# Halmstad Intelligent Home - Capabilities and Opportunities

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**Abstract.** Research on intelligent environments, such as smart homes, concerns the mechanisms that intelligently orchestrate the pervasive technical infrastructure in the environment. However, significant challenges are to build, configure, use and maintain these systems. Providing personalized services while preserving the privacy of the occupants is also difficult. As an approach to facilitate research in this area, this paper presents the Halmstad Intelligent Home and a novel approach for multi-occupancy detection utilizing the presented environment. This paper also presents initial results and ongoing work.

**Keywords:** Intelligent environments · Multi-occupancy detection

## 1 Introduction

Over the past three decades, the concept of smart homes has emerged. Smart homes are residences equipped with technical solutions to enhance the resident's comfort, safety, security, entertainment and to increase energy-efficiency. Recently, smart homes are being constantly promoted to support effective and efficient healthcare of ageing and disabled individuals living alone. Smart homes employ artificial reasoning mechanisms that take into account the current and past states of the environment and its occupants to learn and anticipate needs. In general, smart homes are challenging to build, configure, use and maintain. Smart home systems often require complex algorithms, which in turn have parameters that need testing and tuning before further *out-of-lab* deployments. As a consequence, to deliver robust smart homes, one needs to investigate and experiment with a variety of hardware and software (e.g. system architectures, machine

This work was supported by the Knowledge Foundation of Sweden, Grant Number 2010/0271. Invest Northern Ireland partially supported this project under the Competence Centre Program Grant RD0513853 Connected Health Innovation Centre.


M.U. Ahmed et al. (Eds.): HealthyIoT 2016, LNICST 187, pp. 9–15, 2016.
DOI: 10.1007/978-3-319-51234-1_2

learning methods, reasoning/decision schemes, strategies for interaction) components.

It is argued in this paper that these challenges can be holistically met by the use of the proposed Halmstad Intelligent Home (HINT). The current capabilities and future opportunities and research directions of HINT are described.

There are numerous examples of world-wide smart home implementations which focus on health-related services. The MavHome [2] showed successful prediction of user actions enabling the home to act as an intelligent agent. Another early, yet important example is The Aware Home [4] providing methods and tools for increased awareness of residents location, orientation and behaviours. However, few of the past smart homes extend the focus to go beyond specific algorithms as well as using more advanced sensors (e.g. physiological sensors such as EEG) and implementing services to respond to situations requiring attention. HINT provide the means to address these extensions.

Moreover, this paper presents how HINT is used for the development of robust and novel algorithms for the detection of several individuals in the home (i.e. multi-occupancy (M-O) detection). Robustness of M-O algorithms are important because for commercial smart homes to accurately adapt to residents activity patterns and privacy preferences it is critical to assure that only the patterns of a single person are being used.

## 2 The Halmstad Intelligent Home

At the Halmstad University campus, HINT is a fully functional one-bedroom apartment of 50 m$^2$ built to provide researchers, students and industrial partners with a technology-equipped realistic home environment. The layout of the apartment is illustrated in Fig. 1. HINT is expected to facilitate experiments and studies within the areas of intelligent environments, Ambient Assisted Living (AAL), and social robots. HINT is expected also to facilitate longitudinal studies by allowing subjects to stay in the apartment for extended periods of time.

### 2.1 Capabilities and Opportunities

Research at HINT focus on (1) the intelligent interconnection and collective behaviour of a diverse set of network-enabled technologies, and (2) the mechanisms that make the pervasive infrastructure of the smart environments behave intelligently.

HINT has been equipped with more than 60 sensors, including one “smart home in a box” kit [1], to detect the current state of the environment and its occupants. Magnetic switches detect the opening/closing of doors (label 1 in Fig. 1). Contact/touch sensors are positioned in the sofa and under the seat cushion to detect occupancy (label 2 in Fig. 1). Passive infrared (PIR) sensors are positioned to detect motion or occupancy in the different areas (label 3 in Fig. 1). Magnetic switches detect the opening/closing of cabinet’s doors and

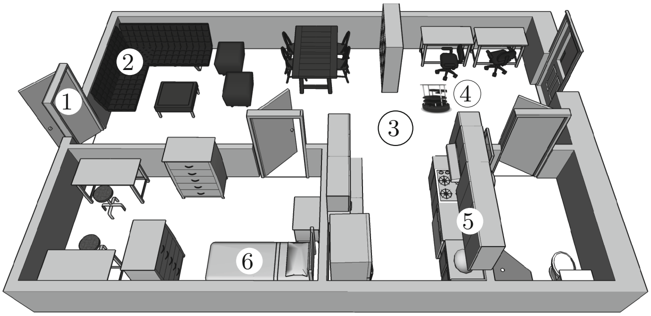


**Fig. 1.** The floor plan of HINT divided into multiple areas. Labels in the figure indicate capabilities.

drawers (label 5 in Fig. 1). Load-cells integrated into the bed frame measure weight and bed entrances and exits, and pressure sensitive sensors under the mattress detect vital signs (label 6 in Fig. 1). HINT has been built on top of a database-centric system architecture, meaning that the logic for the intelligent reactive and responsive behavior of the environment are implemented mostly within a database management system [3]. Following such an approach, HINT provides methods for: (1) physiological monitoring (e.g. vital signs) and safety monitoring and assistance (e.g. automatic lights), (2) functional monitoring (e.g. learning behaviour patterns and detecting deviating activities) [5], (3) emergency detection and response. To react and respond to events, HINT contains actuators. Motor actuators in the adjustable bed enable different bed positions to be selected (label 6 in Fig. 1). A vacuum cleaner-like robot (label 4 in Fig. 1) can navigate autonomously in the apartment and respond to detected anomalies, such as a fall.

Research at HINT is also focusing on technological solutions and seamless interfaces that are capable of recognizing and responding to the presence, health status and needs of residents in a unobtrusive and intuitive way. Although much progress has been made on developing wearable physiological sensors, and detecting and monitoring daily activities, research at HINT also aims to identify and respond to the resident's emotional state. Brain-Computer Interface (BCI) technologies are being currently investigated and will soon be integrated with existing capabilities of HINT to allow sensor fusion with existing sensors for an interpretation of emotional state. Furthermore, the resident's autonomy and participation in social life can be increased if the services are provided out of the home boundaries. Although some approaches have been proposed already [6], additional research is required to develop a middleware that supports self-adaptive systems, which can automatically discover and setup resources and facilitate continuous provisioning of services. Understanding an individual's emotional state is an important step in determining their needs. Consequently, one of the overarching goals of HINT is to develop and validate computational models of user affect using neurophysiological signals. At HINT we use BCI and Affective Computing technologies to develop and validate computational models of user affect. Subsequently, this model will be used to support accessible AAL applications in which intelligent environments can intuitively interact with users, adapting to their emotional state.

**Open Data Initiative.** HINT aligns with the aspirations of the Open Data Initiative (ODI). This is being driven by an international research consortium which is striving to provide a structured approach for the collection and annotation of high quality annotated data sets in an format that is easily accessible by the research community [7]. Previous efforts within the ODI have also been directed towards the generation of simulated datasets. There is, however, an opportunity to further progress the development of protocols for common data collection in addition to a suite of on-line tools for sharing and curating data, algorithms and results.

## 3 Showcase: Multi-occupancy Detection

To demonstrate the usefulness of HINT the development of an algorithm for M-O detection is described. M-O detection is referred to in this paper as the binary classification of the presence of more than one person in the home, at the same instance in time. The task of mapping sequences of events to the classification of the presence of one person or more is less studied than other tasks (e.g. *activity recognition*) and could be considered as challenging due to the following reasons: (A) Detection methods based solely on collected data may result in inaccuracies when residents perform previously unseen activities, not representative in training data. (B) Methods relying on training data where labels are collected from ground truth require tedious manual work to acquire. (C) The number of combinations of sensor events unfolds exponentially with the number of rooms, sensors, residents and potential activities. Therefore, to manually create programmatic rules is a difficult, time consuming and complex task which makes data-driven approaches favourable, however, challenging. Earlier approaches considered these challenges often by learning standard behaviour from the data. A common application concerns energy conservation in multi-resident buildings such as the work by Yang et al. [8]. Their approach targets occupancy modelling in an office environment where the problem is treated as a multi-class estimation where up to ten classes (meaning an environment occupied with nine individuals) were considered. The results illustrated that decision trees performed most accurately compared to alternative methods such as artificial neural networks. A significant difference between HINT and the environment used by Yang et al. is that a more rich sensor setup, e.g. sensors capturing CO2 and humidity was used by Yang et al. whereas in this study only PIR sensors, magnetic switches and pressure sensors were used. Such sensors can be considered to be more of standard sensor technology and often used in the context of capturing activities of daily lives.

**Data:** Events from participants occupying space, $\chi$. Sequence of events, $\psi$, to predict as space occupancy. Sensor distances, $J$.
**Result:** Predictions of occupancy, $\omega$.
1 $\alpha \leftarrow$ ExtractFeatures($\chi$);
2 $\beta \leftarrow$ CombineFeatures($\alpha$);
3 rf $\leftarrow$ TrainRandomForest([$\alpha$, $\beta$], *labels*);
4 $\text{pred}_{RF}$, ambiguities $\leftarrow$ PredictMultOccByRF(rf, ExtractFeatures($\psi$));
5 $\text{pred}_{J}$ $\leftarrow$ PredictMultOccByJ($J$, ExtractTiming($\psi$), thresh_probability);
6 **while** *next prediction and ambiguity is not empty* **do**
7     **if** *$J$ prediction is not M-O* **then**
8         **if** *ambiguity > thresh_ensemble_$\sigma^2$* **then**
9             add ($J$) prediction to $\omega$;
10         **else**
11             add (RF) prediction to $\omega$;
12         **end**
13     **else**
14         add ($J$) prediction to $\omega$;
15     **end**
16 **end**

**Algorithm 1.** Algorithm for Multi-Occupancy Detection.

This paper describes, to the best of our knowledge a new approach to M-O detection using a combination of a classifier-based (Random Forest) and prior knowledge-based approach which eliminates the tedious data collection of M-O data (B) in addition to the need for creating manual rules (C). Training data for S-O observations (class one) is collected and combined in order to create the second class (M-O observations). To address the challenge with unseen patterns (A) the confidence of the classifier is weighted against the likelihood of sensor activations relative to their distance to each other, i.e. if the occurrence of two sensor events are *physically unlikely* then raise an M-O detection event.

### 3.1 Algorithm and Data Collection

The algorithm is designed to monitor when ambiguities are present in the data-driven methodology by following the variance of tree predictions in the forest (line 6 in Algorithm 1) and to adjust the system confidence in the data-driven model accordingly, i.e. less confidence in the data-driven model initiates a switch to the model based on prior knowledge (sensor distances, $J$). Features are represented as a simple count of events for each sensor triggered during a time window of 60 s as well as the last state of each sensor giving a total of 78 features per observation. The S-O dataset are combined (to create M-O dataset) by a summation of the count features as well as using the combined last state of two observations.

The data collection was performed by asking 10 participants to follow a protocol consisting of guidelines to eight activities: *go to bed*, *use bathroom*, *prepare breakfast*, *leave house*, *get cold drink*, *office work*, *get hot drink* and *prepare dinner*. The guidelines were written in a simplified form in order to provide participants with the freedom to perform an activity with a natural variation. All the participants were requested to sign an informed consent prior to the start of experiments. $J$, was compiled manually using measurements from a CAD-drawing of HINT and used with an assumed average in-door gait speed of 2 m/s to compute the probability of two sensors events being likely to be triggered by a single person. The exponential cumulative distribution function was used to model this probability. The algorithm was tested by collecting data at HINT from additional two participants that performed various activities (both according to the protocol but also activities not found in the training data), in total 30 min was collected and contains both M-O and S-O observations.

### 3.2 Algorithm Results

A ROC curve created by varying the threshold for the tree prediction output variance (*thresh_ensembles_*$\sigma^2$) as well as varying the threshold for the probability of gait velocities (*thresh_probability*) can be seen in Fig. 2. A true positive (TP) is regarded as the correct classification of a M-O event. The combination of the data-driven and prior knowledge-driven approach shows the benefit of combining the two classifiers. Besides TP and FP rates the classifiers individually show accuracies of 82% (prior knowledge-based), 75% (Random Forest), and encouraging 96% using the proposed approach.

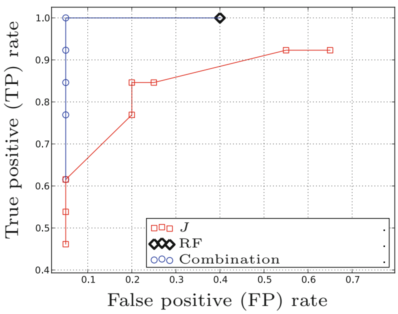


**Fig. 2.** ROC curve depicting TP/FP rates over the classifiers based on prior knowledge (squares), data (diamond) as well as the combination (circles).

## 4 Conclusions

This work presents capabilities and opportunities of the research environment HINT. One of the main goals of HINT is to facilitate algorithm development. The experience of the development of the proposed algorithm for M-O detection is that development time is significantly reduced when compared to designated tests in which environments have to be configured each time. Future work includes development of demonstrators able to showcase services (e.g. M-O detection) to a wider audience than researchers.

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http://www.springer.com/978-3-319-51233-4

Internet of Things Technologies for HealthCare
Third International Conference, HealthyIoT 2016, Västerås, Sweden, October 18-19, 2016, Revised Selected Papers
Ahmed, M.U.; Begum, S.; Raad, W. (Eds.)
2016, XIII, 186 p. 51 illus., Softcover
ISBN: 978-3-319-51233-4