similarly the acoustic sensors help provide the characteristic of room level appliances which is used to recognize the low-level working states of different appliances.

We have used the training data to identify the appliances' finer states. For individual appliance identification, we first

```
Procedure Appliance Recognizer(Input: Segment(S), Feature_
Seg, Output: Appliance States)
1. feature-segment: feature of a segment;
2. S: appliances set;
3. F: appliances segmented feature set;
4. i = 1
5. appliance = null;
6. state = null;
7. For {i ≤ total_appliances}
8. appliance = S[i];
9. segmented_feature_list
   = APPLIANCE_FEATURE_LIST(S[i]);
//Returns segmented feature of appliances
10.j = 1;
11.For {i ≤ total_segments}
12.dist =COSINE-DIST(features[j],feature_seg);
13.      if dist ≤ threshold
14.             appliance_match = True
15.             break;
16.      end
17.end
18.if appliance_match = True
19.   state_seg_list = STATES_FEATURES(S[i])
20.   For {k ≤ total_state_segs}
21.       (state_match, state) =
22. CHECK-STATE(feature_seg,state_seg_list[k])
23.       if (state _ match = True)
24.           break;
25.       end    26. end    27. end
28.end    29. return
```

Fig. 2. Acoustic state identification algorithm

break up the unseen acoustic signal into segments of 1, 3, 5 and 7 minutes. After that for each of the appliances from an appliance/device set $\hat{D} = \{\hat{D}_1, \hat{D}_2, \ldots, \hat{D}_n\}$ consisting of the states $S = \{S_1, S_2, \ldots, S_m\} \in \hat{D}_i$, we check whether the cosine similarity is less than a threshold value. Once we infer that a segment is identified to be a state belongs to a certain appliance, we stop further checking for that specific segment. For the scenario with appliances with overlapped sequences where multiple appliances are running together at one point of time, we continue the previous process of acoustic signal directed appliance-state association instead of terminating a specific appliance until all the appliances are discovered. Fig 2 depicts the detailed procedure for our proposed *intra* and *inter-appliance* state classification and association model in presence of appliances acoustic signatures.

V. Power Consumption and State Characteristics of Appliances

In this section we discuss our data driven analysis of the power consumption of the different appliances. At first we find the different states of each of the appliances and understand their power consumption characteristics. This will be key to design the acoustic augmented energy disaggregation model in our case. Table I shows the steady state characteristics, number of states and usage pattern of most of the common household appliances we have used for our experimentation. Although these appliances have several modes, we have not experimented using all the modes exhaustively (e.g., washer has regular, delicate, fluff modes etc.). However we have tried to identify the individual states (e.g., washing, spinning etc.) in a particular mode.

Characterization of states has to be done by not only the different modes but depending on the rate of usages. To design a generalized version of the state identification algorithm we need to have a mechanism of learning the distinct power states

TABLE I. Characteristics of Energy Consumption

Appliances	Characteristic Type / Usage Pattern	Number of States
Fan	Steady State Energy Consumption / Kitchen fan is on during cooking, bathroom while someone is in, room fan is on only during a season and a certain time of day	1-4
Light	Steady State Energy Consumption / On mostly when someone is present and in night time	1-3
Heater	Steady State Energy Consumption but goes to steady state if it detects ambient temperature is above a threshold / Only on during a season at a particular time	1-2
Humidifier	Steady State Energy Consumption / On mostly at a particular time of day	1-3
Washer	Variable power consumption during different stages, has multiple states in one cycle also it has different modes / On mostly on Friday - Sunday	4-5
Dryer	Stays in steady state with periodic spike of energy which lasts for a few seconds / On mostly on Friday - Sunday and is generally followed by a washer	1-4
Refrigerator	Has periodic 'ON' and 'OFF' cycles with the ON cycle having a ramp like characteristics starting with a spike / Always ON	2-3
Microwave	Has a more or less steady state curve / On time has some relation with Time of Day and Day of week	4-10

associated with an appliance. The problem lies with the low-level power states (micro-states) as they have their own energy consumption characteristics which may be detected as distinct states. We have addressed this problem by looking into two different types of power consumption graphs; one is based on the usage patterns and the other is the histogram/probability distribution function of the specific power consumption in wattage, which can be considered as a basis for defining the appliances micro-states. We have gathered and profiled the energy consumption of several appliances as shown in Table IV using our own collected data and also the several existing datasets [3]. For some of the appliances, like Fan, Heater, Humidifier, Washer and Dryer; we have experimented with our own dataset as collected using Enmetric plug meter at a 1 sec granularity. For a set of other appliances, like Microwave, Refrigerator, and Light we have performed the experiments using REDD dataset [3] interpolating the data at a 1 sec granularity from its publicly available 3 sec rate.

Energy Disaggregation: Our objective is to incorporate acoustic signatures of the appliances to help guide a better prediction on the fine-grained load disaggregation. We have noted the technical feasibility of the acoustic conditioning that can provide additional information for fine-grained analysis of appliances energy consumption. Next we propose to design our framework based on the Conditional Factorial Hidden Markov model [4], and integrate acoustic based microscopic appliance state information as a conditioning observation vector in our hybrid model.

Before delving into the acoustic augmented energy disaggregation model, we first highlight the basic load disaggregation algorithm for multiple appliances using a probabilistic graphical model, namely Factorial Hidden Markov Model. One of the basic problems we have faced implementing the FHMM in cases when we could not gauge the specific enumeration of the number of distinct power states associated with the appliances. In [4] the appliance energy consumption has been considered to have two states, only 'ON' and 'OFF' while in real scenario making such an approximation makes it difficult to scale the model along a set of appliances having more than the two states. Therefore, we have extended the FHMM with this basic assumption to capture the microscopic but distinct power states, while available with the aid of our proposed acoustic conditioned model.

We first mathematically describe the evolution of the microscopic power states of a set of appliances based on their usage and span this beyond a two-state Gaussian model. Consider M appliances $D = \{1, 2, \ldots, M\}$ which are in the states $S = \{S_1^{(t)}, S_2^{(t)}, \ldots, S_M^{(t)}\}$ respectively at time t, where each of them represents a 'hidden state' of an appliance D at time stamp t. The characterization of a state is done by the two factors: one is the range of the energy consumption and the other is the corresponding acoustic characteristics. The observed states are represented by $Y^{(t)}$ at time t (power consumption data). Let A_{ij}^k denotes the transition probability from one state i to j [$i, j \in (S_i, S_j)$] for the k^{th} appliance. The emission probability is a Gaussian distribution and is given by B_{il}^k for the k^{th} appliance being in i^{th} state while observing the energy consumption in the l^{th} state. Initial probability for each of the appliance is denoted by $\pi_{jk}^{(0)}$ which represents the probability of an appliance k to be in state j at the initial state. We solved this by EM algorithm where expected log likelihood of the observed data and hidden states are determined in the expectation step and the learning parameters are determined in the maximization step as discussed next.

$$P(S_t|S_{t-1}) = P\left(S_t = \begin{pmatrix} S_t^{(1)} \\ S_t^{(2)} \\ \cdot \\ \cdot \\ S_t^{(M)} \end{pmatrix} \mid S_{t-1} = \begin{pmatrix} S_{t-1}^{(1)} \\ S_{t-1}^{(2)} \\ \cdot \\ \cdot \\ S_{t-1}^{(M)} \end{pmatrix}; A\right)$$
$$= \prod_{t=1}^{T} \prod_{m=1}^{M} P\left(S_t^{(m)} \mid S_{t-1}^{(m)}; A\right) \quad (1)$$

The energy consumption in all the states are assumed to be a Gaussian distribution having parameters μ, which is the mean of the individual appliance's energy consumption distribution. Power consumption is essentially a continuous data which we have to discretize for constructing this state-space model. Given that Y_t is one-dimensional, the co-variance matrix reduces to variance only and the emission probability is given by the following (Eqn. (2)).

$$P(Y_t \mid S_t) = \frac{1}{\sqrt{2\pi\sigma^2}} \times exp\{-\frac{(Y_t - \mu_t)^2}{2\sigma^2}\}$$

where
$$\mu_t = \sum_{m=1}^{M} \sum_{n=1}^{K^{(m)}} W^{(m)} S_t^{(m)} \quad (2)$$

where $S_t^{(m)}$ is an Indicator Random Variable which means whether it is true that the appliance m is in n^{th} state and $W^{(m)}$ is the mean of the underlying distribution, i.e., the contribution factor of each of the settings of $S^{(m)}$. By plugging Eqn. (2) in Eqn. (1) we get,

$$P(Y; A, B) = \sum_{S} \left(\prod_{t=1}^{T} \frac{1}{\sqrt{2\pi\sigma^2}} \times exp\{-\frac{(Y_t - \mu_t)^2}{2\sigma^2}\} \right) \times$$
$$\prod_{t=1}^{T} \prod_{m=1}^{M} P(S_t^{(m)} \mid S_{t-1}^{(m)}; A) \quad (3)$$

To determine the model likelihood and update the learning parameters (transition and emission probabilities) we propose to investigate a deterministic and greedy Expectation Maximization (EM) algorithm for a faster determination of the micro-states of the appliances. Through this EM problem the probability which needs to be enumerated is shown in Eqn. (4) where we try to find the expected observation probability by iteratively estimating the model parameters.

$$Q(\lambda^{new} \mid \lambda) = E[logP(\{S_t, Y_t\} \mid \lambda^{new}) \mid \lambda, Y_t] \quad (4)$$

where the parameters that are to be updated are μ, σ and the transition probability is $P(S_t|S_{t-1})$ as shown in Eqn. (1). The determination of model likelihood and parameter estimation are done based on the Structural Approximation Method [13]. The forward backward algorithm is applied to estimate the log likelihood of the model in the E-step and the M-step of the parameter estimation process until the Eqn. (4) reaches a maximum. Subsequent to the step of model likelihood determination and parameter update, the inference of the hidden states is computed with a tractable optimization algorithm. Given the model and parameters constructed we propose to use Genetic Algorithm (GA) [21] to solve the problem. After the inference and parameter update we need to solve the problem of which appliances are in what state. This is formulated as in Eqn. (5).

$$\arg\max_{S_t} E\left[logP(\{S_t, Y_t\}; \lambda)\right] = \arg\max_{S_t} \sum_{m=1}^{M} logP(S_1^{(m)}) +$$
$$P(Y_1 \mid S_1) + \sum_{t=2}^{T} [\sum_{m=2}^{M} P(S_t^{(m)} \mid S_{t-1}^{(m)}) P(Y_t \mid S_t)] \quad (5)$$

FHMM based Hidden State Estimation: Simulated Annealing has been proposed to get the most likely sequence of states in [4] and a heuristic algorithm has been developed to solve the optimization problem. The choice of heuristic for updating the states is a problem as it can be confined in the local minima if we choose a gradient descent based approach. For this reason we choose Genetic Algorithm for finding the most probable sequence which will maximize the objective function as represented by Eqn. (5). Thought this introduces some randomness in state search but can help to avoid the local minima. We have applied the GA technique [21] to our objective equation (Eqn. (5)) with Roulette wheel selection [22] methodology.

Acoustic Sensing Augmented Energy Disaggregation: We have extended the FHMM based energy disaggregation algorithm in this section and addressed the challenges we have faced for the real deployment and testing of this algorithm for multiple appliances micro-states identification and energy disaggregation. We note that estimating the mean power consumption associated with the each micro-states solely relying on just the power states of the appliances are not always feasible. Thus we propose to integrate mean energy consumption for each micro-state of the appliances from an external context, in our case using the inference of the power consumption from the acoustic signature of the appliances.

We propose to use the individual appliance identification and micro-state enumeration based on their acoustic signatures as depicted in Fig. 3 to learn the average energy consumption of each appliances in different states. This factor helps estimate the mean values for each of the appliance's energy states and also reduces the extensive deployment of the plug meters which are needed to measure power consumption of each and every appliances. We propose two different factors to create a variant of FHMM model that will provide a faster and more accurate and easier estimation of the disaggregated energy consumption of multiple appliances.

- First factor is the change in energy consumption, denoted as ΔY. This triggers the acoustic sensing unit to search for the noise sensor which shows an acoustic change and subsequently infer which appliance state change might have taken place. This reduces the entire search space for appliances micro-states and its association with the power consumption and acoustic signatures. Also another assumption which constrains the hidden state change is that one appliance can only change state at a given time, as the probability of a pair of appliances changing states simultaneously is highly improbable and thus relaxes the search space.
- The second factor is the inference from acoustic data. Most of the appliances emit certain noise and has a certain pattern of noise in a particular state and when the state changes there is a change in that pattern. While the energy change, ΔY, can pinpoint that some state change has occurred at a particular instant, but it cannot determine which appliance has changed state. On the other hand, acoustic change can find out the appliance which is changing state, but introduces an error in estimating the exact time of change.

Considering these two factors we propose a heuristic algorithm for estimating finer states of the appliances. We check whether there is a change in energy consumption above a threshold which can be considered as factor for a state change. If there is no such changes then the appliances are assumed to be in previous states or else if there is a significant change we check within a temporal difference from that point if any appliance acoustic change has been detected. Based on that we isolate which appliance possibly changes and consider that the state change for that appliance has occurred from the time when the change was detected.

In Fig. 3 the algorithm for acoustic augmented energy disaggregation has been illustrated. We begin by solving the EM-algorithm as mentioned in previous section where we have found the joint probability and estimated the model parameters. The starting states are determined from acoustic inference and the starting probabilities are all initially assumed to be 1. The next step is maximizing the joint probability for energy prediction by taking the log of it as shown in Line 8. We check at each unit time (1 sec) the individual appliance's energy consumption. At each unit time we inspect whether there has been a change in energy consumption more than a certain threshold (ϵ). If there is a change in state for some appliances, we look within a range of δ time from that point whether there is any change in acoustic signal of an appliance which may correspond to a discrete state change. Line 11 shows that when there is no visible change in energy consumption all appliances are considered to be in their previous state. Line 16 states that if the acoustic detector finds a state change for the k^{th} appliance, the joint probability is being updated over the total duration of the operation of all the appliances.

VI. Experimental Results

We first created a dataset for our multi-modal framework. We measured the energy consumption of washer, dryer, heater, humidifier, microwave, refrigerator, fan which have their own distinct acoustic nature. We used Enmetric to measure the energy consumption and our data has been measured at a rate of watt per second. We also used the standard REDD dataset to determine the initial probability values for different appliances. The preliminary data collection is done for the different appliances that produce sound. We have recorded those in closed environment and labelled them separately for single-state and multi-states (sub-states) appliances. The house consists of several rooms that consist of different appliances which are used to perform different activities for collecting acoustic and energy footprints. We tested our results in one house where we considered four rooms - Bedroom (Heater, Humidifier, Fan), Basement (Humidifier, Heater, Fan is alternatively used with previous two), Kitchen (Microwave, Refrigerator, Exhaust Fan) and Basement Closest (Washer and Dryer). Four inhabitants were in the house and we collected acoustic data for two days in a total of six hours in a controlled environment.

Acoustic Based Appliance Identification: Settings for acoustic data collection has been described previously as it was done individually and in presence of interleaved appliances. We have developed a heuristic approach for acoustic cum power state identification as shown in Fig. 2. We have first tried to find the acoustic natures of different appliances and then established the relationships with the finer power consumption states both for non-overlapped and overlapped appliances.

The accuracy obtained for different classification algorithms for two sets of overlapped appliances (Washer and Dryer; Heater and Humidifier) are shown respectively in Figs. 4, 5, 6 and 7. For experimentation we have defined different test sets and tested the classifiers on them and considered the average of the results. We have compared the classification of acoustic states of the appliances using standard classification algorithms, like J48, MLP, Naive Bayes, NBTREE along with our proposed algorithm as shown in Fig. 2. We note that our proposed heuristic approach based on Cosine similarity measure provides better classification accuracy results.

We observe that the overall accuracy considering just one specific segment of acoustic data is not reasonable. There is always a trade-off in choosing the segments as because when the segment size is too small over-fitting takes place which results in poor classification. Again choosing a segment for a very long time is not much useful as it becomes difficult to comprehend the finer state changes. Thus for our acoustic based state recognition problem we have used a combination of three different segments (1min, 3min, & 5min) to devise a better inference strategy for the identification of appliances distinct microscopic power states.

Table II shows the results of multiple appliances microscopic state detection accuracy with respect to different acoustic segment lengths. We note that for a larger acoustic segment length our acoustic state classification algorithm works better to identify an individual appliance from a subset of appliances. We have performed the experiment with overlapped appliances as well. Table III represents the appliance detection accuracy when they are operating concurrently with varying overlapped duration. It is noted that with the increase in the overlapped operating period of multiple appliances the detection accuracy decreases. Let us consider the following scenario to understand the overlapped scenario. Given a 10 min acoustic segment for

Procedure Acoustic Augmented FHMM (Input: aggregate power data (P), Output: appliance identification & power enumeration)

1. E-step: Compute the posterior probability using Eqn. (5)

2. M-step: Update the parameters

3. For m = 1 to M

4. if $A_j^{(m)}$ ==1

5. π_j^m = 1 //Initialize the Starting State Probability with 1

6. end if

7. end For

8. JointProb[1] = $\sum_{m=1}^{M} \log\{\pi_j^m\} - \left(\frac{1}{2\sigma^2}\{Y - \sum_{m=1}^{M} \mu_j^{(m)} \times Q_j^{(m)}\}\right)$

// FHMM State Initialization //JointProb stores the Joint probability

9. For t = 1 to T //T is the total time

10. if ΔY > ϵ *//No change in state for any appliance*

11. JointProb[t] = JointProb[t-1] + $\sum_{m=1}^{M} log\{P(S_t^{(m)}, S_{t-1}^{(m)})\} \times Q(S_{t-1}^{(m)}, S_{t-1}^{(m)}) - \left(\frac{1}{2\sigma^2}\{Y - \sum_{m=1}^{M} \mu_j^{(m)} \times Q(S_{t-1}^{(m)})\}^2\right)$

12. else *//Change in state for an appliance*

13. For t_1 = t - δ to t + δ *//Within the temporal vicinity of the change*

14. Check for change in acoustic state for an appliance $A_j^{(k)}(t)$

15. Change in k^{th} appliance from state at t-1 to t is the new $Q\{S_t^{(k)}, S_{t-1}^{(k)}\}$

16. JointProb[t] = JointProb[t-1] + $\sum_{m=1\&m\neq k}^{M} log\{P(S_{t-1}^{(m)}, S_{t-1}^{(m)})\} \times Q(S_{t-1}^{(m)}, S_{t-1}^{(m)})$ + log$\{P(S_t^{(k)}, S_{t-1}^{(k)}) \times Q(S_t^{(k)}, S_{t-1}^{(k)})\}$ - $\left(\frac{1}{2\sigma^2}\{Y - \sum_{m=1}^{M} \mu_j^{(m)} \times Q(S_{t-1}^{(m)})\}^2\right)$

17. End for 18. End if 19. End for

20. Backtrack the states for the appliances 21. end

Fig. 3. Acoustic Enabled FHMM Energy Disaggregation

any two appliances, such as washer and dryer with a 10% overlapped case; washer and dryer may remain concurrently on for the first 1 min whereas the dryer may remain on for the remaining 9 mins (assuming washer runs first).

TABLE II. INDIVIDUAL APPLIANCE DETECTION ACCURACY

Appliances	State	Accuracy % (1min)	Accuracy % (2min)	Accuracy % (5min)
Fan	Hi	100	100	90
	Med	100	80	70
	Low	100	100	100
Heater	ON	80	100	100
Humidifier	High	40	100	100
Washer	Water-Pouring	100	100	100
	Spinning	100	100	100
	Drain	100	100	100
Dryer	ON	100	100	100
Refrigerator	ON	100	100	100
Microwave	ON	80	100	100

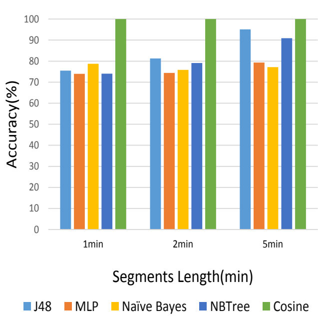

Fig. 4. Washer Comparative Accuracy

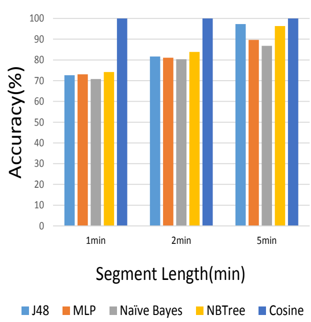

Fig. 5. Dryer Comparative Accuracy

TABLE III. OVERLAPPED APPLIANCES DETECTION ACCURACY

Appliances	Accuracy % (10% Overlap)	Accuracy % (30% Overlap)	Accuracy % (50% Overlap)
Heater	76.92	69.23	61.53
Humidifier	81.25	62.5	56.25
Washer	83.2	69.5	61.2
Dryer	75	71.2	55.4

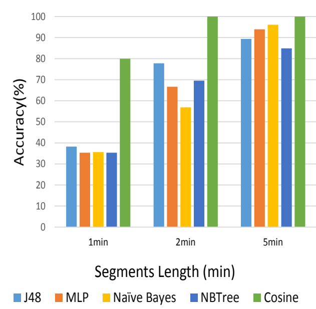

Fig. 6. Heater Comparative Accuracy

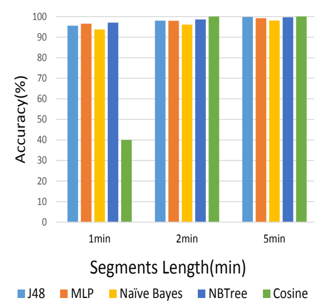

Fig. 7. Humidifier Comparative Accuracy

Energy disaggregation using FHMM: In this section we present the results on the performance of FHMM-based energy disaggregation algorithm solely relying on the appliances power consumption behavior. We articulate the results based on two important factors. First, we show how much closer FHMM-based estimated average energy consumption is to the actual measured energy consumption of the appliances. Secondly, at finer state-level, how close can we detect the most likely state sequence of energy consumption associated with different microscopic states of appliances? To capture this, we define two metrics. i) Total Energy Consumption Error: Total Energy Difference $=|\sum e(t) - \sum \acute{e}(t)|$ and ii) Timewise Error $= \sum \frac{e(t)-\acute{e}(t)}{e(t)} \times \frac{1}{T}$. The measured average consumption is the ground truth of each of the appliances corresponding to their different states (measured by our testbed) while estimated average consumption denotes the average energy consumption of the appliances as enumerated by the FHMM-based energy disaggregation method. The timewise error on the other hand gives an idea about the correctness in estimating the sequence of energy consumption while the total energy difference captures the total difference of energy consumption in terms of Kilowatt-hour. In Table IV, we report FHMM-based energy disaggregation algorithm performance on the measured energy consumption (ground truth), the estimated energy consumption, timewise error and total energy differences for multiple appliances associated with their fine-grained operating states.

Energy disaggregation using Acoustic Augmented Model: We have evaluated the performance of our acoustic enabled energy disaggregation algorithm as presented in Fig 3. We have exploited the appliances hidden power consumption state estimation utilizing the acoustic characteristics of the appliances and maximized the joint probability of the acoustic enabled FHMM. We have retrospected both, the change in energy consumption and the acoustic signals to triangulate the inference of the most likely state and probable appliances. We have considered the same set of appliances for this specific experiment to compare the performance with FHMM-based approach. The performance of our acoustic enabled energy disaggregation algorithm has been articulated in Table IV. We note that our acoustic enabled energy disaggregation algorithm performs an order of magnitude ($\approx$ 2 folds) better than the FHMM-based approach.

TABLE IV. PERFORMANCE COMPARISONS BETWEEN FHMM-GA AND ACOUSTIC ENABLED FHMM

Appliances	Measured Average Consumption	Estimated Average Consumption	Timewise Error (FHMM-GA)	Total Energy Difference (FHMM-GA)	Timewise Error (Acoustic Enabled)	Total Energy Difference (Acoustic Enabled)
FH	84	87	1.97	15	.85	10
FM	67	62	2.5	15	.75	7
FL	58	52	5.67	21	1.27	11
H	1425	1420	8.29	47	4.12	25
HH	329	330	2.51	17	1.74	10
HL	165	163	.45	7	1.78	9
WP	11	14	.75	8.24	1.3	13.24
WS	650	647	5.71	37	4.15	29
WD	450	427	9.81	75	5.23	32
D	330	304	6.42	43	4.19	23
RO	187	194	2.78	17	1.23	9
RS	6	7	.7	8	.7	7
M	1487	1492	6.41	47	3.97	24

Acronyms used in Table IV: Fan (High) - FH, Fan (Med) - FM , Fan (Low) - FL , Heater - H, Humidifier (High) - HH, Humidifier (Low) - HL, Washer (Water Pouring) - WP, Washer (Spinning) - WS, Washer (Draining) - WD, Dryer - D, Refrigerator (ON) - RO, Refrigerator (Standby) - RS, Microwave - M.

VII. CONCLUSIONS

We have proposed an appliance acoustic classification model for fine-grained state analysis. We have provided our findings for both non-interleaved and interleaved appliances in everyday home environment. We have advocated that combining the acoustic based classification model help improve the overall performance of energy disaggregation algorithm, abnormal power consumption event detection and appliances long-term life cycle management. We have designed a conditional probabilistic graphical model for augmenting the acoustic modality with the energy disaggregation algorithm and showed that the 95% appliance detection accuracy can be achieved with a smaller set of appliances. While this approach is promising we believe further augmentation of appliances' other ambient signal modality could help scale this model beyond any specific and limited set of appliances. Currently we have a very basic acoustic setup, using that we have performed staged experimentation, but we have been developing a microphone sensor based acoustic system [25] which will be capable of recording sound, computing MFCC and offloading computational tasks to the server. With the development of a real time system we plan to look for more sophisticated acoustic event detection methods which will consider the ambient noise and reverberation into effect. Although it may seem like unnecessary cost to deploy hardware for data collection and processing, but acoustic signals are omnipresent and continuous source of information in smart environments; which can be leveraged for several purposes and also with the advancement of pervasive computing system it may come integrated with future household appliances.

ACKNOWLEDGEMENT

This work is partially supported by the NSF Award #1344990 and Constellation E^2: Energy to Educate Grant 2013 and 2014.

REFERENCES

[1] P. Dutta, M. Grimmer, A. Arora, S. Bibyk, and D. Culler, *Design of a Wireless Sensor Network Platform for Detecting Rare, Random, and Ephemeral Events*, IPSN 2005.

[2] C. Laughman, K. Lee, R. Cox, S. Shaw, S. Leeb, L. Norford, and P. Armstrong, *Power Signature Analysis* , IEEE power & energy magazine 2003.

[3] J. Z. Kolter, and M. J. Johnson, *REDD: A public data set for energy disaggregation research.* SusKDD 2011.

[4] H. Kim, M. Marwah, M. Arlitt, G. Lyon, and J. Han, *Unsupervised Disaggregation of Low Frequency Power Measurements.* SIAM 2011.

[5] J. Z. Kolter, S. Batra, and A. Y. Ng *Energy Disaggregation via Discriminative Sparse Coding*, NIPS 2010

[6] G. W. Hart, *Nonintrusive appliance load monitoring* IEEE Proc. 1992.

[7] Y. Kim, T. Schmid, Z. M. Charbiwala, and M. B. Srivastava, *ViridiScope: Design and Implementation of a Fine Grained Power Monitoring System for Homes* , UbiComp 2009.

[8] D. E. Phillips, R. Tan , Md M. Moazzami, G. Xing, J. Chen, and D. K. Y. Yau, *Supero: A Sensor System for Unsupervised Residential Power Usage Monitoring*, PerCom 2013.

[9] J. Chen, J. Zhang, A. H. Kam, and L. Shue, *An automatic acoustic bathroom monitoring system*, Pervasive 2005.

[10] H. Lu, W. Pan, N. D. Lane, T. Choudhury, and A. T. Campbell *SoundSense: Scalable Sound Sensing for People-Centric Applications on Mobile Phones*, MobiSys 2009.

[11] http://www.enmetric.com/

[12] http://audacity.sourceforge.net/

[13] Z. Gharamani, and M. I. Jorda *Factorial Hidden Markov Model*, Machine Learning, 1997.

[14] G. Cohn, D. Morris, S. N. Patel, and D. S. Tan *Your Noise is My Command: Sensing Gestures Using the Body as an Antenna*, CHI 2011.

[15] C. Xu, S. Li, G. Liu, Y. Zhang, E. Miluzzo, Y. Chen, J. Li, and B. Firner *Crowd++: Unsupervised Speaker Count with Smartphones*, Ubicomp 2013.

[16] F. Englert, I. Diaconita, A. Reinhardt, A. Alhamoud, R. Meister, L. Backert, and R. Steinmetz *Reduce the Number of Sensors: Sensing Acoustic Emissions to Estimate Appliance Energy Usage*, BuildSys 2013.

[17] C. Huang, Yi-ting Tsao, and J. Yung-jen Hsu, *Abnormality detection by model-based estimation of power consumption* SOCA, 2012.

[18] C. C. Huang et al. *Behavior-Based Detection of Abnormal Power Consumption for Power Saving* Applied Mechanics and Materials, 291-294, 2013.

[19] Z. C. Taysi, M. A. Guvensan, and T. Melodia, *Tinyears: spying on house appliances with audio sensor nodes.*, 2nd ACM Workshop on Embedded Sensing Systems, BuildSys 2010.

[20] J. Z. Kolter and T. Jaakkola, *Approximate Inference in Additive Factorial HMMs with Application to Energy Disaggregation*, AISTATS 2012.

[21] M. Mitchell, *An Introduction to Genetic Algorithms. Cambridge*, MA: MIT Press, 1996.

[22] A. Lipowski, *Roulette-wheel selection via stochastic acceptance*, Neural and Evolutionary Computing 2011.

[23] A. Marchiori, D. Hakkarinen, Q. Han, and L. Earle, *Circuit-Level Load Monitoring for Household Energy Management*, Pervasive Computing journal 2011.

[24] M. Rossi, S. Feese, O. Amft, N. Braune, S. Martis, and G. Trster, *AmbientSense: A Real-Time Ambient Sound Recognition System for Smartphones* PerMoby 2013.

[25] H. Khan, S. Lu, N. Roy, and N. Pathak, *Demo Abstract: A Microphone Sensor based System for Green Building Applications*, in IEEE PerCom 2015