

SolarWalk Dataset: Occupant Identification using Indoor Photovoltaic Harvester Output Voltage

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ABSTRACT

Occupant identification is paramount for many building applications. Regardless, several practical concerns limit existing solutions to be ubiquitously deployed. Current systems are either intrusive, privacy-invasive, or require obtrusive, maintenance-heavy, and special-purpose infrastructure. As an alternative, the shadow pattern of a person reflected in the output voltage of a photovoltaic harvester power supply in many energy-harvesting devices can be used as a unique person identifying feature. In this paper, we present the first dataset containing the time-series open circuit output voltage traces of indoor photovoltaic cell corresponding to occupant door crossing events to perform occupant identification in smart homes. We collect shadow patterns of five participants from two different doors in two rooms of a building. The dataset consists of a total of 900 door entry and exit events during different hours of the day. We sample the voltage at 50 hz and provide the raw timestamped data. We also pre-process the data to filter the event of interest and label the data with associated occupant id and type of door events. Moreover, we provide insights into future research directions using the dataset. The dataset is available at <https://doi.org/10.5281/zenodo.7195748>

CCS CONCEPTS

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

KEYWORDS

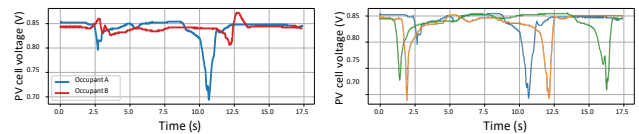
Photovoltaic Harvesters, Occupant Identification

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(a) Voltage fluctuations of occupant A and B are different from each other.

(b) Voltage fluctuations of the same occupant have similar shape.

Figure 1: This figure shows how the output voltage of the solar cell mounted on a doorframe ripples as different occupants pass through the door. First voltage drop corresponds to entering through the door, followed by exiting. The maximum voltage drop and the duration of voltage fluctuations vary differently for occupant A and B. On the other hand, these characteristics remain consistent over multiple trials by the same person.

1 INTRODUCTION

Occupant identification in indoor spaces is a key enabler for many person-specific, human-centered applications including HVAC control, precise water temperature control, occupant-specific energy-metering, and providing time-sensitive critical reminders immediately upon someone entering or leaving home [2, 6]. Such occupant-driven appliance control not only tremendously improves user comfort and convenience, but also plays an instrumental role in resource utilization, reducing energy waste, and better building management [9, 10, 13]. Several solutions exist to accurately identify occupants involving different sensing modalities such as camera/vision audio/acoustic, vibration, infrared, ultrasonic, and RF signals [3, 7, 8, 12, 14]. While all of these approaches have their strengths and drawbacks, we recognize that several limiting challenges still need to be addressed to design an occupant identification system that is non-intrusive, ubiquitous, unobtrusive, and installation-friendly.

To achieve this goal, we designed *SolarWalk*, a novel occupant identification system that adopts a small photovoltaic (PV) harvester's output voltage as a sensing modality to identify persons in a smart home context. Since photovoltaic harvesters is used as a power source to many indoor light energy-harvesting devices, *SolarWalk* is non-intrusive, does not require additional sensing hardware, achieves very small form factor to be ubiquitously deployed, and can be peeled-and-sticked in most indoor spaces. The

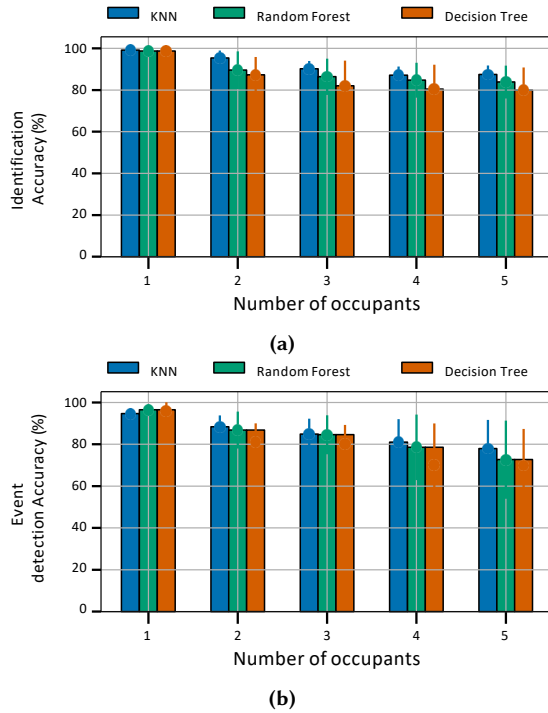


Figure 6: We evaluate *SolarWalk* dataset to identify five occupants from their shadow voltage pattern. With five occupants *SolarWalk*'s KNN classifier achieves 88% accuracy. We also determine whether the participant was entering or exiting the room. Results shows with five occupants the system is 77% accurate to determine the type of events.

with a KNN-based classifier we can identify five participants on average 88% of the time representing a 5-person home and on average 77% of the time, we can determine whether the participants were entering or exiting the room. We compare the performance of two other supervised learning method: decision tree and random forest. To understand how the accuracy is affected with the number of occupants, we evaluate both accuracy with increasing number of occupants. We find that the percentage of accuracy drops from 99% for one occupant to 88% for five occupants.

3.2 Future Directions

Our study shows that shadow pattern on a PV cell can be a unique attribute of a person to distinguish them from other individuals in a small smart home population. One future direction is to investigate how accurately we can determine whether a person is walking or rushing or running by their reflection on the PV cell voltage. Such activity monitoring can provide useful analytics without requiring the user to wear any devices. Moreover, we could estimate the walking speed of a person from the time series properties of their shadow pattern. Previous study shows that a person's gait and walking speed can be an indicator of their mental state and linked to anxiety, depression, and dementia [4, 15]. Therefore such information could benefit many individuals.

4 CONCLUSION

Future sensors will vastly benefit from the contextual ques of their installation location. Simultaneously, the ubiquitous nature of computing demands computers to be simple, unobtrusive, and pervasively-deployable. Taking a step towards this vision, in this paper, we introduce *SolarWalk* dataset that enables occupant identification using small photovoltaic voltage traces. We believe the dataset will help the community to explore further into this research directions and lead to potential applications beyond occupant identification.

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