# Detecting Occupancy in Smart Buildings by Data Fusion from Low-cost Sensors

[Poster Description]

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## ABSTRACT

This poster presents ongoing work on an occupancy detection system based on data fusion of various low-cost sensors within a real smart building and compares the results of different classification approaches.

## CCS Concepts

•**Hardware** → *Sensor applications and deployments; Smart grid;*

## Keywords

Occupancy Detection, Information Fusion, Smart Building

## 1. INTRODUCTION & RELATED WORK

Automated energy management in buildings benefits from occupancy detection and prediction, because occupancy is directly related to energy usage. This ongoing work investigates the possibilities of detecting the occupancy in a residential building using only commonly available and low-cost sensors, enabling the integration of an occupancy detection and subsequently an occupancy prediction service into an automated building energy management system.

High occupancy detection rates have been achieved in commercial buildings by combining data from multiple and expensive sensors in strictly controlled offices [1, 5, 15]. Occupancy detection using infrared sensors [9], $CO_2$ sensors [5], and motion sensors [13] has also been used to enhance buildings' energy efficiency, e. g., by controlling heating, ventilation, and air-conditioning (HVAC) systems. Occupancy as well as movements in residential buildings have also been detected using energy measurements [7], activity in the local Wi-Fi network [11], or using privacy-invading video surveillance [4, 14].

Hence, this work's essential contribution is to detect occupancy in a residential building without a sealed HVAC system and controlled environmental conditions.



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## 2. ENVIRONMENT & DATA SOURCES

The occupancy detection system is deployed to enhance the automated building energy management system (cf. [12]) of the *KIT Energy Smart Home Lab* (ESHL), a smart residential building comprising distributed generation, energy storage, flexible loads, and multiple sensors [8].

The laboratory's message bus based middleware is used for data acquisition realizing a strict separation between abstractions and services for easy access to information [2]. One service is the building energy management system *Organic Smart Home* that utilizes sensor data and prognosis to optimize the local energy system according to goals provided by the user and controls the devices via the middleware [12].

First results of a system using only air quality sensors have been presented in [3]. In this work, the following sensors and data sources are used, providing input data for classification:

**Air quality sensors** Six low-cost sensors (*AppliedSensor Indoor Air Monitor AS-MLV-P*) for the measurement of volatile organic components (VOC) are installed in the different rooms of the ESHL, recognizing a change of the air quality caused by humans and their actions (e. g., cooking, opening a window) with a sampling rate of 10 s.

**Network connections** The number of connected network devices (NW) is monitored by a service using the Address Resolution Protocol. Hence, a change in the number of devices (e. g., smart phones or laptops) is interpreted as arrival or leaving of an inhabitant.

**Bluetooth key fobs** Each regular user of the ESHL carries a *blukii Smart Sensor S* key fob sending *Bluetooth® Low Energy* (BLE) advertising packages every 10 s for identification. These packages are detected by a receiver station in the building and logged as an event.

**Calendar entries** The ESHL has a dedicated *Microsoft Exchange* calendar (CAL), where some of the usage times of the building are listed as appointments. The entries are accessed and provided by a module of the laboratory's Internet of Things middleware [2].

**Training data** Presence has been recorded manually by the ESHL's users for 52 days in summer 2016. The list contains 298 events of persons entering or leaving the ESHL[1].

## 3. INFORMATION FUSION

The fusion of data from different sensors is realized using the following steps and mechanisms:

[1]Data set: https://github.com/aifb/eshl-occupancy

Table 1: **Statistical measures for the binary and multi-class classification (F1-scores)**

| Classifier | Class | Mean | Std. | Min. | 75 % | Max. |
|---|---|---|---|---|---|---|
| Binary | 0 | 0.94 | 0.04 | 0.70 | 0.96 | 0.99 |
| | $\geq 1$ | 0.62 | 0.23 | 0.00 | 0.78 | 0.90 |
| Multi-class | 0 | 0.94 | 0.04 | 0.70 | 0.96 | 0.99 |
| | 1–3 | 0.60 | 0.23 | 0.00 | 0.76 | 0.89 |
| | $\geq 4$ | 0.15 | 0.22 | 0.00 | 0.35 | 0.59 |

**Data acquisition** The training and test data is gathered from a database using a dedicated microservice, which is described in detail in [2].

**Pre-processing** As a compromise between the expected computing time and the building's inertia affecting in particular the concentration of VOC, all data is re-sampled to a resolution of 0.1 Hz using forward fill for event-based data. Potential errors are determined by using a 95 % quantile and a limit of the changes between two time steps. They are corrected by removing them.

**Feature extraction** Based on results given by Lam et al. (2009) [10], a (rolling) first derivative (deltaVOC), and a distinction between workdays (WD) are chosen as additional features. Afterwards, the data is normalized and scaled.

**Classification problem statement** In addition to the binary classification whether at least one person is present in the ESHL or not $(0, \geq 1)$, a multi-class classification is used, which determines whether $0, 1–3,$ or $\geq 4$ persons are present.

**Classifier selection** Following Khalegi et al. [6], four algorithms and their combinations are chosen for classification: Multilayer Perceptrons (MLP), k-Nearest Neighbors (kNN), Decision Trees (DT) and Random Forrests (RF).

## 4. EXEMPLARY CLASSIFIER RESULTS

This section presents a brief evaluation of the classification approach using the data from multiple low-cost sensors.

**Comparison of binary and multi-class classification** In our case, none of the tested classifiers[2] (see Tab. 1) is able to detect the presence with an average F1-score of $\mathrm{F1} = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision}+\text{recall}} \geq 0.7$. The inferior results when detecting four and more persons call for more training data and probably more data sources to cope with the amount of disturbances generated by the users.

**Classification quality by sensor fusion** The F1-score of the classification whether there is at least one person present is increasing with the number of features used up to a score of $\sim$0.75 (see Fig. 1). Furthermore, the value of the best achieved result is slightly decreasing, asking for a closer analysis of the used features.

**Assessment of the used data sources** The quality of the used features has a large variety (see Fig. 2), explaining the mentioned decrease of the F1-scores of the classification results by the number of features (see Fig. 1), especially when using calendar entries or the distinction between the different days of the week.

[2]We forgo to weight the F1-scores from the classes for the calculation of the aggregated values to maintain the balance between the stated classes.

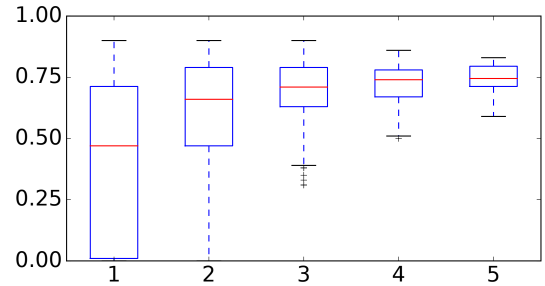


**Figure 1: F1-scores of the classification of the presence of $\geq 1$ person achieved by all combinations having a certain number of used features**

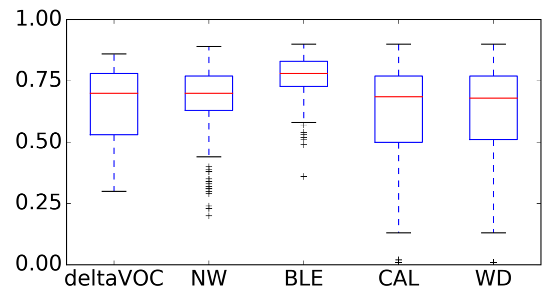


**Figure 2: F1-scores of the results containing only a certain feature for classifying $\geq 1$ person**

## 5. CONCLUSION & OUTLOOK

This poster presents an approach to occupancy detection for a smart residential building using only commonly available and low-cost sensors. First evaluations show that the quality of predictions from such data sources is sufficient for a binary presence detection, i. e., whether there is a person present or not. However, a more fine-grained classification shows unsatisfactory results.

The prediction of occupancy may help enhancing automated building energy management systems by improving the prediction of the building's energy consumption. Furthermore, if the occupancy prediction is realized as a standalone microservice, other applications, such as building automation, may utilize the occupancy information, too. Therefore, we work on extending our approach by further sensors to facilitate a more reliable detection and prediction of the number of inhabitants.

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