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A framework for allocating personalized appliance-level disaggregated electricity consumption to daily activities

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ABSTRACT

Residential and commercial buildings account for more than 74% of total annual electricity consumption in the United States. Studies have shown that occupants' awareness of their behaviors in consuming electricity encourages them to change their unsustainable behaviors and improves the sustainable ones. As behaviors impact the ways that daily activities are performed, in order to develop a personalized appliance level model of an occupant's behavior, precise activity recognition is required. In this paper, we introduce a novel framework to allocate personalized appliance-level disaggregated electricity consumption to daily activities. In our framework, using ontology-based approach, the input appliance usage data is first separated into categories of non-overlapping activity events. The separated data sets are then segmented to detect activity segments, which are next mapped into activity classes using a trained classification model. To evaluate the performance of our presented framework, an experimental validation was carried out in three test bed apartment units. Results of validation showed a total *F*-measure value of 0.97 for segmentation and an average accuracy of 93.41% for activity recognition. Following the activity recognition, the approximate electricity consumption associated with the recognized activities was estimated and the results of each test bed unit were compared with the others.

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1. Introduction

United States is the second largest electricity consumer in the world [1]. In 2014, residential and commercial buildings consumed more than 74% of the total electricity in the United States. Of this amount, about 60% was used for electric appliances/devices including lighting fixtures, kitchen appliances, computers, electronics and other household appliances/devices. An increasing amount of work supports the idea that awareness of personalized and detailed electricity consumption could assist occupants to reduce their consumption [2]. Along this line, various techniques have been successfully used to measure electricity consumption down to the device/appliance level [3–5]. With the aid of disaggregated electricity consumption data, occupants are able to distinguish inefficient appliances with anomalous electricity consumption and discover possible savings by substituting them with more efficient ones. However, the way these appliances are used by occupants also affects the total electricity consumption in buildings [6]. For example, Fechner showed that chefs, using the same equipment for cooking the same meal, had electricity consumptions with up to 50% difference [7]. In another study, careless behavior has shown to increase a building's electricity consumption by one-third, while conservation behavior can save a third [8]. As behaviors impact the ways that occupants perform their daily activities, in order to achieve insight about occupant's behavior, exploration of activities is required.

Daily activities are combinations of different actions performed by an occupant in order to satisfy a specific need. These actions and their durations are case sensitive. Even for a specific case, they could be inconsistent under different circumstances. For example, the activity of preparing breakfast can be formed by a variety of actions in different ways. Fig. 1 shows two possible behaviors in performing this activity.

Here, the slight difference in the associated actions by which the activities are formed causes more electricity consumption in

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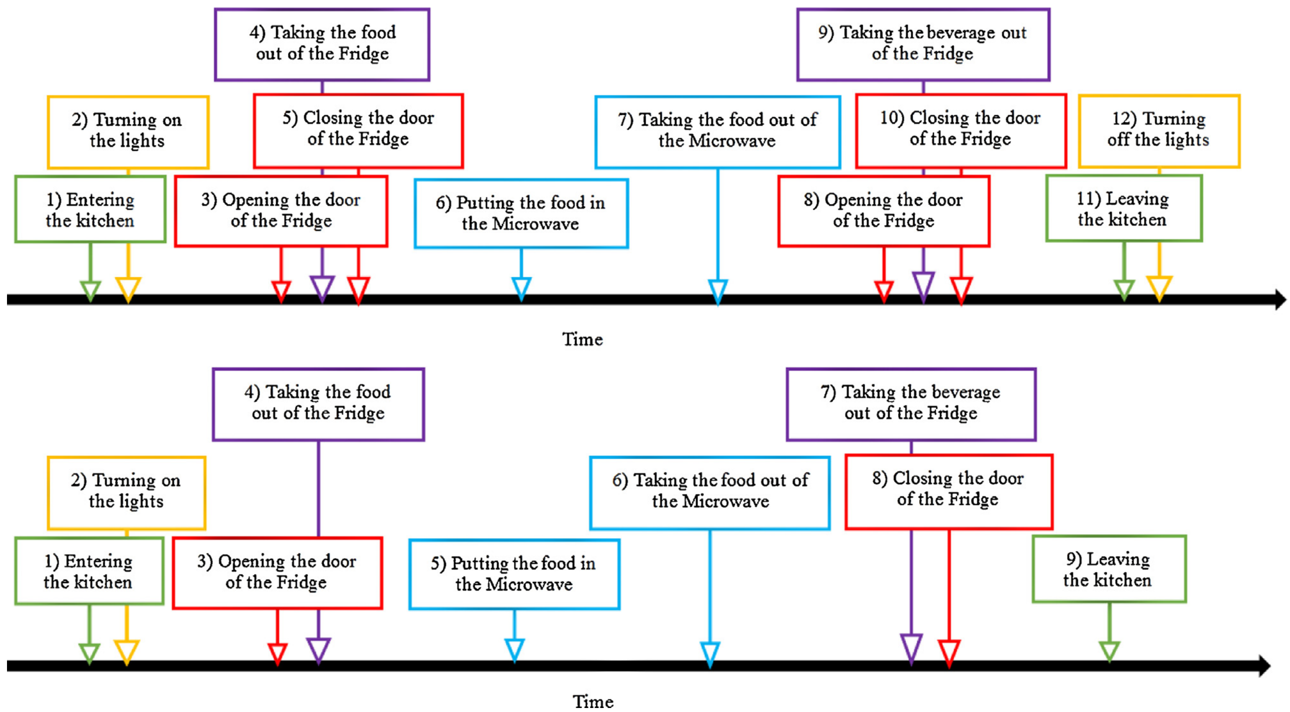

Fig. 1. Two sample behaviors in performing the activity of preparing breakfast. Reversed activities are shown by the same color (e.g., turning on lights and turning off lights).

the second behavior, as the fridge door is left open when the microwave is used and the lights are also left on after leaving the kitchen. As illustrated in this example, by recognizing and exploring activities, it is possible to develop an actual and personalized appliance level model of an occupant's behavior, based on which it is possible to detect potential energy savings and give feedback to occupants. Along this line, in this paper, we introduce a context-aware data-driven activity recognition framework using appliance-level disaggregated electricity usage. In contrast to the commonly used activity recognition approaches that require installation of multiple sensors in a building or require carrying wearable sensors by occupants, our approach relies solely on the data provided by a Non-intrusive Load Monitoring (NILM) system [9], using a single sensing point. The main contributions of this paper can be summarized as follows: (1) investigation of the application of the NILM technique in activity recognition by introducing a framework that recognizes occupant's daily activities using a single sensing point in the context of building energy efficiency; (2) introduction of a context-aware data-separation approach to determine the possible overlapping activities via ontological reasoning; (3) introduction of an unsupervized approach to detect the length of activities; and (4) real-world implementation of the framework in three residential units. Following the summary of related studies presented in Section 2, the details of our proposed framework are provided in Section 3. The implementation of our framework in real-world test beds along with validation and discussion parts are presented in Section 4. Finally, limitations of the framework and future work are presented in Section 5 and Section 6 concludes the paper.

2. Related prior work

Researchers have been exploring activity recognition for a variety of applications over the past decade. One of the domains, in which activity recognition has been effectively explored, is the healthcare domain [10]. Supporting the idea of independent living, various studies have investigated activity detection approaches to monitor daily activities of elderly people in order to detect abnormal behaviors resulting from illnesses or emerging medical conditions and also to observe the progress of age-related diseases, such as Alzheimer [11–13]. In addition to daily activities, detection of physical movements has also been investigated for healthcare purposes, specifically to detect emergency situations via fall detection [14].

Another application domain of activity recognition is the energy management domain. Unlike the majority of the studies in the healthcare domain, where specific groups of people are investigated, i.e., patients and elderly people with limited level of activity due to their health conditions, there are usually higher variations and complexities associated with regular occupants' activities, which are to be detected for energy management purposes. Focusing on the energy management domain, there are studies that explored the influence of occupant's behavior on building's electricity consumption for smart grid [15–19]. In these studies, in order to create high-resolution energy demand models, historical time use and ownership data sets have been analyzed to create probabilistic models of activities and their associated electricity consumptions. Since these types of studies are based on large historical data sets, they do not reflect precise personalized consumption patterns. In another group of studies, activity recognition has been used for appliance standby mode or lighting system control [20–22]. Finally, there are a few studies that focus on possible applications of activity recognition for creating energy consumption awareness. For example, relying on smart meters, Chen et al. proposed an approach to map the electricity consumption to detected activities in smart homes [23]. Since in this study activities are first detected by a separate sensor network and then correlated to aggregated electricity readings from a smart meter, the approach lacked the disaggregated information of appliance usage for each activity. As compared to the healthcare domain, fewer studies exist in the energy management domain. Therefore, further investigation of activity recognition in the energy management domain, specifically for energy consumption awareness, is needed.

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