Multimedia Content Identification Through Smart Meter Power Usage Profiles*

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Abstract. Advanced metering devices (smart meters) are being installed throughout electric networks in Germany (as well as in other parts of Europe and in the United States). Unfortunately, smart meters are able to become surveillance devices that monitor the behavior of the customers. This leads to unprecedented invasions of consumer privacy. Our research shows that the analysis of the household's electricity usage profile at a $0.5s^{-1}$ sample rate does reveal what channel the TV set in the household was displaying and to identify content in the power profile that is displayed on a CRT[1], a Plasma display TV or a LCD[2] television set with dynamic backlighting. Our test results show that two 5 minutes-chunks of consecutive viewing without major interference by other appliances is sufficient to identify the content.

1 Introduction

A smart meter is an electrical meter that records consumption of electrical energy at intervals and has the capabilities of communicating between a central server of its recorded information. The installation of smart meters at private homes is planned in Germany, as well as in EU in the near future. By 2020, the smart metering devices are supposed to replace 80% of the existing conventional meters. Smart metering is believed to be a crucial factor for the future availability of supply, energy efficiency and renewable energy[3]. From a consumer perspective, smart metering offers potential benefits such as: consumers by using a smart meter are able to view their detailed energy consumption data via a web-browser. The visualization of these data lets consumer to see into details how energy at home is used, therefore providing possibilities for devising energy saving strategies in view of their energy consumption habits.

[1] Cathode Ray Tube
[2] Liquid Crystal Display
[3] *80% Smart Meter Adoption By 2020 Through EU Mandate*: Yahoo Finance Report from Sep 29, 2011 8:10 AM

Smart meter data contain consumer's personal information. Also depending on the granularity of measurement and the resolution of data, we show in this paper that it is possible to deduce personal behavior of an individual in a private home. These behaviors include for example what TV channels, and which movies an individual has viewed in the course of a smart meter recording. In view of the concerns above, there are henceforth urgent calls for researchers to provide means of better protecting data transmitted by a smart meter.

2 Related Work

Even before the advent of smart meters, extensive researches have been done on techniques of non-intrusive load monitoring (NILM). Various NILM methods [7, 9] are introduced in order to glean into detailed energy consumption pattern in a household. Using these techniques, it turns out that a remarkable number of electric appliances in a private home can be identified by their load signatures with impressive accuracy. The same NILM techniques can be applied to analyze smart meter data in order to peek into household activities [10].

There have been privacy concerns over the deployment and usage of smart meters [2, 8, 11] in U.S. and Europe, precisely because they can inadvertently leak detailed information about household activities. In the literature, one can find proposed countermeasures such as: 3rd party escrow for authenticating anonymous meter readings [4], reduction of device load signatures by inserting a rechargeable battery model [5, 6], anonymous smart meter billing using a zero-knowledge protocol [3].

3 Experimental Results

Our investigation aims to answer the following questions: (1) What are the possible ways of obtaining and evaluating data coming from a calibrated smart meter? (2) What can be deduced from smart meter data regarding a person's TV watching habit in a private home? The experiments mentioned in this paper took place from August to November, 2011.

3.1 Hardware Background

The tested smart meter had been acquired from the company Discovergy GmbH (Heidelberg, Germany) after signing a private household contract. This calibrated smart meter is installed in a typical private house in the region North Rhine-Westphalia, Germany. After the installation, the new meter replaces the conventional meter which is manufactured by the German public utility company RWE AG.

The Discovergy product is based on the smart meter model manufactured by EasyMeter GmbH, Bielefeld (Electronic 3-phase meter Q3D-A1004 v3.03). The smart meter takes measurement at an interval of two seconds. All data are transmitted to the servers hosted by Discovergy. The customers are then able to access these data via a web-browser. Discovergy[4] claims in its contract complete data encryption for each smart meter equipped household.

4 TV/Film Detection

4.1 Television Hardware

The first part of tests were performed on an home LCD television set in a household where the operational smart meter was installed. Liquid Crystal Display televisions use the display technology to produce colored images. Since the total amount of visible brightness of a picture is a combination of the backlighting and LCD shuttering, a technology dubbed *dynamic backlighting* is applied on modern LCD TVs to improve the contrast ratio[12]. While the shutters produce a contrast ratio of 1000:1, dynamic backlighting enhances this ratio up to 30000:1. The LCD TV power consumption is mainly influenced by the backlighting activities [1].

The experiment results presented in the following sections were obtained by using the household's Panasonic LCD television set[5]. Section 4.6 contains comparison results which use other TV models. The power consumption difference of a frozen white picture to a frozen black picture for this particular television was measured to be about 70 watts.

4.2 Power Consumption Prediction Function

The core of our content identification program is the power consumption prediction function. We explain below in details the construction of the function. The input of the function is the multimedia content, the output is power usage prediction as would displayed by a smart meter.

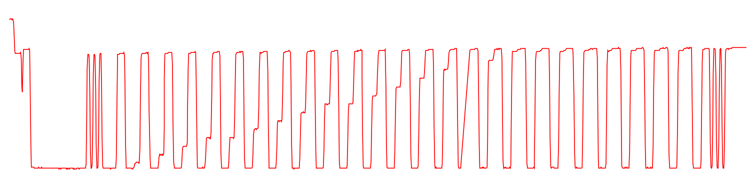

Fig. 1. Determination of b_{min}

The first step is to measure the power consumption for a series of pictures consisting of elementary shades. We use the additive RGB color notation with one byte (i. e. values 0–255) per red, green and blue portion. The sequence of

[4] www.discovergy.com

[5] Panasonic model number TX-L37S10E

$$n := 2 \text{ times (no. of frames per second)}$$

$$m_i := \begin{cases} 1 & \text{if } b_i > b_{min} \\ \frac{b_i}{b_{min}} & \text{otherwise} \end{cases} \qquad pp_k := \frac{1}{n} \sum_{i=nk}^{n(k+1)-1} m_i$$

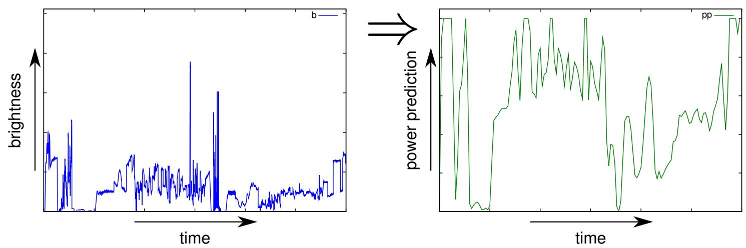

Fig. 2. Power prediction is computed on frame brightness values

pictures are then RGB 0-0-0, RGB 1-1-1, . . . , RGB 255-255-255 that increase the brightness from black to white running over 254 shades of gray. Our observation shows that maximum power consumption is reached with rather dark pictures (e. g., RGB 32-32-32). But this also depends on the television user settings. For the rest of the paper, we denote this value by b_{min} which is the minimum brightness value that maximizes TV power consumption. A typical b_{min} value for the tested LCD TVs lies in the range $\{26, \ldots, 58\}$.

Figure 1 shows one of the test runs we had performed in order to determine the value b_{min}. A sequence of pictures was shown: *black-white* (3 times) as a trailer to find the signal, then *black-(RGB-2-2-2)-white-black-(RGB-4-4-4)-white-black-(RGB-6-6-6)*. . . to see the increasing power consumption. One can then count the number of peaks until the gray picture (here: RGB-38-38-38) reaches maximum power consumption, i.e. becomes indistinguishable from white with regard to the power profile. At a later stage we did not need to run these tests anymore since we developed a script that performs content identification by automatic parameter detection.

The next step (shown in Figure 2) is to extract frames from the movie and determine the brightness of each frame. By assuming a linear function (suggested by the results of step one) we can then let the predicted power consumption m_i (for a frame with index i) to be at the TV set's maximum power consumption for all frames being brighter then ($RGB\ b_{min}$-b_{min}-b_{min}) and being equal to $(max - min)(b_{min} - b)$ for all frames with brightness $b < b_{min}$.

As we obtained our experimental results with a smart meter operating on a two-seconds interval, we then calculate an average value of power consumption for a number of consecutive frames adding up to two seconds of a movie. This data can be correlated with any subsequent power profile data of the same length in order to search for the content.

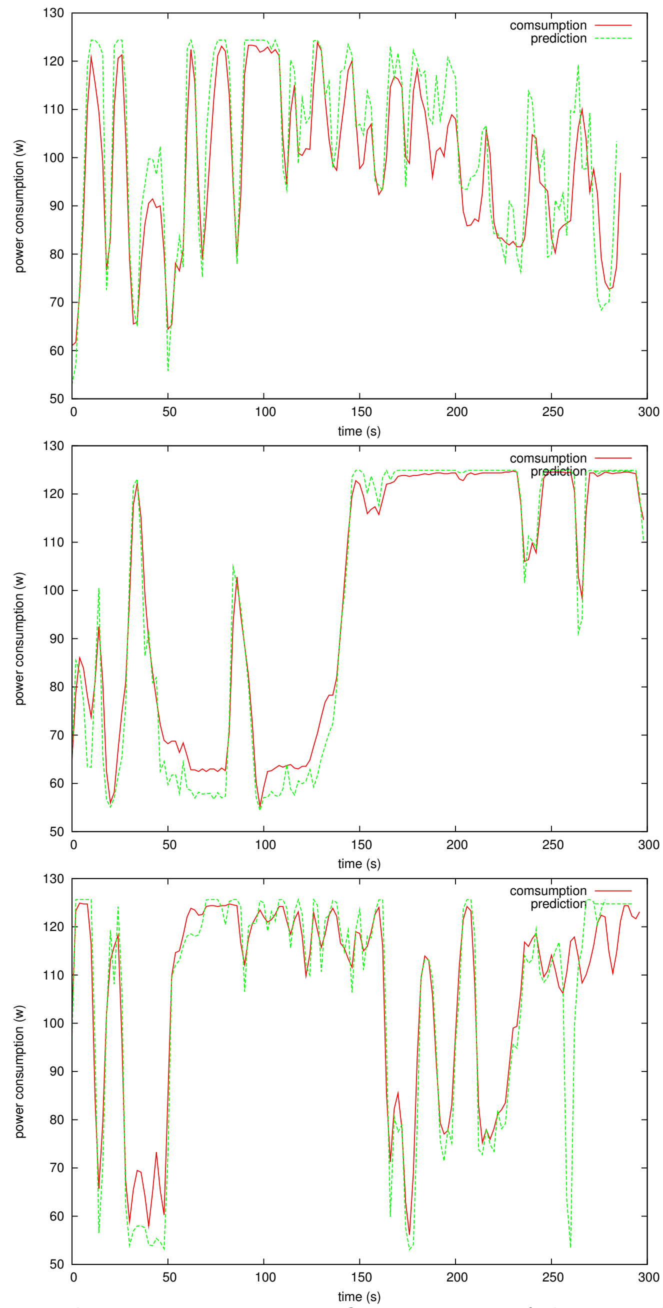

Fig. 3. power prediction vs. consumption: first 5 minutes of the movie Star Trek 11 (top), of episode 1, Star Trek TNG season 1, of the movie Body of Lies (bottom)

4.3 Preliminary Analysis

To test our prediction function, we did a preliminary run on some films. We extracted first 5 minutes of each movie file, and then compared the actual power consumption against values produced by the prediction function. The movies we used for the test are:

1. Movie *Star Trek* (2009). Directed by J. J. Abrams. Release date: May 8, 2009.

2. Star Trek episode *Encounter at Farpoint* (1987). Directed by Corey Allen. Original air date: September 28, 1987.

3. Movie *Body of Lies* (2008). Directed by Ridley Scott. WarnerBros. Pictures. Release date: October 5, 2008

The actual power consumption was measured using the sealed operational smart meter while the films are playing on the household television set.

Figure 3 contains the experimental results. The green dotted curve is the prediction, and the actual power consumption data is plotted in red. We also calculated the Pearson product-moment correlation coefficients between the actual and predicted power consumption data. The correlation for the three movie events are 0.94, 0.98 and 0.93 respectively.

4.4 Corridor Algorithm

During the experiments, we have noticed that the power consumption curve as observed by a smart meter oscillates in a normal household situation (without TV running) in a way that could lead to false positive identification of TV content. The reason for that is while searching for 5-minute chunks of movie files, if the chunk is for example showing a long dark scene, followed by a long bright scene (both scenes added exceed five minutes), it will correlate strongly with a power curve that reflects the switching-on of a simple electric appliance (e. g. a light bulb). To make movie load signature more distinguishable, it is desirable to eliminate possible false matches reflecting this effect during the analysis stage. For that purpose, we have developed a *Corridor Algorithm*. If too many values of predicted or actual power consumption fall in one of two corridors, this movie-chunk will be discarded.

4.5 Work-flow

This section describes the work-flow that are involved in the movie identification process. The Figure 4 illustrates all the steps involved. These steps are performed automatically by a software script we developed for the research being described in this paper and which could be regarded as a proof-of-concept for a forensic tool performing content identification on power consumption data.

The entire film is first divided into 5 minute chunks, and the brightness of each frame is calculated. The correlation value for the chunk is then computed using the predicted power values.

It should be noted that the identification process fails on some of the 5-minutes movie chunks due to either power disturbance or user interaction with the TV or the playing device. For a typical 90 minutes playback, we have $90/5 = 18$ blocks at disposal, so in a actual test there should be a good chance that at least two or three of these chunks *survive* other appliances' activities and can be found in the power curve matching.

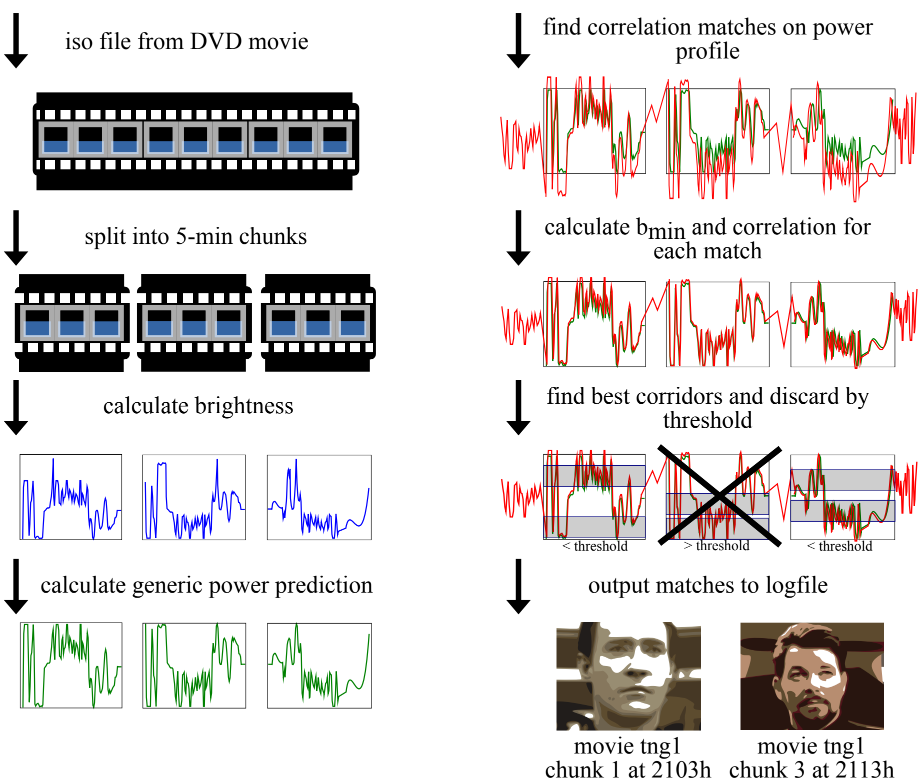

Fig. 4. Work-flow to detect chunks of a movie

4.6 Other Television Models

Experiments described in the previous sections were performed on a home LCD TV[6] equipped with dynamic backlight enhancing technology. To support our claim that content identification is in general possible, we have performed experiments on other TV models as well.[7] We connected a out-of-box smart meter

[6] Panasonic model number TX-L37S10E

[7] The authors wish to thank graduate student Stephan Brinkhaus BSc. who conducted various tests with the smart meter on several TV sets and other appliances.

(meter Q3D from Easymeter GmbH) with specific TV sets. Successful test results for cathode ray tubes and plasma displays affirm our belief that movie/TV content identification via fine-grained smart meter data is possible (with the exception of LCD TVs without backlighting).

4.7 False Positives with Other Appliances

In order to get some consolidated findings regarding false content identification, we used our scripted content identification work-flow to search for content in several 24h-periods, in which power metering data are concurrently generated by different household appliances.

```
INFO   First correlation discard threshold: 0.0
INFO   Second correlation discard threshold: 0.85
INFO   Corridor discard threshold: 0.5
INFO   Corridor height: 5
INFO   Power consumption corridor discard threshold: 0.5
INFO   Power consumption corridor height: 5
INFO   Analyze log file "discovergy-Raw-2011.11.19_0100-2011.11.19_2359.csv"
INFO   *(_csv_5Min.Saw.6.1080p.mkv.csv) at  07:14:50
         cor =          0.8582734470331655    bMin =         40.0
         delta =        2.160000520199958     distance =      0.40085441550795814
         corridor =     0.4533333333333333    pcCorridor =    0.31    [...]
INFO   *(_csv_5Min.Spaceballs.mkv.csv) at  11:06:43
         cor =          0.8554506191367586    bMin =         28.0
         delta =      316.08000034434         distance =     57.05935049506766
         corridor =     0.42                  pcCorridor =    0.3333333333333333
INFO   *(_csv_5Min-Jackie.Chan.-.Action.Hunter.avi.csv) at  12:54:07
         cor =          0.8794719071839578    bMin =         48.0
         delta =     4239.1799992422          distance =    466.5877682097706
         corridor =     0.25333333333333335   pcCorridor =    0.36    [...]
```

Fig. 5. Log file clipping showing false positive matches on other appliances

A straightforward strategy to identify content and avoid false positives would be to count only findings consisting of more than one match of a 5-minute chunk. A log entry showing two corresponding chunks of the same content (like the example of Figure 4: chunk 1 at 21:03h and chunk 3 at 21:13h) ruled out false positives on other appliances during the experiments.

5 Conclusion

Smart meters are able to become devices that monitor the behavior of their customers. The personal privacy invasion is obvious if the smart meter data are available to malicious parties or being used by members of the same household to spy on each other.

A new generation of smart meters generating high-resolution energy consumption data could henceforth cause new potentials concerns regarding consumers' privacy sphere. We have demonstrated that particular information available on appliances in the household via its detailed power profile allow a fine-grained analysis of the appliance's behavior. Taking measurements at an interval of two seconds is sufficient to enable the identification of a television program or audiovisual content if favorable conditions are in place (e.g., no major interference of other appliances for minutes long). Our research has shown that the electricity usage profile with a $0.5s^{-1}$ sample rate leads to a *invasion* into a person's private sphere regarding his TV watching habits. Five minutes of consecutive playing of a movie is in many cases sufficient to identify the viewed content by analyzing the smart meter power consumption data.

Note that we only used 653 content files for our experiments; a forensic investigator who is searching for copyright-protected content of all movies and TV productions ever been produced might have to solve a more challenging false-positive-problem. We did *not* have sufficient content files to reach a proper assessment on the feasibility of a forensic software.

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