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Virtual occupancy sensors for real-time occupancy information in buildings

Yang Zhao*, Wim Zeiler, Gert Boxem, Timi Labeodan

Department of the Built Environment, Eindhoven University of Technology, Eindhoven, The Netherlands

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ABSTRACT

This study aims at developing a generic, feasible and low cost occupancy detection solution to provide reliable real-time occupancy information in buildings. Currently, various low cost or even free occupancy measurements are common in offices along with the popularization of information technologies. An information fusion method is proposed to integrate multiple occupancy measurements for reliable real-time occupancy information using the Bayesian belief network (BBN) algorithm. Based on this method, two types of virtual occupancy sensor are developed at room-level and working zone-level respectively. The room level virtual occupancy sensors are composed of physical occupancy sensors, chair sensor, keyboard and mouse amongst others. The working zone-level virtual occupancy sensors are developed based on real-time GPS location and Wi-Fi connection from smart device like smart phones and occupancy access information from building management systems. The developments of these two types of virtual occupancy sensors can be conducted automatically with functions of self-learning, self-performance assessment and fault detection. The performances of the developed virtual sensors are evaluated in two private office rooms. Results show that the developed virtual occupancy sensor are reliable and effective in providing real-time occupancy information. The paper also discusses application of the virtual occupancy sensors for demand driven HVAC operations.

1. Introduction

Demand driven operations of comfort systems like heating, ventilation and air conditioning (HVAC) systems in buildings can avoid significant amount of energy wastes compared with conventional operations. The term demand mainly refers to real-time occupancy requirements of indoor air quality and thermal comfort. Energy wastes occur when the supplies of HVAC systems are more than demands; an example could be in an instant when the HVAC system for a room is operational but the room is unoccupied for a long period. Past studies indicate that about 10%–20% of HVAC energy consumption [1,2] and 30% of lighting energy consumption [3] can be reduced using demand driven controls by considering real-time occupancy information in building management systems. This is because real-time occupancy population is usually less than the design population. For instance, the actual occupancy diversity factors in an office building could be as much as 46% lower than the values published in ASHRAE 90.1 2004 energy cost method guidelines [4,5]. Further evidence of this trend is illustrated in the references [6–9].

Real-time occupancy information is crucial for demand driven HVAC operations. In recent years, various types of occupancy detection methods have been developed using tools such as passive infrared (PIR) sensors [10], cameras [11], wireless sensor networks [12], radio frequency identification (RFID) sensors [13,14] and CO_2 sensors [15–17] amongst others. Each method has its own advantages and applicability; in addition each has specific limitation(s) in real practice. It is known that occupancy detection might be unreliable when only based on an individual physical sensor [10]; this is due to uncertainties of occupant activities (for example steady occupants cannot be detected by PIR sensors) and sensitivities of occupancy sensors. Dodier et al. [10] found that the six PIR sensors in their study detected 20%, 39%, 50%, 70%, 76% and 76% of occupancy events respectively. Duarte et al. [4] found that 2.56% of data measured by 629 infrared/ultrasonic sensors in an office building should be removed since the measurements indicated continuous occupancy for 48 h or more. They estimated that the same amount of failure data should exist failing to detect occupants. Demand driven HVAC operations based on individual physical occupancy

* Corresponding author.
E-mail address: y.zhao.1@tue.nl (Y. Zhao).

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sensor of such a quality cannot guarantee indoor air quality and thermal comfort. Occupants' complaints would consequently result to change from demand driven operations back to conventional operations or manual operations.

Information fusion is a technique that combines use of independent sensor measurements and information from multiple sources to improve accuracy and reliability. Along with the popularization of information technologies, occupancy information/ measurements of multiply sources are available in low costs. It is possible to consider introduction of information fusion in occupancy detection. Personal computers are presently quite common in offices. Subsequently, real-time status of keyboard and mouse could be used to provide meaningful occupancy status of the room in which the computer is located. The use of smart devices like smart phones are widely. Wearable smart devices such as smart watches and smart bands tend to be popular. With wireless technologies inside, smart devices have potentials to provide real-time individual occupancy-related information, for example. Wi-Fi connection from smart devices or from wireless routers (details can be found in Section 3.1), GPS location from smart devices and RFID information. The information teased from this can reveal individual occupancy status that may be useful for demand driven operations. For instance, the HVAC systems for a room can be switched on prior to arrival of occupant if the GPS location shows that the occupant is approaching the building and vice versa. Some types of information cannot provide accurate occupancy status directly; however the information provided may still be useful in improving the reliabilities of occupancy detection through information fusion. For instance, the smart phone of an occupant always connects to a certain Wi-Fi hotspot during working hours. The belief of occupancy in the room would as a result be lower than in the case when there is no connection. Building management systems also provide useful information such as entrance information and car parking information. A straightforward idea of utilizing such type of information would be directly tap individual information source for demand driven HVAC operations. Problems would however arise when parts of these information sources fail to work; example would be in cases whereby the smart phone is powered off, or when faulty measurements are registered. Occupancy detection would thus be more reliable by fusing these measurements with multiple information sources. However, comprehensive literature survey reveal that information fusion for occupancy detection has not attracted much attention.

Bayesian belief network (BBN) is a powerful tool proposed in the early 1980s which has been successfully applied in the domain of information fusion, knowledge discovery and probabilistic inference [18,19]. In the domain of HVAC, applications can be found in fusing diagnostic information for fault detection and diagnosis [20,21]. Hawarah et al. [22] developed a BBN to predict and diagnose user's behavior in housing for home automation system. Compared with other information fusion algorithms in theory, BBN could be an outstanding in developing information fusion models for occupancy detection. Firstly, it is possible to develop a generic BBN for occupancy detection. A specific BBN for a certain situation can be easily developed based on the generic BBN considering various types and amounts of measurements/information. Secondly, parameters in BBN can be assigned by estimations of experts. In this way, the BBN can work without training at the beginning of usage. In practical applications, there are generally no historical occupancy data for training. Thirdly, BBN is a straightforward method which can be easily understood by operators. Also, the associated computation load is low. Dodier et al. [10] developed a BBN for occupancy detection using three PIR sensors and a detector of telephone handset status for occupancy detection in two private offices respectively. Results showed that the method improved occupancy detection accuracy significantly. In Dodier et al.'s work, occupancy patterns were not considered in the BBN. Only two types of sensors were used. Ideally, the BBN should be trained using ground truth values of occupancy statuses; this might be a major barrier in practical applications. The term ground truth value of occupancy status refers to the real occupancy status. Measurements from occupancy sensors cannot be regarded as ground truth values of occupancy statuses due to associated inaccuracies. Ground truth values of occupancy statuses in Dodier et al.'s work were obtained by human observers.

This study attempts to propose a generic, reliable and low cost occupancy detection solution to provide reliable real-time occupancy information for demand driven HVAC operations in buildings. Two types of virtual occupancy sensors are developed for individual occupants, i.e. room-level virtual occupancy sensors and working zone-level occupancy sensors. The term virtual sensor refers to an emerging form of multiply sensors and information, which has no differences compared with a physical sensor from the users' perspective. The room-level virtual occupancy sensors provide occupancy status in a private office room, i.e. occupied and vacant. The working zone-level virtual occupancy sensors provide occupancy status of individual occupant in a working zone, such as leaving, coming, in the working zone, or not in the working zone. They are useful inputs for demand driven HVAC operations.

This study is based on Dodier et al.'s work [6] with following improvements: (i) various types of sensors are considered after a comprehensive survey; (ii) a new sensor and a new information source are proposed, i.e. chair sensor, and keyboard and mouse status; (iii) occupancy patterns are also considered in the BBNs; (iv) Expectation–maximization (EM) algorithm is introduced to train the BBNs. Its benefits include avoidance of requirements for ground truth values in the developments of BBNs. In addition a sensor performance assessment method is proposed to detect inefficient and faulty sensors/information sources. The proposed virtual occupancy sensors are evaluated in two office rooms.

2. Bayesian belief network (BBN) and expectation–maximization (EM)

This section presents an introduction of the two algorithms used in the development of virtual occupancy sensors.

2.1. Bayesian belief network theory

A BBN is defined by two components, i.e. structure and parameters. The structure of a BBN is a graphical and qualitative illustration of the relations among the modeled variables. It is a directed acyclic graph in which nodes represent variables and arcs represent direct probabilistic dependences among them. Each arc starts from a parent node and ends at a child node. An example is shown in Section 4.3. A node contains all possible states of the variable it represented. For instance, node *InRoom?* in Fig. 6 has two states, i.e. *Occupied* and *Vacant*. The parameters of a BBN represent quantitative direct probabilistic dependences among nodes. Each child node has a conditional probability table based on parental values. An example is shown in Section 3.4.

The inference in a BBN is to calculate posterior probability $P(X_q|X_e)$, where X_q is the node of interest and X_e is a node or a set of nodes which is/are observed. In the case of the BBN in Fig. 6, X_q is the *InRoom?* node, X_e is a set of nodes whose states are observed like node *TimeOfDay*, *PIR2* and *Keyboard & mouse*. The posterior probability $P(X_q|X_e)$ is the belief (probability) of occupancy. More details about BBN are illustrated in Zhao et al. [21], Xiao et al. [20] and [18,19].