Signature-based Detection for Activities of Appliances

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Abstract—The large-scale placement of smart meters brings concerns about privacy of individuals in their own homes. Energy consumption data can reveal precise appliances’ usage information with Non-Intrusive Load Monitoring (NILM). To mitigate behavior leakage in homes with smart meter measurement, Battery-based Load Hiding (BLH) is widely studied. In this approach, a rechargeable battery is used to store and supply power to home appliances at strategic time to hide appliances’ consumption. However, because different appliances have different energy consumption signatures, it is still possible to detect activities of appliances. In this paper, we developed signature-based detection (SBD) method, which utilizes the signatures of appliances to detect appliances usage. We conducted extensive system evaluations with 40 homes. Results indicate i) our consumption signature detection method has higher detection accuracy than edge detection; ii) our consumption detection method can still detect more than 70% of appliances’ events even with BLH.

I. INTRODUCTION

Smart meters are deployed in homes to record high granularity energy consumption for power grid monitoring. However, the large-scale placement of smart meters has introduced potential leakage of private and valuable information about occupants’ activities [1]. Moreover, many utility companies are providing third-party companies access to traces of smart meter data, which results in high probability of privacy leakage. With the deployment of Non-Intrusive Load Monitoring (NILM) [2], the high granularity energy usage data obtained can be analyzed to reveal personal information such as usage of individual appliances, sleep patterns, number of occupants and even occupants’ health conditions. The widely used technique is the edge detection [3], which looks for the sharp edges that reveal the significant changes in the steady current consumed by the household. To prevent private information leakage, researchers propose Battery-based Load Hiding (BLH) algorithms [4] [5], which employ batteries to partially supply the net demand load from the house to alter the external load as seen by the smart meter. The battery is charged and discharged at specific time to hide the energy consumption events. However, BLH algorithms have to cope with limited battery capacity and discharge rates. Current methods also require users to charge and discharge batteries frequently, which will significantly decrease the battery’s lifetime. Furthermore, batteries will introduce the energy conversion loss during charging and discharging stages.

Recently, researchers revealed the empirical power consumption signatures of different electrical loads [6]. The results show that the power consumption of electrical loads is not only either zero or stable power consumption. During the usage, the power consumption of electrical loads varies significantly at different stages while follows a unique signature. The signatures of electrical loads provide great opportunity for appliances detection. We developed a new consumption detection method, called signature-based detection (SBD) method, which reveals appliances’ usage more accurately than existed approaches (e.g., edge detection). SBD can be used by utility companies to provide energy-efficiency recommendations for consumers. However, by taking advantage of our method, the malicious third parties can also easily detect appliances’ usage if they have empirical power consumption data. This will result in a serious private information leakage.

To evaluate our proposed SBD method and compare it with existing ones, we conduct real-world experiments by deploying energy meters in multiple homes to get the energy consumption signatures of individual appliances. We also run large-scale simulations by using the empirical energy consumption traces from 40 homes. Our simulation results indicate i) SBD method has higher detection accuracy than edge detection; ii) SBD method can still detect more than 70% of appliances’ events even with BLH.

The rest of the paper is organized as follows: background of edge detection, BLH and appliance consumption signatures are introduced in §II; the detailed design of SBD is described in §III; implementation and simulations are provided in §IV; finally, we conclude the paper in §V.

II. BACKGROUND

In this section, we i) state current problem of privacy exposure in sensing system; ii) introduce the widely used edge detection method; iii) demonstrate the mechanism of BLH; and iv) describe the recently developed energy consumption signature models of different appliances.

A. Privacy in Sensing Systems

With the large deployment of different types of sensors, privacy issue of sensing systems has become an important problem [7]. In [8], a new theoretical scheme called SensorSift is introduced for balancing utility and privacy in smart sensor applications. In [9], a theoretical framework is proposed to allow users to quantify the utility-privacy tradeoff in smart meter data. In [10], authors explore three case studies and analysis of secure cyber-physical systems: wireless medical devices, robots, and automobiles.

More seriously, many utilities are providing third-party companies access to traces of smart meter data. Third-party
companies are now employing cloud-based platforms to analyze large amount of smart meter data [12] [11]. The data collected from smart meters can be applied in different energy management applications [13] [14]. While the purpose is to provide consumers energy-efficiency recommendations, companies are also mining the data for profitable information such as usage of certain brand of appliances, which can be used for future advertisement. Some people may argue that there is no need to hide those information. However, appliances usage information can be used to reveal more private information. For example, usage time of certain appliances (e.g., water heater) can reveal the number of people that live in the house. Besides that, changes of appliances’ usage patterns can also indicate other personal information. For example, if your water dispenser only works at evening when you come back home, and suddenly your water dispenser works frequently in daytime and other appliances’ usage pattern stays the same; we can guess that you may be sick at home and need to drink a lot of water. As a result, it is critical to protect energy consumption privacy for individuals.

B. Edge Detection Method

NILM algorithms have been widely used in research of residential settings to reveal usage of individual appliances with consumption data [15]. Moreover, many applications have been proposed to extend existing NILM algorithms. In [1], appliances’ usage patterns are possible to be extracted from power consumption data without prior knowledge of household activities and training. In [3], NILM algorithms are extended to evaluate the threat to individual privacy by considering results on potential disclosure from smart meter data. Most of these NILM algorithms are based on edge detection.

Edge detection technique aims to looks for significant changes in the energy being consumed by the household [5]. Such changes are characterized by sharp edges in the energy consumed by the appliances. These edges are then clustered and matched against known appliance profiles. For instance, if someone turns on a 20W lamp, then the net power consumption increases by 20W. Conversely, when the lamp is turned off, the net current drops by the same amount. This is because the lamp draws zero, or some minimal amount of power on-off model.

On-Off Growth/Decay Model. An on-off growth/decay model is a variant of the on-off model that accounts for an initial power surge when a load starts, followed by a smooth increase or decrease in power usage over time until it reaches a stable consumption. An example of this model is a refrigerator (AC) and its consumption pattern can be formulated as [6]:

\[
p(t) = \begin{cases} 
    p_{on} & 0 \leq t \leq t_{on} \\
    p_{off} & t \geq t_{on}
\end{cases}
\]

(1)

Stable Min-Max Model. A stable min-max model maintains a stable maximum \(m_{\text{max}}\) or minimum power consumption when in active state, but frequently with a spike \(m_{\text{spike}}\) from this stable state. \(r(t)\) can only be 0 or 1. For example, refrigerator works with minimum power at most of time and periodically wake up to keep temperature low with high power consumption. The consumption pattern can be formulated as [6]:

\[
p(t) = p_{\text{max}} \cdot r(t), \ 0 \leq r(t) \leq 1
\]

(3)
Random Range Model. A random range model draws a random amount of power within a fixed range \((m_{\text{min}} \text{ to } m_{\text{max}})\). Television is an example of Random Range model because its energy consumption depends on display content and varies from a minimum and maximum power. The consumption pattern can be formulated as [6]:

\[
p(t) = p_{\text{min}} + (p_{\text{max}} - p_{\text{min}}) \cdot r(t), 0 \leq r(t) \leq 1
\]  

(4)

Composite Model. An composite model exhibits characteristics of multiple basic model types either in sequence or parallel. For example, a washing machine with different working stages may consume different energy signature at different working stages.

During the usage, the power consumption of electrical loads varies significantly at different stages. The signatures of electrical loads provide great opportunity for appliances detection.

III. SIGNATURE-BASED DETECTION METHOD

While edge detection methods are simple, they are often inaccurate, because they fail to capture the complex power usage patterns of different loads. With the energy consumption signatures of different appliances described above, we can design a better method than edge detection to reveal appliances’ usage patterns with a home’s energy consumption data. The key idea is to detect appliances usage by the similarity between real power consumption and appliances’ consumption models.

If consumption model of an appliance \(a_i\) is most similar to real power consumption, then it is highly possible that appliance \(a_i\) is working but not other appliances. In this paper, we propose a Euclidean distance-based function to quantify the similarity between two vectors. Let \(e(t)\) be the real energy consumption and \(m_i(t)\) be energy consumption data generated by models at time \(t\), where \(\text{length}(a_i)\) is the signature length of appliance \(a_i\). The similarity between two vectors can be calculated as:

\[
\rho_i = \frac{1}{1 + l_{(e,m_i)}}
\]

(5)

where

\[
l_{(e,m_i)} = \frac{1}{\text{length}(a_i)} \sum_{t=1}^{\text{length}(a_i)} (e(t) - m_i(t))^2
\]

(6)

Equation (6) is used to calculate the distance between two vectors. Because different appliances’ models have different lengths of signature sequences, we use \(1/T\) to normalize the distance of two vectors. For example, signature sequences of a lamp is short due to the on-off model; while the signature sequences of TV is long due to dynamic power consumption during usage. Equation (5) is used to transfer distance to similarity with range of \([0, 1]\).

Based on the similarity between consumption models of different appliances and real consumption data, we detect the appliances’ usage patterns. Suppose appliance \(i\) has highest similarity with real power consumption from time \(t\), we then detect as appliance \(i\) is working. Because several appliances can be working at the same time, we can remove the detected appliance’s model from real data and then repeat the detection process again. When similarity between rest of appliances and real consumption is low, we end the detection process for time \(t\) and continue the detection process from the time when detected appliances stop working.

The details of detection algorithm is shown in Algorithm 1. For power consumption data from \(t = 1, \ldots, T\), we first initialize \(t = 1\) (Line 1). While \(t < T\), we calculate similarity between power consumption data and signatures of each appliances based on Equation (5) (Lines 2-5). If we find the similarity between power consumption and signatures of an appliance is higher than current maximum similarity, we reassign maximum similarity and mark \(s = i\) (Lines 6-9). Then we calculate similarity between power consumption data and zero power consumption to get minimum similarity \(\rho_{\text{min}}\) (Line 10). If \(\rho_{\text{max}} > \rho_{\text{min}}\) we then detect appliance as is working at \(t\) and update power consumption by removing the signature of appliance as (Lines 11-13). Note \(t\) stays the same value to continue detecting other appliances working at time \(t\). Otherwise, it means we already detect all the appliances working from \(t\), thus we update \(t = t + \text{length}(a_s)\) for further detection (Lines 14-17).

IV. IMPLEMENTATION AND EVALUATION

In this section, we evaluate the performance of our signature based detection method and compare it with edge detection method.

A. Data Collection

We deploy eGauge power meters at individual homes to collect the total energy consumption data every one second. One of the experiment setup is shown in Figure 1(a). In our simulation, we use the energy consumption traces collected
B. Evaluation Results

With empirical consumption and load events data collected in 40 homes, we run both edge detection and SBD methods. An example of detection results at one home is shown in Figure 2. Microwave oven belongs to On-Off model; refrigerator and trash compactor belong to Stable Min-Max model; oven and coffee maker belong to Composite model; AC belongs to On-Off Decay model; TV belongs to Random Range model. We also show whether appliances can be detected by using only edge detection or SBD methods. Because the microwave oven and coffee maker have similar power consumption, they cannot be detected by edge detection. However, the coffee maker has two working stages, which can be differentiated from the microwave oven by using SBD. Trash compactor and TV also have similar power consumption but different working stages, thus they cannot be differentiated by edge detection but signature detection. The summary of different appliances detection is shown in Table I. Therefore, our signature detection method can detect appliances’ usage more accurately.

We also evaluate appliances detection accuracy when power consumption is hidden by BLH. The power consumption for charging a battery is shown in Figure 4. The average power for charging the battery is around 160W. The BLH algorithm we choose is from [5]. Yang et al. proposed four battery-based algorithms to hide power consumption. In our paper, we select (Lazy Stepping) LS2 because LS2 performs best in most of their simulations. We show the power consumption

<table>
<thead>
<tr>
<th>Appliance</th>
<th>Model</th>
<th>Edge</th>
<th>Signature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Microwave Oven</td>
<td>On/Off</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Refrigerator</td>
<td>Stable Min-Max</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Oven</td>
<td>Composite</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Trash Compactor</td>
<td>Stable Min-Max</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Coffee Maker</td>
<td>Composite</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>AC</td>
<td>On/Off Decay</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>TV</td>
<td>Random Range</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Fig. 3. Detection accuracy with original power consumption

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\[
r = \frac{N_d}{N_t}
\]

In the simulation, we use collected appliances events and appliances’ real-time power consumption to generate total power consumption to detect. With original power consumption data, both edge detection and SBD can detect appliances usage with more than 70% accuracy. With more appliances to detect, the detection accuracy of edge detection and SBD both drops. This is because different appliances may have similar power consumption signature, which increases the difficulty to detect more appliances. However, compared to edge detection, detection accuracy of SBD drops much slower.

We also evaluate appliances detection accuracy when power consumption is hidden by BLH. The power consumption for charging a battery is shown in Figure 4. The average power for charging the battery is around 160W. The BLH algorithm we choose is from [5]. Yang et al. proposed four battery-based algorithms to hide power consumption. In our paper, we select (Lazy Stepping) LS2 because LS2 performs best in most of their simulations. We show the power consumption
of BLH algorithm LS2 with comparison of the original loads in Figure 5. To make the difference between original load and power consumption with BLH visible, we show only 300 seconds of consumption data in one home. The LS2 tries to maintain power consumption at certain levels, thus its consumption can be only -2kW, 0kW, 2kW, 4kW and 6kW. However, we can still find that the shape of LS2 is similar to the original load. The results of two detection algorithms are shown in Figure 6. For edge detection, the detection accuracy of 7 appliances drops below 50% while the detection accuracy for SBD is still higher than 70%.

With our proposed SBD method, appliances’ usage can be detected accurately even power consumption is hidden by BLH. Thus, there will be stronger demand for homeowners to protect their appliances’ usage.

V. Conclusion

In this paper, we demonstrate the recently proposed energy consumption signature models and develop our energy consumption signature detection method, called SBD, which is more accurate than the widely used edge detection method. With the empirical data from more than 40 homes, we conduct extensive system evaluations. Results indicate that i) SBD has higher detection accuracy than edge detection; ii) SBD can still detect more than 70% of appliances’ events even with BLH.

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