SPOTLIGHT: Personal Natural Resource Consumption Profiler

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ABSTRACT

The impending energy and natural resource crisis forces us to research innovative ways of optimizing our resource consumption. Recent studies have shown that a better understanding of an individual's energy consumption helps people to lower their energy footprint significantly. We propose SPOTLIGHT, a system that profiles an individual's natural resource consumption pattern in real time using wireless sensor network technology. The current SPOTLIGHT prototype consists of power measurement, activity monitoring and energy resource management subsystems. We explore challenges and issues of each subsystem and discuss lessons we have learnt from the prototype deployment. Additionally, we will provide an outlook of extensions of SPOTLIGHT for water and gas management.

Categories and Subject Descriptors

H.5.m [**Information Interfaces and Presentation**]: Miscellaneous - Individual Energy Consumption Report

General Terms

Measurement, Economics, Experimentation, Human Factors.

Keywords

Individual Resource Management, activity based computing

1. Introduction

Oil price rose for the first time over 100$/barrel and the U.S. Department of Energy reported in 2006, that 85% of electrical energy was generated from non-renewable fossil fuels such as coal, natural gas, and petroleum. Furthermore, the water consumption of the U.S. rises with increasing population and growing urbanization. The energy production and general natural resource consumption comes with a significant cost and increasing environmental concerns. Recently, more government agencies and companies are becoming aware of the cost of energy consumption. But the high price of energy, and the restricted availability of other natural resources, doesn't just stop with companies. More and more it also impacts each individual household, as we could observe in last years severe drought in the south-eastern part of the U.S., and the yearly reoccurring power blackouts.

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The traditional way of measuring the resource consumption is coarse grained: typically at household level and monthly basis. It gives only a partial awareness of an individual's resource consumption. However, measurement of energy, water, and other resources at a per person level would help us pinpoint habits or trends, and thus improve resource efficiency by modifying them. For example, Stern [1] and McMakin [3] showed that people are willing to conserve energy as their desire to do the right thing, and to save energy cost. Environmental concerns also motivate [3] individuals to want to have fine grained information to be more aware of where they spend the most resources [18]. For these reasons, demand for such feedback information emerges. We believe that profiling at a finer granularity aids in pinpointing consumption patterns to improve resource efficiency.

We propose SPOTLIGHT, a resource measuring system that is capable of estimating an individual's personal resource consumption profile using sensor network technology. The goal of SPOTLIGHT is to give people the possibility to monitor their own resource consumption and it thus has to be easily installable by non experts. Therefore, we took special care in SPOTLIGHT's design to use commercially available components that are non-intrusive (don't have to cut wires or pipes) and that are installable by everyone. Our initial prototype focuses on electrical energy, and we will show at the end how it can be extended to monitor other resources.

The rest of the paper is structured as follows. In Section 2, we give detailed information on the SPOTLIGHT system architecture and describe its challenges. Section 3 details the prototype design and implementation. In Section 4, we evaluate our prototype system against the ground truth and its performance. Then we discuss lessons from the deployment in Section 5 then conclude in Section 6.

2. SPOTLIGHT System Architecture

SPOTLIGHT envisions that the overall system architecture leverages inherent network, interfacing and various sensing capabilities of sensor networks.

The main components of the system consist of:

a) *Resource Monitoring Subsystem* that profiles appliances' resource consumption.

b) *Activity Monitoring Subsystem* that is analogous to the activity recognition in [12,14,17]. However, it is slightly different as it uses the information from the resource monitoring subsystem that helps disambiguate uncertain cases because the resource consumption of appliances is always related to a subset of an individual's activities.

c) *Resource Management Subsystem* that has two inputs: resource consumption of appliances and tenants' activity profile. And it provides feedback to the users.

2.1 Resource Monitoring Subsystem

Available technologies for resource monitoring either provide information at coarse spatial granularity, like the power and gas meters for an apartment, or at small appliance level scale [4,19]. The problem is that they miss to show the consumption at a per individual level.

Technical challenges associated with sensing of appliance resource consumption are three folds. Firstly, it has to be scalable. Appliance resource monitoring has long been explored and many different types of measurement technology exist, especially for power measurement of electrical devices [4,7,19]. For example, a commercially available appliance level electrical energy consumption profiler can be a good option for a small number of appliances in a small apartment. But these systems get infeasible as the number of appliances increases beyond the one of a very small household. It's deployment complexity and cost would be just too much.

Second, it has to provide fairly accurate resource consumption. One approach which improves scalability is to monitor the infrastructure itself, like the power line [6,19] or the plumbing system [5] to detect the current total usage of the infrastructure and hence infer the status of appliances. But getting precise resource measurements is challenging because the infrastructure is not designed for such purposes.

The third challenge is to be non-obtrusive due to aesthetic, privacy, and security concerns. Nonintrusive load monitoring techniques [19] can classify appliances in terms of signature types by just monitoring the main power line. Real power consumption, imaginary power consumption, and power state transition models can help with this classification, since most appliances are purely resistive, e. g., heating elements and incandescent lights, and/or have a reactive component, e. g., motors. However, as number of different appliances increases, ambiguity emerges. In addition, electrical energy consumption significantly vary depending on vendors and/or energy efficiency level.

To maximize monitoring accuracy, SPOTLIGHT aims to aggregate both types of information to hit the balance among these conflicting criteria. Since most households already have measurement units, e.g., main power/gas/ water meters, SPOTLIGHT can profile energy consumption of each appliance based on the status of an appliance and the total resource consumption. For example, a light sensor can detect the on/off status of a light and a switch sensor may detect the on/off status of a microwave oven, fridge, etc. This appliance status along with the main power consumption helps identify average power consumption of each appliance. It is promising that many types of appliances are purely resistive and/or reactive and power consumption can be written in average real and imaginary power [19]. While maximizing the accuracy of energy monitoring, it also aims at minimizing the number of obtrusive sensors.

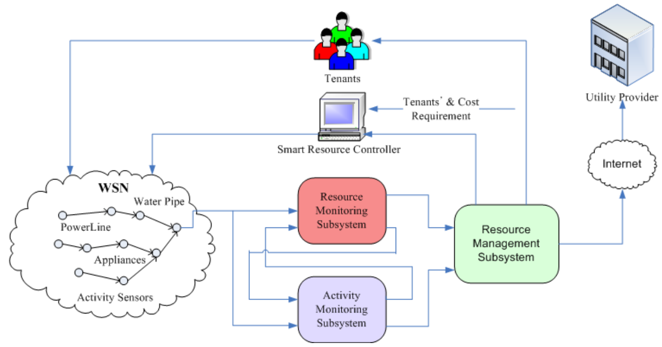

Figure 1. SPOTLIGHT System Architecture

Thus, research questions regarding the resource monitoring subsystem are:

- optimality in terms of number of sensors and monitoring accuracy
- development of machine-supervised machine learning algorithm as direct sensors can act as supervisors of the resource monitoring subsystem by providing accurate appliance state information
- parameter estimation and inference techniques of appliance resource consumption model as it has to infer resource consumption based on a priori knowledge and/or history of resource consumption in case of insufficient information

2.2 Activity Monitoring Subsystem

The Activity Monitoring Subsystem identifies *who* and *what activities* happens in area of interest. Many researchers have focused on activity recognition. Two approaches in terms of sensing technology have been explored. In [12] Wilson et al. explored ways of identifying activities based on simple switch type sensors. On the other spectrum, [14,17] use high-end sensors, such as microphones, strain sensors, CCD cameras, etc, for activity recognition. Both approaches are similar in that they are distributed over the area of interest and sense the event they want to detect directly. As their detection rate becomes accurate, it becomes possible to correlate different types of activity recognition algorithms to balance pros and cons. While their results are very promising, the issue regarding mass deployment still persists due to the complexity and cost reasons.

A different approach monitors existing infrastructure to identify activities. [5,6] monitors power lines and pluming systems respectively to infer activities based on the fact that activities result in the usage of the infrastructure. This has the advantage that it requires less sensors, thus less deployment and maintenance cost. Therefore, it could be a viable solution for mass deployment in everyday life.

However, due to its machine learning nature, complex training mechanisms need to be employed in order to calibrate the system.

While activity recognition is still a hard problem[5,6,12,15,17], SPOTLIGHT aims to fuse the information from both the activity and resource monitoring subsystems to improve accuracy because they are inherently intertwined. Activities result in resource consumption and resource consumption implies some activities. SPOTLIGHT uses the output of both systems to improve data quality and precision. For example, if the activity monitoring algorithm has multiple solutions for a set of activity measurements, it could say that one person is either watching a TV or reading a book. Current status of the TV can help disambiguate this. E. g., if TV is on he is likely to watch TV. Conversely, when the resource monitoring system has two solutions, e.g., either the TV or the table lamp is consuming 20W. If the activity monitoring subsystem knows that the tenant is watching TV, this helps disambiguate these problems as well.

2.3 Resource Management Subsystem

The goal of the Resource Management Subsystem is to provide useful information to the user, by fusing the data provided by the resource monitoring subsystem and activity monitoring subsystem. A persuasive resource usage report is required to motivate users to improve their efficiency, and thus to lower their resource cost. Additionally, a Smart Resource Controller (SRC) could use new appliance control technology such as X10 and Insteon [21] to improve resource savings even further. For example, based on the current occupancy of a room, the SRC turns off unnecessary appliances, thus resulting in considerable energy saving[4]. Furthermore, it can account for user's requirements of comfort level and cost[20], while supporting activities in a specific area. In addition, utility providers may use this information in their planning and load balancing of their power plants or water systems.

3. Prototype Implementation

As a feasibility study, we chose to implement SPOTLIGHT to monitor and profile the power consumption of a small household. We set up an application where the system can determine activities and electrical energy consumption easily. For instance, participating appliances only include lighting, coffee machine and TV from which users only can benefit within a certain physical proximity. The system regards the physical proximity and the appliance status as an activity indicator. This is intuitive since physical proximity to an appliance usually means that a user is interacting with said appliance[13,15]. According to this activity indicator of a user, the system can account the consumed energy of that appliance to the user using it.

The prototype design of SPOTLIGHT is centered around instrumentation of participating appliances. Each appliance is powered through a commercially available power meter [4] that measures the energy consumption for the appliance. This power meter provides a serial interface for external logging with a documented serial protocol. The serial interface connects to a MicaZ 'appliance' mote that forms the sensing and communication hub for the appliance. The sampling rate of the power meter is set at 1 Hz. Upon receiving power measurements from its UART, the appliance mote forwards the messages to the SPOTLIGHT server.

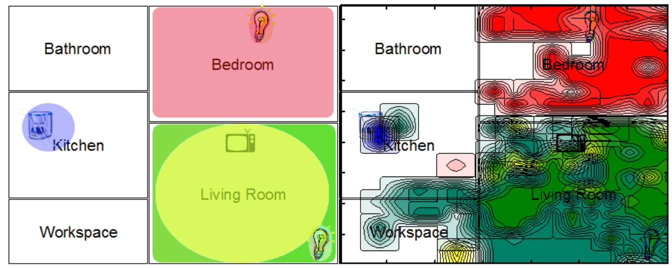

Figure 2. User defined and measured activity region

The MicaZ mote is equipped with a 2.4 GHz IEEE 802.15.4 compatible radio that is used for sensing the proximity of participating users to an appliance and for communicating with the SPOTLIGHT server. Users carry MicaZ 'tag' motes that send out periodic beacon messages advertising their presence and IDs. The appliance motes listen to present beacons and forward the radio signal strength (RSSI) for any message it receives to the SPOTLIGHT server. Due to the range problem, we chose the RSSI based method instead of the passive RFID technique.

The SPOTLIGHT server receives beacon strength and power measurements from the various appliance motes and processes them together to identify user proximity and eventually individual electrical energy consumption. The SPOTLIGHT server is connected to the appliance motes through a 'base station' MicaZ mote attached to its serial port. The SPOTLIGHT server uses SensorBase [16], an easy to use database application, to store and process the measurements from the appliance motes. The advantage of SensorBase is a consistent interface to access the data from different applications, i.e., the information collected by SPOTLIGHT can easily be accessed from within other research projects and provide various security levels.

4. Evaluation

This section describes our experimental results in three aspects: evaluation of RSSI as a proximity and activity indicator, performance of energy profiling, and analysis of user's energy consumption patterns.

4.1 Deployment Setting

As shown in Figure 2, we connected four power measurement units and MicaZ appliance motes to the living room lamp, TV, coffee machine and bedroom lamp in a 1 bedroom and 1 bathroom apartment. Two users carry tag motes. The motes on the appliances are used for snooping and collecting power measurements of the appliances and RSSI information [10,11]. A laptop functions as the SPOTLIGHT server. For the post-deployment data analysis, we stored RSSI, power measurement, and time stamp on SensorBase. During the deployment, the users were expected to use the appliances as they usually would do.

4.2 Evaluation of RSSI based Activity Region

To confirm RSSI based activity regions, we measured the number of issued tokens, an indication of current activity. E.g. if a user has a token for the TV, he/she is watching the TV. First, the users define a rough activity region for the participating appliances. Then users traverse along the boundaries with their tag motes and the system averages RSSI for the initial calibration. After setting up the activity region, we made 30x30cm grids throughout the house. Then we tried to issue 5 tokens at each point based on the RSSI values, and counted the number of issued tokens. Based on these numbers, we plot the contour maps of the space. In Figure 2 the four shaded regions give the activity region of the TV, the bedroom lamp, the living room lamp and the coffee machine, respectively. Due to the imperfection of RSSI values, we see some outliers, and see some non-uniform contours in the figure. Although the RSSI based activity region is roughly static and definable, RSSI values are very noisy, especially near the boundaries of the activity region. To overcome such cases, we added hysteresis features into the processing of the proximity measurement.

4.3 Comparison with Ground Truth

To compare our experimental data with the ground truth, the household of the deployment was also instrumented with two cameras monitoring the activity region of the television, living room lamp and bedroom lamp. The cameras took a picture every 10 seconds and gave information about who was present in the activity region of the appliances. The pictures were tagged by a user in the household to retrieve the ground truth for the occupancy data. The ground truth for both users for the television is given in Figure 3 (i) and (j). A '1' indicates that the user was present in the activity region of the television and a '0' indicates that the user was not present. Figure 3 (a) and (b) give the RSSI values of the two users as reported by the reader mote on the television. Figure (c) through (h) give the issue and expiry of tokens based on the RSSI values using the simple, calibrated and hysteresis threshold techniques.

The simple threshold and calibrated techniques suffer significantly from slight variations in the RSSI values of the tag motes. The calibrated threshold performs better as it has been calibrated for each individual tag mote. The hysteresis is most resilient to the variations in RSSI values as it can also cope with slight variations in the RSSI values of the tags. Since the hysteresis technique has been identified as the superior technique, and the technique that comes closest to the ground truth, all sequential data will be characterized using this technique.

4.4 Energy Consumption Report

We outline some results and observations made by analyzing the found data from our deployment. Figure 4 details the power consumption of the users for the different instrumented appliances and the total energy consumption in subfigure (f). Only user201 used the coffee maker so no data was collected for user200. The graph in subfigure (e) shows the sum of the power consumption of all the graphs (a) through (d) and subfigure (f) is the integral of subfigure (e).

Using this data, and the activity from each user we can now identify useful and wasteful energy consumption. Figure 5 highlights the amount of useful and wasted energy consumed by the TV. The energy consumed is useful if one of the users was within the proximity and hence benefiting from the consumption. The energy is wasted if no user was present in the proximity. As per our energy accounting policy, we count this wasted energy against the person who was the last one to exit the service range of the appliance. Figure 5 (a) and (b) show the vicinity values for the two users as collected by the appliance mote on the television. Using the hysteresis technique, Figure 5 (c) and (d) show the token issuance and expiry for the two users.

5. Discussion

Our simple prototype showed us that it is possible to identify certain user activity with very simple measurement methods. These measurements can then be used to attribute energy consumption to specific user. Additionally, the system showed us that users can identify where they use most of the energy, and where they waste a lot of energy.

Nevertheless, our prototype is far from complete. First of all, it only measures energy for specific applications and doesn't make any use of the total energy measurement of the household. In addition, a low cost measurement tech-

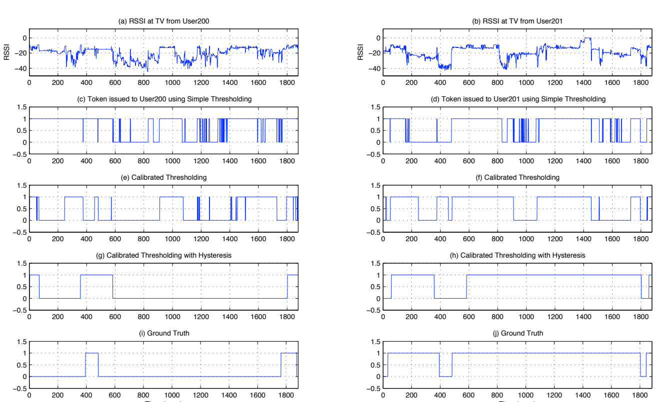

Figure 3. Performance of various RSSI->Proximity->Token Mechanism

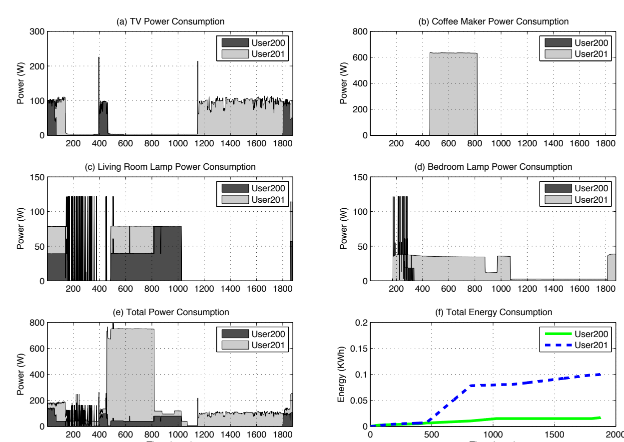

Figure 4. Appliance power and energy consumption per user

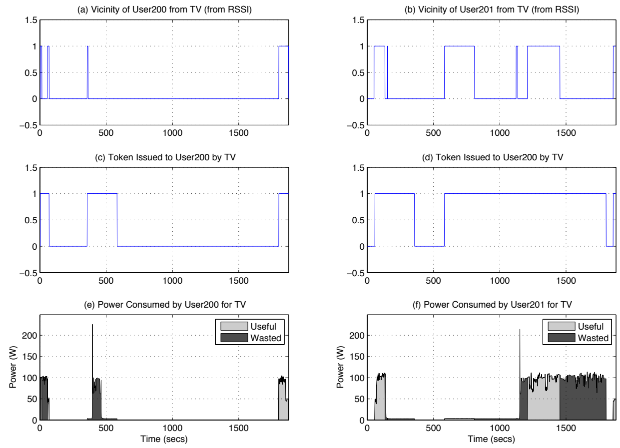

Figure 5. Useful/Wasted Power and Energy for TV

nique is essential. We are currently working on integrating this feature into the resource monitoring subsystem. A small CCD camera is connected to the main power meter and reads out its value. Additionally, we are investigating non-intrusive, economical ways of measuring the water consumption of a household. One simple way is by using an accelerometer connected to the water pipe. The vibration of the pipe is a very good indicator of how much water flows through the pipe. Figure 6 shows a simple test we conducted on one water faucet. We can clearly see the correlation of vibrating variance and water flow rate. We hope that in the next version of SPOTLIGHT, we can not only measure energy consumption, but also the consumption of water which gets more and more important in the future.

One last improvement of the SPOTLIGHT prototype is the user interface, presentation of the data, and fairness of the resource accounting policy among users. Currently, the prototype still needs a lot of analysis by hand, uses a very simple accounting policy, and lacks a realtime response. We believe, however, that by gaining more confidence in our sensing subsystem and obtaining a general resource consumption accounting model, such an interface and a comprehensive policy will be possible in the next version.

6. Conclusion

Providing a personalized report on resource consumption at an appropriate spatiotemporal resolution to each individual in a household can be a particularly powerful means for inducing resource-conserving personal behavioral changes, besides facilitating more targeted incentives by the utilities. We showed in this paper that such a system needs to fuse several different networked embedded sensing systems, and machine learning techniques and algorithms in order to provide an accurate resource consumption estimation. Our SPOTLIGHT prototype is a step to such a system, where we can evaluate different approaches and sensing systems.

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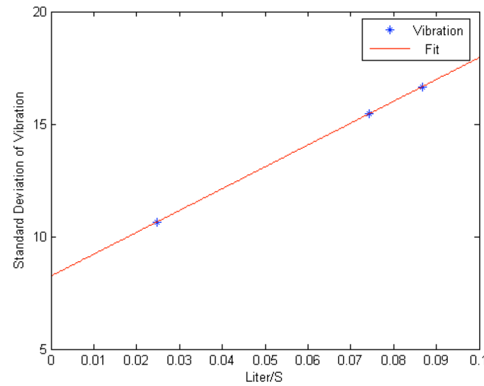

Figure 6. Water Flow Rate and Water Pipe Vibration

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