Predicting Room-Level Occupancy Using Smart-Meter Data

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ABSTRACT

Occupancy information in buildings is a crucial information to enable automated load controlling resulting in significant energy savings. Unfortunately, current methods obtain occupancy data by using additional infrastructure, which can be expensive and inefficient. In this paper, we propose a method to predict room-level occupancy by utilizing only smart-meter data. Several classifiers are used to estimate room-level occupancy information. We identify the best feature set consisting of appliances energy data, appliances state, and house-level occupancy data. The features are obtained using only smart meter data along with non-intrusive load monitoring and house-level occupancy prediction. We show that the proposed methods can achieve up to 90% accuracy for room-level occupancy prediction using only smart meter data.

KEYWORDS

Energy Disaggregation, Multilabel Classifier, Non-Intrusive Load Monitoring (NILM), Occupancy Prediction, Principal Component Analysis (PCA), Support Vector Machine (SVM)

INTRODUCTION

Residential and commercial buildings consume almost 60% of world’s electrical energy. Around 54% of electrical energy in these buildings are used for Heating, Ventilation, Air Conditioning (HVAC) and lights (Johansson, 2012). Smart building initiatives aim to reduce energy consumption by optimizing appliance usage, based on occupancy and user preference. Occupancy information is crucial to enable energy optimization, especially room-level occupancy data. PreHeat and TherML, similar to the commercially available Nest thermostat, uses occupancy information to optimize heating system energy consumption (Scott, 2011; Koehler, 2013). Furthermore, it can also be used to enable contextual personalized services such as child monitoring, intrusion detection, and elderly care.

Currently, room level occupancy data can be obtained using additional infrastructure, for example, passive infrared sensor (PIR sensor) (Scott, 2011), camera, radio frequency identification (RFID) tag, or Bluetooth beacon. However, most of the existing households does not have such infrastructure in their house. Adding them will be an expensive and cumbersome to maintain. Indirect occupancy sensing aims to estimate occupancy using existing infrastructure and is easier to adopt in real life.
WiFi-based localization is a possibility, but it requires extensive setup and training to map rooms and WiFi signals (Balaji, 2013). On the other hand, energy-consumption information is also available from smart meters which are already installed in buildings. In this paper, we try to answer the question, using smart-meter data, can we identify occupants’ location in a house accurately? Unlike WiFi-based localization, this approach only requires mapping of appliances and rooms, which remain constant most often.

Several challenges exist to obtain room-level occupancy information using just the smart-meter data. First, smart-meter data needs to be translated into appliance-level energy data. From this appliance-level energy information, we need to distinguish their state i.e., on or off. The translation from smart-meter data to appliance-level energy data must be accurate to obtain correct set of appliances and their states. Another challenge is to distinguish foreground and background appliances. Foreground appliances -- loads that are actively controlled by users’ actions, while background appliances -- loads that typically run without user intervention (Iyengar, 2016). For example, a refrigerator being turned on does not necessarily mean somebody is in the kitchen, or even home. By removing background loads from consideration, room-level occupancy can be predicted more accurately.

In this paper, we propose to use NILM-based energy analytics approach to obtain appliance-level energy data from smart-meter data. Furthermore, we also include house-level occupancy data into the feature set. We perform house-level occupancy prediction, using both a simple threshold mechanism and a classification technique, based on smart-meter data. This house level occupancy prediction data can help to distinguish cases where an appliance consumes power, but no one is actually in the building. We also use association rule to provide a smarter way to group appliances that are commonly used together. This way, we can get a consistent set of appliances that helps to indicate whether the room that contains such appliance set is being used or not. Finally, we use features mentioned above to train a multilabel classifier, which helps us to predict room-level occupancy. Several classification algorithms are evaluated to obtain the most suitable classifier for room-level occupancy prediction. The proposed system requires a one-time mapping of appliances present in the household along with their location.

Finally, the contributions of this article are:

1. A novel approach to perform room-level occupancy prediction from smart meter data. Previous works mostly deal with house-level occupancy prediction. We use ordinary smart meter (maximum frequency up to 1 Hz) to make this work applicable in real-world scenarios;
2. Investigate the effect of sampling rate in order to optimize resources and reduce concerns about privacy;
3. Explore multilabel classifiers and association rules in order to improve room-level occupancy prediction accuracy.

RELATED WORK

Previous work related to room-level occupancy sensing required additional infrastructure, for example, RFID (Li, 2012), PIR, CO2 (Naghiyev, 2014), or camera (Liu, 2013). These works are similar to ours in the sense that they are trying to investigate whether a room in a house is occupied or not. However, these approaches are intrusive since they need additional sensor deployment. Furthermore, people usually do not install these sensors in their houses. Therefore, the adoption rate for these intrusive methods are low.

To increase the adoption rate and scalability of an occupancy monitoring solution, other works tried to exploit readily available infrastructure. One example of this non-intrusive method is by using existing infrastructure like Wi-Fi access points to sense occupancy. Wi-Fi-based occupancy monitoring uses either localization technique (Balaji, 2013; Vasisht, 2016) or exploit the fact that human body absorbs Wi-Fi signal (Naghiyev, 2014). Even though Wi-Fi is readily available in most houses, Wi-Fi-
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