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Learning occupants' workplace interactions from wearable and stationary ambient sensing systems

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HIGHLIGHTS

- A framework to learn occupant interactions from ambient sensing technologies is proposed.
- Several machine learning algorithms are tested and the one that outperforms others is selected.
- The framework selects proper the technologies and averaging windows.
- 221 employees of federal agencies participated in this study.
- Using random forest algorithm an accuracy of 86.72% to predict interactions was obtained.

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ABSTRACT

Having access to real-time information on building occupants' state of interactions enables optimization of building systems for improved energy efficiency, well-being and productivity of the occupants. In this paper, we propose a framework to learn occupant interactions from ambient sensing technologies (e.g., sensing of variables such as sound (dB), CO2 (ppm), light intensity (lux), dry-bulb temperature (°C), relative humidity (RH%), pressure (mbar)) from both stationary and wearable devices and select the technologies and averaging windows which contain the required information for learning. In this framework, several supervised machine learning algorithms are tested on the labeled datasets and the algorithm which outperforms others is selected. Two types of sensing devices were utilized for analyses: wearable devices worn around the neck by the test subjects, and a network of stationary devices located in the test subjects' working indoor spaces. 221 employees of federal agencies housed in facilities managed by the US. General Services Administration in the mid-Atlantic and Southern states participated in this study, answering questions about their current task every hour. Overall accuracies were observed of 86.72% for wearable and stationary devices, 81.25% for only wearable-only, and 85.16% for stationary-only for prediction of the mixed multi-label classification via Random Forests algorithm. The high prediction allows for identifying subjects' tasks when training labels are not available. Predicting occupants' interactions as a main indicator of occupants' behavior have significant implications for the energy efficiency of building systems (up to 20% savings).

1. Introduction

In the built environment, an occupant interacts physically with building elements and socially with other occupants. Both of these interactions have implications for different types of efficiencies (e.g., building energy use and organization workflow). Occupants interact

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physically with the building in adjusting environmental conditions (e.g., lighting level, temperature) according to their preference, and in activating appliances (e.g., plug loads) necessary for a service [1]. Social interactions among occupants also impact building systems performance through variations in space utilization and the energy necessary to keep the indoor environment conditioned. Buildings account for approximately 40% of the total energy consumed in the United States [2]. Previous research has shown that optimizing building systems performance based on occupant behavior and interactions can reduce overall building energy consumption up to 20% [3,4]. In addition, energy required to service unoccupied spaces may account for almost 50% energy used in buildings [5], which could be reduced if occupancy were monitored through real-time occupant workplace interactions. The International Energy Agency has also emphasized the monitoring of the occupants' behavior and specifically interactions as a tool for more efficient building systems [6]. Beyond energy issues, interactions between people in work spaces have been shown to affect productivity within organizations [7]. Variations in patterns of communication may account for up to 40% variation in productivity. Occupants' behavior is shaped by social circuits (formed by the back-and-forth pattern of signaling between people, unconscious reflexes evolved for social coordination) that work to fuse us together into a coordinated whole [8]. Considering the importance of topics like building energy consumption, building space utilization, and productivity research has begun to focus on learning the state of interactions among occupants in buildings. Given a real-time access to the interactions state among occupants, building energy and workplace efficiency can be improved by better allocating resources and optimizing systems performance. Information on interactions among occupants can determine personal spaces which are unoccupied and require less services. A real-time feed of the required services to the building management systems can for example issue on/off system commands to appliances or lighting systems or change temperature setpoints in the HVAC system.

However, most information about interactions among building occupants is currently obtained from occupants' direct feedback (i.e., self-reporting), which is error-prone and may not provide information in a timely manner. In addition, sustaining such participatory involvement for long periods of time is challenging due to survey fatigue. To address these challenges, environmental sensing has been used to indirectly capture human interactions by tracking human social signatures in the indoor environments. Due to advancements in sensing technologies and reductions in sensor costs, indoor and personal sensing arrays have become commercially feasible. Collected environmental signatures can also be used for further understanding the environmental quality and human interactions that occur within the built environment. However, research in the literature thus far has been limited to small case-studies with few subjects and sensing technologies. No large-scale and long-duration studies have been performed monitoring occupants' workplace interactions. In addition, there is a gap in the literature about methods for selecting machine learning techniques and sensing technologies among a group of potential ones in a hierarchical order for predicting occupants' workplace interactions.

In this study, we have proposed and validated a framework for predicting occupants' workplace interactions as defined by an organization (e.g., U.S. General Services Administration (GSA)) based on stationary and wearable sensing arrays. The framework also uses a recursive feature elimination method to select sensing technologies that provide the optimal information gains and prevent overfitting. Major performance measures for the interaction modeling are introduced and the advantages of each one is discussed. Due to the fact that short term measurements of sensors might not correctly capture the dynamics of ambient conditions as they relate to the interactions, we included a component in the framework to generate different sliding window lengths and select the optimal values. In cases where labels are mutually exclusive and could be coupled for a more in depth understanding of interactions in an environment, the framework utilizes a multi-label classification reformulation. The data collection was conducted in facilities managed by GSA in the mid-Atlantic and Southern states. 221 employees of federal agencies participated in this study and were asked about their current task every hour. Ambient sensing technologies (e.g., sensing of variables such as sound (dB), CO_2 (ppm), light intensity (lux), dry-bulb temperature (°C), relative humidity (RH %), pressure (mbar)) were collected from wearable devices worn around the neck by the test subjects, and from a network of stationary devices located in the test subjects' working spaces. After cleaning the dataset, the framework was validated based on the described performance measures.

The structure of the paper is as follows. Section 2 provides a review of recent studies of the occupants' interaction learning and modeling, and the gap that this study addresses. In Section 3, we describe our proposed methodology for modeling the interactions, selecting sensing technologies, and optimizing the performance by using moving averages and labels refinement. In Section 4, the data collection set up and procedures done by GSA which paved the path for our explorations are discussed. We present the results of our methodology in Section 5. In Section 6, we provide the energy savings opportunities from control schedule modifications based on occupants' workplace interactions real-time feed. Section 7 provides a discussion on the generalization of the results and Section 8 describes the limitations and future steps of the study. Finally, Section 9 summarizes the results and concludes the paper.

2. Literature review

Direct occupants' feedback via an online or offline survey or questionnaire is the most common technique for assessing occupants' interactions in indoor environments. This technique is subject to reporting errors by occupants. In addition, lack of such information from occupants ultimately results in inefficiencies in building systems and excessive operation costs due to conservative operation choices made when real-time feedback is not available. Research has shown that filling out surveys over extended periods of time experiences reduction in participation by the occupants. Previous research has shown that temporal patterns in multiple streams of sensor data could help automatic analysis of human behaviors and habits in the ambient environment [9]. Specifically, for monitoring occupants interactions, Choudhury [10] used a wearable device having infrared transceiver, a microphone, and two accelerometers and applied dynamic Bayesian Networks to model interactions for a group of eight researchers for a few days. Various techniques for interpreting resident behavior patterns and determining when multiple residents are interacting based on sensors data such as power consumption meters and contact sensors were used. The effectiveness of their techniques was evaluated using two physical smart environment test beds. The performance accuracy in detecting conversations was 63.5% overall and 87.5% for conversations greater or equal to one minute. To account for the small sensor variability and analysis methods, Pentland [11] describes analyzing wearable sensor data with several statistical learning methods such as principal components analysis and clustering methods in order to make reliable estimates of users' interactions. He presents a detailed description of eigenbehavior modeling for learning and classifying user behavior from proximity and location data, and influence modeling for predicting the behavior of a subject from another subject's data. A binary decision boundary at 0.45 produces an equal-error accuracy of 87% of prediction. Later, Paradiso et al. [12] demonstrated the use of electronic badges as a tool that aids social interactions in the large conference events using large LED display, wireless infrared and radio frequency networking, and a host of sensors to collect data. Without taking into account personal characteristics, history, or other prior knowledge over 80% accuracy of personal interactions was realized. However, all these methods focus on a small group of test subjects and sensors are often preselected for learning based on the expert