SolarWalk: Smart Home Occupant Identification using Unobtrusive Indoor Photovoltaic Harvesters

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ABSTRACT

The key to optimal occupant comfort as well as resource utilization in a smart building is to provide personalized control over smart appliances. Additionally, with an exponentially growing Internet-of-Things (IoT), reducing the need of frequent user attention and effort involving building management to control and manage an enormous number of smart devices becomes inevitable. One crucial step to enable occupant-specific personalized spaces in smart buildings is accurate identification of different occupants. In this paper, we introduce *SolarWalk* to show that small and unobtrusive indoor photovoltaic harvesters can identify occupants in smart home scenarios. The key observations are that i) photovoltaics are commonly used as a power source for many indoor energy-harvesting devices, ii) a PV cell's output voltage is perturbed differently when different persons pass in close range, creating an unique signature voltage trace, and iii) the voltage pattern can also determine the person' walking direction. *SolarWalk* identifies occupants in a smart home by training a classifier with their shadow voltage traces. *SolarWalk* achieves an average accuracy of 88% to identify five occupants in a home and on average 77% accurate to determine whether someone entered or exited the room. *SolarWalk* enables an accurate occupant identification system that is non-invasive, ubiquitous, and does not require dedicated hardware and rigorous installation.

CCS CONCEPTS

• **Human-centered computing** → **Ubiquitous and mobile computing systems and tools**.

KEYWORDS

Photovoltaic Harvesters, Occupant Identification

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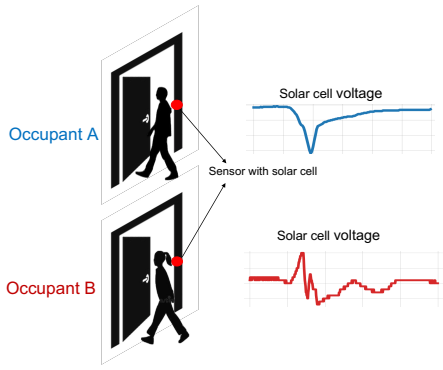

Figure 1: The photovoltaic harvester's output voltage attached to an indoor light energy-harvesting sensor fluctuates differently as different occupants of a home passes by. *SolarWalk* leverages this voltage fluctuations as an unique attribute to differentiate occupants.

1 INTRODUCTION

Accurate occupant identification can upgrade today's buildings from *smart* spaces to *intuitive* spaces. The knowledge of *who* is present over *someone* is present instruments indoor spaces with personalized control in applications such as HVAC, ambient lighting and many more. Such instrumentation of spaces has proven to significantly increase occupant comfort, reduce human intervention in building management, and decrease overall building energy consumption [1, 32, 40].

However, occupant identification is yet an unsolved problem due to several practical challenges. Device-based solutions that use wearable or carried devices require users to wear or carry the device most of the time [5, 22, 33]. Such approaches are intrusive and often less feasible in real-life scenario. Some solutions adopt device-free approach using camera/vision-based, audio-based techniques [2, 17, 29] to relieve the user off previous requirements, but people are likely to be reluctant to install these privacy-invasive devices. To eliminate privacy concerns, previous works explored special infrastructure/hardware-based solutions using ultrasonic, infrared, and vibration [20, 25, 37]. However, such systems often

demonstrates a novel and accurate non-invasive, infrastructure-free occupant identification system, but also introduces the concept of empowering the power sources of battery-less energy-harvesting applications with meaningful contextual data. We believe innovation flourishes more rapidly when systems build on existing resources, which would otherwise just be wasted. We envisage this work would enable more interesting applications in the field of smart building research.

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