Energy and Buildings 125 (2016) 254–266

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

An evidence based approach to determining residential occupancy and its role in demand response management

Joel Chaney*, Edward Hugh Owens, Andrew D. Peacock

School Energy, Geoscience, Infrastructure and Society, Heriot-Watt University, Edinburgh, Scotland, EH14 4AS, UK

ARTICLE INFO

Article history:
Received 3 December 2015
Received in revised form 2 March 2016
Accepted 23 April 2016
Available online 30 April 2016

Keywords:
Demand response
Occupancy
Sensor fusion
Context-aware
Smart meter
Dempster-Shafer
Hidden Markov Model

ABSTRACT

This article introduces a methodological approach for analysing time series data from multiple sensors in order to estimate home occupancy. The approach combines the Dempster-Shafer theory, which allows the fusion of 'evidence' from multiple sensors, with the Hidden Markov Model. The procedure addresses some of the practicalities of occupancy estimation including the blind estimation of sensor distributions during unoccupied and occupied states, and issues of occupancy inference when some sensors have missing data. The approach is applied to preliminary data from a residential family home on the North Coast of Scotland. Features derived from sensors that monitored electrical power, dew point temperature and indoor CO_2 concentration were fused and the Hidden Markov Model applied to predict the occupancy profile. The approach shown is able to predict daytime occupancy, while effectively handling periods of missing sensor data, according to cross-validation with available ground truth information. Knowledge of occupancy is then fused with consumption behaviour and a simple metric developed to allow the assessment of how likely it is that a household can participate in demand response at different periods during the day. The benefits of demand response initiatives are qualitatively discussed. The approach could be used to assist in the transition towards more active energy citizens, as envisaged by the smart grid.

1. Introduction

One of the primary motivations of occupancy detection in buildings has been reduction of energy use whilst maintaining occupant comfort through the control of heating, cooling and ventilation systems [17]. However, with the increase of intermittent distributed renewables on the power grid, occupancy sensing provides further opportunities to assist in the flexible management of consumer demand to better match supply [43]. Periods of active occupancy (when people are at home and awake) have a high correlation with user demand profiles [9,1], because it is during times of active occupancy that consumers are most likely to be carrying out activities that require the consumption of energy, such as utilising appliances, heating, lighting etc. Torriti [51] considers variation in occupancy and suggests that the extent to which peak loads can be shifted is not only a function of incentive or price, but is largely dependent upon patterns of occupancy, especially for incentivised-based forms of Demand Response (DR). Indeed, for this type of DR, it is only during occupied periods that people have the capacity to modify their energy consumption behaviour. Furthermore, even 'smart' actuated DR strategies will benefit from knowledge of occupancy patterns for effective appliance scheduling [55]. At the same time it is also important to take into account user comfort [46,54], which is of course only important during occupied periods (both active and non-active), and is closely linked with energy consumption and peak demand [50]. For these reasons the determination of occupancy profiles is important when accessing the potential opportunities for both incentivised and actuated DR.

One of the main challenges is reliable non-intrusive approaches to determine when occupants leave and arrive in the home and to map the associated patterns of occupancy. Most approaches to occupancy estimation sensing require ground truth training data (e.g. [34,25]), but this requirement places a barrier to the rapid uptake of DR. To take full advantage of the potential benefits of occupancy sensing there is a need for blind occupancy estimation strategies through inference [18].

1.1. Occupancy inference

There have been various attempts at inferring occupancy using ubiquitous sensors. One very promising approach is use of electricity data from smart meters or electricity clamps. Statistical

* Corresponding author.
E-mail address: joel.chaney@gmail.com (J. Chaney).

http://dx.doi.org/10.1016/j.enbuild.2016.04.060

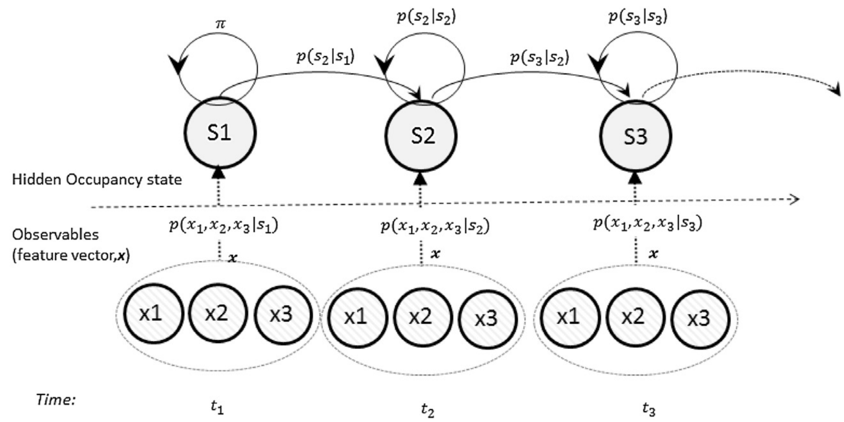

Fig. 1. The combined belief of a given set of features occurring is estimated using the Dempster-Shafer method.

approaches classifying this data have been suggested that are able to provide estimates of occupancy with accuracies of more than 80% [11,31]. Smart meter data could be used to provide this functionality meaning it could be delivered with no extra hardware expense.

Occupants generate heat, moisture and water vapour and therefore environmental sensors provide a potential approach to inferring occupancy [16]. One of the most common approaches is to use a CO_2 sensor combined with a detection algorithm (e.g. [25,52,34]. Jin et al. investigate the use of indoor CO_2 concentration to infer occupancy, by modelling the *dynamics* of human generated CO_2 concentration in a room, demonstrating a strong link between the behaviour of CO_2 levels in the room and occupancy. However, changes in ventilation rates caused by opening doors and windows affects the reliability of approaches relying solely on CO_2 measurements [42].

Various studies include relative humidity in occupancy estimation (e.g. [30,34,17]. The problem with using relative humidity is that it is a function of the air temperature, where a temperature decrease in a building due to thermostat setbacks for example, will result in an increase in the relative humidity because colder air is able to hold less moisture [36]; therefore without considering the effect of temperature, the cause of a change in relative humidity will not be clear.

Additional sensors that have been used to determine occupancy, often in combination with other sensors include: door sensors [3], acoustic sensors [8,48,13,24], cameras [7], PIR sensors [15,42,47] and ultrasound [22]. Alternative approaches include the use IT infrastructure: using GPS information from smartphones [32], although this requires active participation of the occupants, and a phone (with sufficient battery), which must be carried at all times; and by monitoring MAC and IP addresses [40].

1.2. Processing sensor data

The output from different sensors captures different possible interactions between an occupant and the environment in which they are in [34]. Therefore, by combining multiple sources of data from different sensors, it is possible to exploit information from a range of interactions, and thus to increase occupancy state classification accuracy. For instance, Lam et al. [34] looked at combining various sensors, including CO_2, relative humidity (RH), PIR and sound. These capture information on the following interactions, respectively: exhalation of CO_2 as the occupant breaths within the space; the occupant respiring and giving off moisture; the occupant moving in the environment; and the occupant making noise while in the space.

One of the key factors in achieving greater accuracy in occupancy prediction is processing the data in an appropriate way to generate distinguishing features. The following features have been successfully used in occupancy sensing classification problems: moving average [34,24], range, standard deviation [11], 1st order difference, 2nd order difference (e.g. see Refs. [17,19]). Different features will have stronger and weaker correlations with occupancy, for example, in the study of Lam et al. [34], which focused on an office space, CO_2 and acoustic parameters were shown to have the strongest correlation out of all the studied variables. Once the best features are established, classification of the feature set can then be carried out.

1.3. Classification to determine occupancy

How sensor information is processed and combined is critically important for the success of the method. For instance, the work by Hailemariam et al. [24] on combining multiple sensor data using decision trees to predict occupancy, showed that over fitting can occur when combining a large number of sensors, even reducing overall accuracy. Careful selection of the classification technique for the occupancy inference problem is vital.

The work by Lam et al. [34] compares three classification methods for multi-sensor data: Support Vector Machine, Neural Networks and Hidden Markov Model (HMM). The HMM classifier was found to be the method that produced a profile that best described occupancy presence. The effectiveness of the HMM for classifying occupancy profiles was confirmed by Kleiminger et al.'s [31] who compared K-Nearest Neighbour (KNN), Support Vector Machines (SVM), Thresholding (THR) and Hidden Markov Model (HMM) classifiers for predicting occupancy from electricity consumption profiles. The HMM showed the best overall and consistent performance, even without taking into account prior probabilities. This was further demonstrated by Chen et al. [12]. The HMM is a tool for representing probability distributions over a sequence of observations in time series data and they are well known for their applications in pattern recognitions systems (e.g. [20,5,28,14]), such as in handwriting and speech. One of the major advantages of the HMM compared with other methods, is that it has a time dimension, which takes into account the transition probability between occupied and unoccupied states as a function of the sequence of observed features.

One of the challenges of using the HMM with a large feature vector is the number of training examples required: the number of parameters needed to describe the model grows exponentially with the number of observation variables or states [44]. Indeed this could become an issue with a large distributed network of sensors to predict occupancy. In order to address this shortcoming,