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## Energy monitoring in residential spaces with audio sensor nodes: TinyEARS $\frac{4}{3}$



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#### article info

Article history: Received 5 January 2012 Received in revised form 30 July 2012 Accepted 8 October 2012 Available online 26 October 2012

Keywords: Energy monitoring House appliances Audio data classification Wireless audio sensor networks

#### **ABSTRACT**

Awareness on how and where energy is consumed is being increasingly recognized as the key to prevent waste in next-generation smart buildings. However, while several solutions exist to monitor energy consumption patterns for commercial and industrial users, energy reporting systems currently available to residential users require time-consuming and intrusive installation procedures, or are otherwise unable to provide device-level reports on energy consumption. To fill this gap, this paper discusses the design and performance evaluation of the Tiny Energy Accounting and Reporting System (TinyEARS), an energy monitoring system that generates device-level power consumption reports primarily based on the acoustic signatures of household appliances detected by wireless sensors. Experiments demonstrate that TinyEARS is able to report the power consumption of individual household appliances within a 10% error margin.

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### 1. Introduction

Residential spaces account for approximately 21% of the total energy consumption in the United States [\[2\],](#page--1-0) with raising figures worldwide. This motivates the growing interest in smart building technology to automate and otherwise promote energy conservation in residential and commercial spaces. Several techniques, including insulation and energy harvesting from solar panels, or integration with pervasive sensing and actuation technologies, are being proposed and discussed to reduce the carbon footprint of buildings by preventing energy waste.

However, while businesses rely increasingly on procedures and best practices to save energy and reduce costs, energy usage patterns. The main resources in a typical household are electricity, water, natural gas, and heating oil. Saving a small portion of each in each residential space could have a significant impact on reducing costs, energy consumption, and impact on the environment. Several studies have shown the necessity of fine-grained energy monitoring to encourage conservation. In [\[3\],](#page--1-0) Darby explored the effectiveness of different forms of feedback on energy consumption, such as self-meter-reading, interactive feedback via a PC, frequent bills based on readings plus historical feedback, among others, and emphasized the necessity and the benefits of direct feedback mechanisms. He concluded that immediate direct feedback can be extremely valuable in influencing behavior with savings in the range of 5–15%.

most home users do not have any means to control their

Stern [\[4\]](#page--1-0) states that awareness not only encourages people to actively participate in doing the right thing in preventing waste of energy, but also provides indirect monetary benefits because of the reduced cost of resources. Therefore, a great promise lies in monitoring systems designed to reduce energy wastage in residential





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A preliminary version of this paper was accepted for publication in Proc. of ACM Workshop on Embedded Sensing Systems for Energy Efficiency in Buildings (BuildSys), Zurich, Switzerland, November 2010 [\[1\]](#page--1-0).

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spaces by reporting device-level energy usage information to the home user, with potential reductions in costs and emissions of harmful gases like  $CO<sub>2</sub>$ .

Motivated by this, in this paper we discuss the design and implementation of a wireless monitoring system for residential spaces based on a multi-layer decision architecture and called Tiny Energy Accounting and Reporting System (TinyEARS). TinyEARS is based on wireless audio sensor nodes and a real-time power meter deployed to monitor device-level energy consumption in the household. The objective of TinyEARS is to detect and classify ''on'' devices based on their acoustic signatures and report device-level energy consumption by correlating node decisions with time and power information obtained from a real-time power meter. Although the multi-layer decision architecture of TinyEARS is currently implemented by using audio sensors only, clearly the coordinated use of multiple types of sensors, such as light and magnetic, would increase the system performance. There are also silent devices, such as modem, laptop, and mobile phones, which cannot be detected by their acoustic signatures. The energy consumption of these devices can be measured by using an additional node equipped with magnetic sensors [\[5\].](#page--1-0)

However, the main focus of this work is to show how acoustic signatures of house appliances can be used to enable device-level monitoring of energy consumption in residential spaces, with (surprisingly) excellent performance. The key component of TinyEARS is what we refer to as the house appliance sound recognition system (HASRS), which we implemented on Imote2 [\[6\]](#page--1-0) sensors to obtain node-level decisions in real-time. The HASRS employs the mel-frequency cepstral coefficients (MFCC) as a feature extraction algorithm and minimum distance classifier (MDC) as a classification algorithm.

The paper discusses the architecture, communication subsystem, signal acquisition and processing, and algorithmic details of TinyEARS. The key contributions of our work are as follows:

- We propose a multi-layer architecture that enables energy monitoring at the device level by leveraging the acoustic signatures of house appliances. This information is correlated with the overall power usage information of the house obtained from a real-time power meter.
- While most existing solutions for device-level monitoring require one sensor node per appliance, in TinyEARS a single sensor node monitors house appliance in a room based on their acoustic signatures. Deploying one sensor node per room reduces both the overall cost and communication burden of the wireless sensor network.
- TinyEARS, being based on a limited number of sensor nodes, is an easily deployable and maintainable system.
- We show that house appliances can be recognized with an overall success rate of 94% by their acoustic signatures with relatively simple processing algorithms implemented on the motes.
- Finally, we discuss the main system design challenges and their solutions in implementing an audio classification process on an Imote2 sensor node.

The rest of this paper is organized as follows: In Section 2, we review existing solutions for energy monitoring in residential spaces. In Section 3, we introduce the system architecture of TinyEARS. Section 4 describes the details of the house appliance sound recognition system. In Section 5, we describe the data acquisition and correlation process of TinyEARS. In the same section, we also discuss the issues and challenges of implementing the HASRS on Imote2. Section 6 describes our experimental environment and presents the test results obtained using Imote2 and the TED5000 power meter.

#### 2. Related work

Previous work on monitoring energy consumption in residential spaces, shown in [Table 1](#page--1-0) can be broadly classified into two categories. The first group is concerned with systems designed to measure the overall energy consumption with a single sensor, usually located in a power box. The second approach is to monitor each household appliance individually, with fine-grained consumption feedback.

There exists several commercially available products to measure the overall energy consumption of a household, including Power Cost Monitor [\[7\],](#page--1-0) Wattson [\[8\],](#page--1-0) Onzo [\[9\],](#page--1-0) EM-2500 [\[10\]](#page--1-0) and TED-xxx [\[11\].](#page--1-0) These products generally consist of two units, a central unit connected to a fuse box and a display unit. Even though it is moderately difficult to install these devices, they do not require any maintenance once deployed. They have simple user interfaces reporting power usage in scales of seconds or minutes. However, while these products are able to present the overall energy consumption and detect anomalies in energy usage, they cannot provide per-appliance energy measurement. The Google Power Meter [\[12\]](#page--1-0) is another option to visualize power meter readings. It is an opt-in software tool that allows users to visualize detailed home energy information. A secure Google gadget displays data on home energy consumption received from either a smart meter or another electricity monitoring device.

The Non-Intrusive Load Monitoring (NILM) [\[13\]](#page--1-0), uses a single whole-house energy meter and attempts to identify and disaggregate the energy usage of individual devices by identifying changes in steady-state levels where the power is constant. The success rate of the NILM system varies between 75% and 90% in detecting the on/off status of working household appliances [\[14\]](#page--1-0). The key limitations of NILM are that loads are indistinguishable, and data is batch-processed [\[13\]](#page--1-0). To simplify the training process of NILM systems, in [\[15\],](#page--1-0) the authors present an inexpensive contactless electromagnetic field event-detector that can detect appliance state changes within close proximity, based on magnetic and electric field fluctuations.

Device-level monitoring has recently received attention in the literature because of its fine-grained feedback on energy consumption. To monitor each device individually, two approaches have been considered in the literature, i.e., (i) installing electrical current sensors inline with each appliance, and (ii) deploying multiple sensors throughout the household. Some commercial products, based on

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