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Generating Power Footprints without Appliance Interaction: an Enabler for Privacy Intrusion

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Abstract—Appliance load monitoring (ALM) systems are systems capable of monitoring appliances’ operation within a building using a single metering point. As such, they uncover information on occupants’ activities of daily living and subsequently an exploitable privacy leak. Related work has shown monitoring accuracies higher than 90% achieved by ALM systems, yet requiring interaction with appliances for system calibration. In the context of external privacy intrusion, ALM systems have the following obstacles for system calibration: (1) type and model of appliances inside the monitored building are entirely unknown; (2) appliances cannot be operated to record power footprints; and (3) ground truth data is not available to fine-tune algorithms. Within this work, we focus on monitoring those appliances from which we can infer occupants’ activities. Without appliance interaction, appliances’ profiling is realised via automated capture and analysis of shapes, steady-state durations, and occurrence patterns of power loads. Such automated process produces unique power footprints, and naming is realised using heuristics and known characteristics of typical home equipment. Data recorded within a kitchen area and one home illustrates the various processing steps, from data acquisition to power footprint naming.

I. INTRODUCTION

A. Fine-Grained Electricity Monitoring

Electricity represents 41% of the total energy used in the United States [1], and about one third of it is wasted [2]. Recent efforts for a modernised electrical grid—smart grid—are primary triggers to counterbalance and reduce electricity consumption [3]. Smart meters are being introduced within homes for providing real-time access to power readings remotely [4], [5], facilitating utilities’ global control and management of electricity consumption and generation, respectively.

As a short-term alternative to longer-term smart meter widespread deployment, commercial electricity monitors reduced to mere electricity reading and local reporting are also being made available. Such devices can be clamped to buildings’ main circuit board to measure a rich cocktail of electrical parameters and provide real-time power consumption feedback to electricity consumers.

This work demonstrates that access to electricity readings via the introduction of smart meters and electricity monitors enables illicit monitoring of private activities of daily living.

B. Enabler for privacy intrusion

Activities of Daily Living (ADLs) include, but are not limited to cooking, showering, washing, and sleeping; they therefore involve interactions with electrical equipment. Appliance load monitoring (ALM) systems are systems capable of monitoring appliances’ operation within a building using a single metering point. As such, they uncover information on occupants’ interactions with electrical equipment and subsequently an exploitable ADL privacy leak. The privacy of ADLs is a matter well-discussed elsewhere [6], [7], [11]. For instance, such privacy intrusion may be inappropriately used to infer medical conditions [8] or to simply inquire a person’s presence for a potential burglary [11]. Related work has shown monitoring accuracies higher than 90% achieved by ALM systems, yet requiring interaction with appliances for system calibration. In the context of external privacy intrusion, ALM systems have the following obstacles for system calibration: (1) type and model of appliances inside the monitored building are entirely unknown; (2) appliances cannot be operated to record power footprints; and (3) ground truth data is not available to fine-tune algorithms.

Within this work, we focus on monitoring those appliances from which we can infer occupants’ activities. Without appliance interaction, appliances’ profiling is realised via automated capture and analysis of shapes, steady-state durations, and occurrence patterns of power loads. Such automated process produces unique power footprints, and naming is realised using heuristics and known characteristics of typical home equipment.

II. RELATED WORK

The potential abuse of ALM systems for surveillance purpose has been discussed abundantly. Power-based surveillance for monitoring the activities of suspected criminals or political opposition; identifying the movements of occupants to time a break-in; advertising consumers lacking consumer appliances; taxing bad electricity users turning on their air-conditioning system in restricted hours are exemplars. Privacy intruders may range from single individuals to enterprises and utilities themselves.

Appliance load monitoring systems are designed to achieve a building’s power decomposition, down to equipment level.
Appliance signatures are measurable parameters of the total load that provide information about the nature or operating state of individual appliances in the load [14]. They are therefore the patterns that ALM systems try to extract from a congested building power signal. Knowing appliances’ signatures, complex pattern recognition techniques return the list of appliances which combination of signatures provides the best match with the measured signal, e.g. [9], [14].

Mature research in the area of appliance load monitoring has as yet not been transferred to actual commercial integration. Indeed, most ALM systems require complex calibration and verification to be carried out by a trained technician or an auxiliary system [10] before it can be used in a domestic or commercial environment. Hart et al. proposed an automatic set-up nonintrusive appliance load monitoring system (AS-NALM), setting the basic steps for an automated capture and naming of appliance signatures. Since then, a number of calibration-free systems have been proposed. Molina-Markham et al. [12] utilise statistical methods to derive complex appliances’ usage patterns from electricity readings, claiming no prior knowledge of household activities and no training phase. They however relate to power activity journals annotated by home occupants and used to map opaque labels to real-life events. Unless occupants agree to be monitored and provide such brief logs, those cannot be assumed for configuring appliance load monitoring systems. Lisovich et al. [13] provide a technical study showing how activity information can be extrapolated from power-consumption data. They assume that the adversary has a list of appliances present inside, as well as their turn-on/turn-off profiles.

Although automated calibration and risks of privacy issues are well-known, few systems have been implemented and evaluated for exploiting effectively such privacy leaks in a real-world scenario where pre-calibration is impossible. This work proposes an initial experimental evaluation of such system in an ADL privacy case study. We argue that identifying the monitoring purpose and objective prior to operation is essential to achieving high accuracy, focusing monitoring on the subset of appliances of interest and discarding uninteresting power activity.

III. MONITORING ACTIVITIES OF DAILY LIVING USING A SINGLE ELECTRICITY MONITOR

Primary challenges in deriving activity patterns of a building occupant from a single electricity monitor are threefold. First, the attacker needs to have access to the building power flow. Second, the attacker requires an appliance load monitoring system that can disaggregate a power load without prior knowledge of the building appliances’ signatures. Finally, appliance activities need to be matched to ADLs.

We investigate the case of power flow captured at the live wire, via illicit clamping of an electricity monitor, see Figure 1. Electric meters may be located in the power pylon serving the property; in a meter-box external to the house; in a public space such as a building’s corridor or an office open distribution board; or inside the premises. Once the electricity monitor is clamped, raw electricity consumption of the building under surveillance is reported wirelessly to the attacker’s PC-class machine.

A. Profile-free Appliance Load Monitoring System

In order to disaggregate a building’s power flow without access to the premises, the appliance load monitoring system used by the attacker needs to be free of any human supervised calibration procedure.

The technique we propose takes advantage of the attacker’s prior knowledge of the kind of appliances and patterns that he wishes to recognise. In an ADL intrusion context, appliances that will indicate an occupant activity are the ones of interest, reducing the monitoring objectives to their detection. For instance, detecting the activity of a fridge compressor has no intrinsic value as it is not linked to any user activity, and is either filtered out or kept unnamed.
of a one-person household, captured by the electricity monitor.

Two initial processing steps consist of detecting and recording
occupant being tracked. Figure 3(a) shows the apparent power
for the attacker. At this point, the attacker does not know
any power steps on the electricity reading that may be useful
for understanding the nature of the appliances.

The proposed technique follows a four-step processing on
the raw power flow, as shown in Figure 2. The following
describes in greater details the four steps of data processing
conducted to retrieve appliances’ signatures, illustrated with
experimental data.

1) Noise filtering and capture of power signatures: These
two initial processing steps consist of detecting and recording
any power steps on the electricity reading that may be useful
for the attacker. At this point, the attacker does not know
anything about the appliances, habits and patterns of the
occupant being tracked. Figure 3(a) shows the apparent power
of a one-person household, captured by the electricity monitor
over a period of one day. Activity is visible in the morning
between 8 and 9am, and in the evening between 7 and 10pm.

In an ADL attack context, noise is considered as being
power associated to always-on appliances and periodic patterns
such as the periodic power step visible on Figure 3(a). A
first processing step is therefore to cancel out the noise via
filtering with thresholds and pattern recognition. The output
of Figure 3(a) after filtering is given in Figure 3(b).

Resulting peaks will often be a superposition of multiple
appliances signatures, when several appliances are used
concurrently—see zoom to 8-9am time slot on Figure 4(a).
However, as Figure 4(b) shows via a zoom on the 9-10pm
apparent power data, single appliance signatures often appear
on a power reading, facilitating their capture. The range of
electrical parameters as well as a timestamp are recorded for
each of the unique power footprints that are detected after
filtering. The objective of this second processing step is to
aggregate a pool of power footprints to later cluster them
type and time wise, in order to facilitate their naming.

2) Clustering of identical power signatures: The third
processing step is to cluster identical power footprints, and
analyse the times at which they appear. The goal is to derive
a distribution of occurrences for each power footprint that will
be used for understanding the nature of the appliances.

Figure 5 shows as an example the distribution of
occurrences of the power footprint that appears at the very
right of Figure 4(b) over a period of 7 days. Vertical lines indicate when the power
footprint has been detected.

3) Naming of appliances signatures: Naming is facilitated
by the fact that the attacker knows the typical shape and power
characteristics of the appliances signatures he is interested in.
Figure 6 recalls generic power footprints for three appliances
that can be used for detecting ADLs. They are signatures of an
Toileting, Moving

of bridging appliances’ activities to ADLs. The last step of the ADL monitoring consists of characterising breakfast-type of machines such as toaster and morning-only distribution of occurrences would be helpful for concluding on the appliance name. A direct indication for concluding on the appliance name. A morning-only distribution of occurrences would be helpful for characterising breakfast-type of machines such as toaster and coffee machines. We however see that the given appliance is used at random times during the day, and several times per day. Such facts rule out appliances such as hair dryers that are used at maximum a few times per day. Furthermore, the distribution of occurrences shows that the appliance is sometimes used many times over relatively short periods of time. This extra indication together with the observed power characteristics give indication that such signatures corresponds with high probability to a kettle.

Once names are given to each power footprint, the appliance load recognition system is ready to disaggregate in real-time the power flow. The last step of the ADL monitoring consists of bridging appliances’ activities to ADLs.

### TABLE I
ADLS AND ASSOCIATED APPLIANCES.

<table>
<thead>
<tr>
<th></th>
<th>Eating</th>
<th>Toileting</th>
<th>Moving</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dish-washer</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Electric heater</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Electric shower</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fitness equipment</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hair-dryer</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Induction cookers</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kettle</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Microwave</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Oven</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Toaster</td>
<td>x</td>
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</table>

### B. Matching appliances’ activities to ADLs

There exist a number of basic ADLs including eating, dressing, washing, and transferring (moving). Such ADLs can be inferred when interaction with appliances exists. For instance, detecting that the microwave is on is a good indication of eating activity. Table I categorises the set of ADLs and associated home appliances that may be used by an attacker in the context of an health condition privacy intrusion. Health condition relates importantly to the ability of a person to eat, wash and move independently. As shown in Table I, there are only few direct activity relationships between appliances and ADLs. Yet, more reasoning may provide extra information not visible in Table I. For instance, observing appliances being switched on consecutively in supposed different rooms, say the oven and the hair dryer, may indicate an occupant’s mobility.

### IV. Implementation

We developed RECAP-free, a calibration-free appliance load monitoring (ALM) system, based on RECAP, an ALM system capable of recognising appliance activities in real-time using a neural network machine learning technique and prior appliance profiling [9]. RECAP-free reuses the recognition components from RECAP, but handles discovery and naming of power footprints without equipment interaction.

RECAP-free has been implemented in Java. The four conceptual processing steps described in Section III-A have been integrated to provide more efficient coding and have been automated to minimise human supervision. Noise filtering is realised as soon as electricity readings are read. Whether a power step is detected, the program makes a record of a new signature; other small variations are filtered out. When a new signature is recorded, the program captures the associated power parameters, and check whether a similar power footprint exists in the signature database. The objective is to immediately cluster occurrences of identical signatures. If a similar signature exists, the system records the new timestamp at which the signature has been observed, generating over time a list of timestamps for each single signature. In case the signature does not exist, a new entry is created. At the end of the process, RECAP-free profiling engine provides a list of single signatures and associated timestamps at which they occurred. At this stage, naming of power signatures is the only step done manually. We are currently populating a database of power signatures, that we plan to use to develop automated power signature comparison for further deployments.

### V. Experimentation

We have initially restricted our tests to a kitchen area, in order to fine-tune our algorithms in a controlled environment with a limited subset of appliances. After validation, we ran our algorithms within a real domestic environment for a period of one week.

#### A. Fine-tuning the system

A kitchen area has been equipped with an Episensor electricity monitor [15]. The monitoring setup is similar to that
presented in Figure 1. The PC-class unit stores data readings transmitted by the electricity monitor at a granularity of one sample every 10 seconds and runs RECAP-free.

<table>
<thead>
<tr>
<th>Table - disc Appliances Profiling</th>
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<th>Table - disc Appliances Profiling</th>
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<tr>
<td>Appliance ID</td>
<td>Timestamp</td>
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<tr>
<td>u2724711204596</td>
<td>2014-10-23 16:23:45</td>
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<td>74005.0000</td>
</tr>
</tbody>
</table>

The first data reading is taken before the power step has been detected, and the other two data readings correspond to moments after the power step has been detected. The third data reading is recorded to handle cases when the second data reading has been sampled while the power level was in a transient state between the appliance off and on power states. Power footprint registration with RECAP-free is also timestamped, but discrepancies in software configuration generated a one-hour time difference between table time stamps and graph timing. Furthermore, as one can see on Figure 7 and Figure 8, RECAP-free appliances’ signatures have been generated once a power footprint has appeared 3 times. For instance, the first signature has been generated at 16:20 (17:20 on Figure 7), even if the same power footprint has appeared at 17:05 and 17:15.

Figure 8 shows that the three appliances have been instrumented several times during data capture but without any meaningful usage pattern, see Figure 7. Within this study, longer data capture has provided a better view on appliances’ frequency of usage. Figure 9 shows a data capture made during afternoon working hours, exhibiting numerous repetitions of one power signature at lunch time, and random appearance of another power signature throughout the day. Such usage pattern information is vital to associate names to the discovered footprints. Based on these times of occurrence as well as power characteristics of discovered power footprints, the first signature captured is named as a kettle, and the third one as a microwave. More data will however be necessary to name confidently the second power footprint. This example has shown the importance of the amount of data that needs to be gathered to achieve an accurate and effective processing.

**B. Real world testing**

One home has been equipped with an Episensor electricity monitor [15] for a period of 7 days. In that deployment, data readings are sampled every minute.

Figure 10 shows the apparent power measurement over the 7-day period. Immediately, one can see the difficulty at hand with real-world experimentation; noise and number of appliances are increased. We ran RECAP-free over that data and Figure 11 shows that 4 primary power footprints have been discovered. The power consumption for those power footprints is given, and they are initialised with a non-meaningful name. RECAP-free generated as well a table of activities, showing the power state of those four power footprints over time. The
Table, shown in Figure 12, contains the times of occurrence of each footprint and will be used to name power footprints.

In order to depict the recognition process with an example, we focus in the following on the Jan 28, 2011, see Figure 13. We can see that the power measurement is composed of a baseline power, as well as a recurrent power block pattern, and power peaks.

Figure 14 illustrates the filtering done by RECAP-free. Periods with insignificant power activities have been cut off (in effect filtered out by RECAP-free). We remove those periods from Figure 14 to improve visualisation. As highlighted with various symbols, a number of similar power steps can be grouped together. Those similar power footprints are those discovered by RECAP-free and registered in the appliance tables, see Figure 11.

[TO DO: Naming of the 4 footprints]

### VI. Conclusions

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### References


