# Occupancy Detection using Gas Sensors

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Abstract: Room occupancy is an important variable in high performance building management. Presence of people is usually detected by dedicated sensing systems. The most popular ones exploit physical phenomena. Such sensing solutions include passive infrared motion detectors, magnetic reed switches, ultrasonic, microwave and audible sensors, video cameras and radio-frequency identification. However, in most cases either human movement is needed to succeed in detection or privacy issues are involved. In this work, we studied occupancy detection using chemical sensors. In this case, the basis for detecting human presence indoors is their influence of chemical composition of air. Movement of people is not needed to succeed and privacy of occupants is secured. The approach was reported effective when using carbon dioxide, which is one of major human metabolites. We focused on volatile organic compounds (VOCs). Their consideration is justified because numerous human effluents belong to this group. The analysis showed that VOCs' sensors, such as semiconductor gas sensors, offer comparable occupancy detection accuracy (97.16 %) as nondispersive infrared sensor (NDIR) (97.36 %), which is considered as the benchmark. In view of our results, semiconductor gas sensors are interesting candidates for nodes of sensor nets dedicated to detection of human presence indoors. They are smaller, cheaper and consume less energy.

## 1 INTRODUCTION

Occupancy, is commonly recognized as the act of occupying. The information about occupancy is useful for numerous applications. First of all, it is an important variable in determining the heating and cooling loads as well as ventilation rates necessary to maintain appropriate thermal comfort and indoor air quality.

The availability of occupancy information allows to significantly reduce energy consumption by heat, ventilation and air conditioning (HVAC) systems (Erickson and Cerpa, 2010; Erickson et al., 2011; Brooks et al., 2014; Brooks et al., 2015; Goyal et al., 2015). It is also extensively used for determination of occupancy profiles, which are widely applied in building simulations (Erickson et al., 2014). Occupancy should be taken into account by building commissions, for proactive building management, diagnosis of indoor air quality complaints, and investigation of building energy consumption.

Real time detection of occupants presence is fundamental for control of lighting. It plays key role in security systems for detecting abnormal human activity. It was shown that the detection of changes in occupancy patterns can be even helpful in revealing clinical diseases such as depression (Dickerson et al., 2011).

Occupancy is typically sensed by especially dedicated sensing systems, which employ passive infrared (PIR) motion detectors, magnetic reed switches, ultrasonic, microwave and audible sensors, video cameras, radio-frequency identification (RFID), gas sensors, etc. (Nguyen and Aiello, 2013).

Currently, most of commercial systems which perform occupant detection are based on PIR motion detectors. These devices measure infrared light radiating from objects in their field of view. Apparent motion is detected when an infrared source with one temperature, such as a human body, passes in front of an infrared source with another temperature, such as a wall. PIR motion detectors do not generate or radiate any energy for detection purposes. PIR detectors are particularly effective for controlling lighting in infrequently occupied, small, closed spaces such as storage rooms where a defined detection pattern is required. They are ineffective for more open layouts such as offices (Neida et al., 2001;



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Dodier et al., 2006). Although willingly applied for occupancy detection, PIR sensors are rarely deployed alone, because human motion is required to trigger these detectors. In most practical applications, they are used in conjunction with other sensors, e.g. with magnetic reed switch door sensors to detect occupancy for controlling HVAC (Agarwal et al, 2010).

Microwave and ultrasonic detectors utilize Doppler shift principle. They transmit respectively high frequency microwaves or sound waves in the area. The occupancy is detected from the change of pattern in the reflected wave. If the reflected pattern is changing continuously then room occupancy is assumed. If the reflected pattern remains the same for a pre-set period of time, the detector sends information about the lack of people inside. Compared to other types of occupancy detectors, microwave detectors have high sensitivity to objects which move, as well as much greater coverage (detection range). Additionally, they can detect through glass. Therefore, careful consideration of location is required in certain applications. The major drawback associated with such detection principle is that ultrasonic detectors, similar as microwave ones, fail to detect objects which remain relatively still or inactive for some time. For this reason, these devices are mostly used in conjunction with detectors based on audible sound sensors. However, audible sound sensors are not able to distinguish between human and non-human noises, which makes them inclined toward false alarms.

Occupancy detection can also rely on the use of video cameras (Ramoser et al., 2003). Camera networks are perhaps the most common type of sensor network. They are deployed in a variety of real-world applications including surveillance, intelligent environments and scientific remote monitoring (Funiak et al., 2006). A wireless camera sensor network installed in large multi-function building for collecting data regarding occupancy estimated occupancy with an accuracy of 80% (Erickson et al., 2009). In many applications human detection systems using video cameras are not a preferred choice. It results from the intrusive nature of these devices, the cost associated with their deployment, large amounts of data for storing and complexity of image processing.

Radio-frequency identification (RFID) uses electromagnetic field to automatically identify and track tags attached to objects. It can be applied for occupancy detection. As demonstrated (Scott et al., 2011), the authors put the RFID tags on the house keys and RFID receiver was plugged in the server to detect whenever a user carrying a key enters a house. The information was used for automatic control of house heating. Systems based on RFID identification and video cameras can be used to detect occupancy, but mostly they have been applied for security purposes rather than in building control systems. In general, practical applications prefer to avoid techniques which require changes in user behaviour such as RFID or which are a concern to user privacy such as video cameras.

Current systems for occupancy detection usually require the installation of dedicated sensors. They need to be purchased, fitted, calibrated, powered and maintained. This poses a number of critical constraints, especially in domestic environments. On the other hand, in typical households many sensor devices are already available and they can be used to perform occupancy detection in an opportunistic manner. These devices can contribute to improve the overall reliability of the detection system or reduce its cost (Kleiminger et al., 2013a; Kleiminger et al., 2013b). Examples involve taking advantage of GPS coordinates from residents' mobile phones, traces of connections to WiFi access points or other data like readings from digital electricity meters (Kleiminger et al., 2011; Kleiminger et al., 2013a; Kleiminger et al., 2013b). Other example is the occupancy sensing where existing IT infrastructure can be used to replace and/or supplement dedicated sensors in determination of building occupancy (Melfi et al., 2011). This approach is largely based on monitoring MAC and IP addresses in routers and wireless access points, followed by correlating these addresses to the occupancy of a building, zone, and/or room. Occupancy data obtained in this way can be used to control lighting, HVAC, and other building functions to improve building functionality and reduce its energy use.

Despite the large number of potential capabilities, detection of building occupancy is still the complex and unsolved problem. Systems based on gas sensors are the worthwhile option in applications such as control of ventilation, heating and cooling installations. According to the definition, given by the International Union of Pure and Applied Chemistry (lUPAC), these devices transform chemical information, ranging from the concentration of a specific sample component to total composition analysis, into an analytically useful signal. In other words, gas sensors can detect the presence of appropriate gases in a near surrounding of these devices.

Occupants themselves affect the chemical composition of indoor air. They are a source of emission of various chemical substances, e.g. carbon dioxide, water vapour, volatile organic compounds as well as biological agents. This emission results mainly from normal metabolic processes. The occupants influence on indoor air arises also from their activities, lifestyle and behaviour. For these reasons, chemical composition of indoor air very often reflects the occupancy state, especially in non-industrial environment.

Different gases can be used as indicators of this factor. For example, under some circumstances the number of occupants can be estimated from the real-time measurements of the $CO_2$ concentration (Wang et al., 1999; Jiang et al., 2016; Labeodan et al., 2015). Occupancy information is also included in the total concentration of volatile organic compounds emitted by people inside room. Therefore, it can be extracted from signals generated by $CO_2$ and VOCs sensors. Different operating principles cause that measurement characteristics, price and requirements for use of these devices are also different.

The aim of this work is to compare properties of $CO_2$ and VOCs sensors as detectors of occupancy.

## 2 EXPERIMENTAL

The occupancy detection was studied using a university classroom as an example of the periodically occupied space. The schematic drawing of the classroom is shown in Fig. 1. Its dimensions are: 7.35 x 9.60 x 3.20 m. The space was designed to host forty students and the lecturer. The room is fitted with openable windows and naturally ventilated.

The study focused on working days i.e. when the classroom was busy with students. Eighteen days of this kind were considered.

In the classroom there were performed measurements involving gas sensors. The daily measurement session started in the morning and it was completed in the evening. The session consisted of a survey and instrumental measurements. The main aim of survey was to collect information about room occupancy. For this purpose, an appropriate enquiry form was prepared and used. The data about room load was later used as reference, for training occupancy detection models.

Instrumental measurements consisted in recording responses of gas sensors of various kind. The following devices ware used in the study: non dispersive infrared sensor (NDIR) for $CO_2$ concentration measurement, photo-ionization sensor (PID), flame ionization sensor (FID) and semiconductor gas sensors for the determination of total concentration of VOCs. In the last group there were included commercial sensors offered by Figaro Engineering, Japan (www.figarosensor.com). The following sensors were chosen: TGS800, TGSn822-A0, TGS823, TGS825, TGS826, TGS830, TGS832, TGS842, TGS2180, TGS2600, TGS2602, TGS2620, TGS2104, TGS2444, TGS2201-gasoline (two), TGS2201-diesel (two). The sensor data was the basis for occupancy detection.

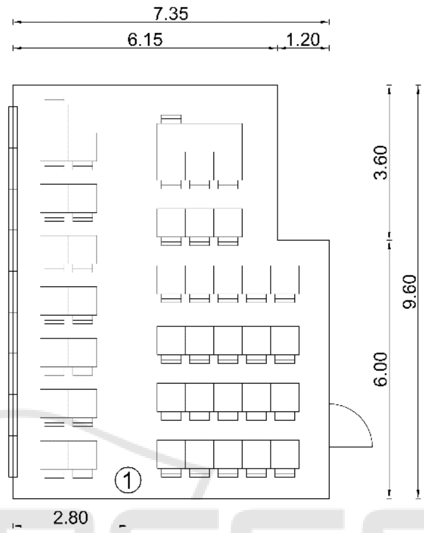


Figure 1: The schematic drawing of the classroom and the location of measurement point (circle).

The listed sensors may be applied to measure chemical characteristics of indoor air. The response of NDIR sensor is proportional to $CO_2$ concentration in gas mixture. The response of PID sensor is indicative for the amount of volatile compounds contained in gas sample, which can be ionized by the PID lamp under photon emission energies of 10.6 eV. These compounds include: aromatics, mercaptans, organic amines, ketones, ethers, esters, acrylates, aldehydes, alcohols, alkanes and some inorganics, like ammonia and hydrogen sulfide. PID cannot detect water vapor. FID sensor response is indicative for the amount of organic compounds contained in gas sample, which are ionized during combustion in a hydrogen flame. Flame ionization detectors cannot detect inorganic substances and some highly oxygenated or functionalized species. Both PID and FID sensor determine total concentration of all species they detect. Semiconductor gas sensors respond to wide range of species contained in air samples. In particular, the sensing element of Figaro gas sensors is a tin dioxide ($SnO_2$), semiconductor which has low conductivity in clean air. In the presence of a detectable gas, the sensor's conductivity increases depending on the gas concentration in the air. We chose sensors from two series 8xx and 2xxx. Devices in the first series have ceramic base. They are featured by good long term stability, but typically consume around 830 mW for their operation. Sensors in the second series were manufactured using thin film technology. In most cases they have lower energy consumption and smaller dimensions compared with series 8xx.

Passive sampling was used for measurements involving NDIR sensor. Measurements with PID sensor, FID sensor and TGS sensors were performed with the application of dynamic sampling. In the last case, air sample was drawn from the measurement point and it was delivered to the measurement devices. Teflon tubes were used for this purpose.

Indoor air was monitored in one location, as shown in Fig. 1. Data was recorded continuously, in real time, with constant time resolution of 1 min.

# 3 METHODS

The following assumptions were made about the occupancy detection.

1. Occupancy detection intends to deal with only two states - when occupants are present or absent in the space of the room.
2. Classifier is applied for distinguishing between the two states.
3. The basis for the distinction are measurements performed indoors using gas sensor.
4. The measurement data has the form of time series $\{X_i, i = 1, \ldots, n\}$ where n is the most recent moment of data acquisition.
5. Occupancy detection is performed on-line, for the current time moment n. The time resolution of detection is the same as data collection.

## 3.1 Classification

Occupancy detection was represented as a classification problem. It consisted in distinguishing two categories of room state: presence and absence of people.

Two kinds of features were considered as the basis of detection: sensor response $X_{n-j}$ where $j \in \{0,\ldots, L\}$, and change of sensor response $\Delta X_k = X_n - X_{n-j}$, where $j \in \{0,\ldots, L\}$. We used time lag j, j=0, 1, …, L to move back from the time point of occupancy detection in order to identify the period when the time series contains information, which is useful for the purpose of occupancy detection. In this work, we assumed L=30 min.

In this work, there were considered three kinds of feature sets.

Type 1 feature sets consisted of values of sensor responses $\{X_{n-j}\}$. The following sets of features were involved in classification: $A1=\{X_n\}$, $A2=A1\cup\{X_{n-1}\}$, $A3=A2\cup\{X_{n-2}\}$, $A4=A3\cup\{X_{n-3}\}$, $A5= A4\cup\{X_{n-4}\}$, $A10=A5\cup\{X_{n-10}\}$, $A15=A10\cup\{X_{n-15}\}$, $A20=A15\cup\{X_{n-20}\}$, $A25=A20\cup\{X_{n-25}\}$, $A30=A25\cup\{X_{n-30}\}$. With these sets of features we tested the usefulness of sensor responses recorded between 0 and 30 min back from the moment of occupancy detection.

Type 2 feature sets consisted of changes of sensor responses $\{\Delta X_{n-j}\}$. The following sets of features were involved in classification: $B1=\{\Delta X_n\}$, $B2=B1\cup\{\Delta X_{n-1}\}$, $B3=B2\cup\{\Delta X_{n-2}\}$, $B4=B3\cup\{\Delta X_{n-3}\}$, $B5=B4\cup\{\Delta X_{n-4}\}$, $B10=B5\cup\{\Delta X_{n-10}\}$, $B15=B10\cup\{\Delta X_{n-15}\}$, $B20=B15\cup\{\Delta X_{n-20}\}$, $B25=B20\cup\{\Delta X_{n-25}\}$, $B30=B25\cup\{\Delta X_{n-30}\}$. With these sets of features we tested the usefulness of changes of sensor responses encountered between 0 and 30 min back from the moment of occupancy detection.

Type 3 feature sets consisted of both, values and changes of sensor responses $\{X_{n-j}, \Delta X_{n-k}\}$. The following sets of features were involved in classification {A1, B1}, {A1, B2}, …, {A30, B30}.

Sets of features were constructed individually for each sensor.

For classification, we applied *k*-Nearest Neighbors (*k*-NN) algorithm (Webb, 1999; Park and Kim, 2015). The major reason for choosing it was that the properties of the classifier fit the characteristics of data used for occupancy detection. *K*-NN is a non-parametric method. i.e. none assumptions are made about the distribution of the input data. Test vector (whose label is unknown) is classified by assigning the label which is most frequent among the *k* training vectors nearest to the vector in question. Training vectors are simply stored in the memory and no explicit training phase is involved. Considerable advantage is the simplicity of *k*-NN algorithm, which makes it is easily implementable in hardware solutions.

Certain characteristics of data used for occupancy detection caused that *k*-NN was chosen for classification. 1) It was observed that the measurement data which represents distinct categories of room state exhibit very limited grouping. In such circumstances, parametric classification approaches would not be favoured. 2)

In feature space, its parts occupied by data representing categories *presence* and *absence* of people heavily overlapped. In such cases, data point-to-data point distance is preferred as the basis of classification, compared with distance between the data point and the centre of the group.

Classification of test vectors was performed in leave one out mode. By trial and error method we chose the parameter of the classifier $k$=3.

### 3.2 Performance Assessment

The occupancy was detected with predefined temporal resolution. For the purpose of algorithm evaluation, each result of detection was compared with the true state of the room. The possible combinations of detection outcomes versus possible true states of the room are shown in confusion matrix (Table 1).

Table 1: Confusion matrix for the detection of classroom occupancy.

| | | True state | |
|---|---|---|---|
| | | People present | People absent |
| Detected state | People present | TP | FP |
| | People absent | FN | TN |

The true positive case (TP) was when the presence of people was detected and really, there were people in the room at that time. True negative case (TN) was when the absence of people was detected and really the space was empty. The false positive case (FP) was when the presence of people was detected, while in reality there was no one in the room. False negative case (FN) was when the absence of people was detected while there were people inside.

The accuracy of occupancy detection was defined as the ratio of TP and TN cases jointly to the overall number of detections:

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

In this work, we additionally analysed false negative rate:

$$FNR = \frac{FN}{TP + FN} \tag{2}$$

and false positive rate:

$$FPR = \frac{FP}{TN + FP} \tag{3}$$

False negative rate indicated how frequently the occupied room was classified as empty. False positive rate showed how frequently the empty room was classifies as occupied.

## 4 RESULTS

We studied occupancy detection in lecture room. The complete study spanned over 18 working days. During 61 % of this time, the room was occupied and it stayed empty over the remaining 39 %. Presence of people was associated with the classes held. According to the general rules, the duration of classes at the university is 45 min or 90 min. They are separated by 15 min or 10 min breaks, depending on the time of the day. In reality, the temporal variation of room occupancy was much more complex. On many occasions classes started or finished earlier or later than assumed. Sometimes, the adjacent classes were aggregated by cancelling the break. As reported, the number of people in the lecture room was constant during most of the classes. The size of groups varied between 9 and 43 students. However, during some classes the number of occupants varied, in particular at the very beginning and at the very end of classes. The occupancy detection was expected to cope with both kinds of room load variation, temporal and related to the number of people.

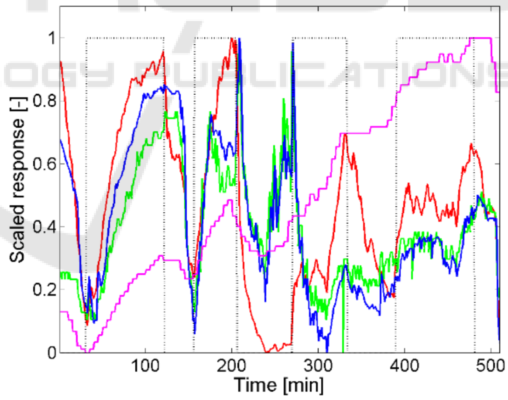


Figure 2: Time series of sensor responses recorded in the classroom during an exemplary day together with occupancy indication (black). Responses of the following sensors are presented: NDIR sensor (red), PID sensor (green), FID sensor (blue), TGS2201g2 (magenta).

In Fig. 2 we present the time series of scaled responses of gas sensors recorded during an exemplary day together with room occupancy. The group of semiconductor sensors was represented by one selected sensor TGS2201g2.

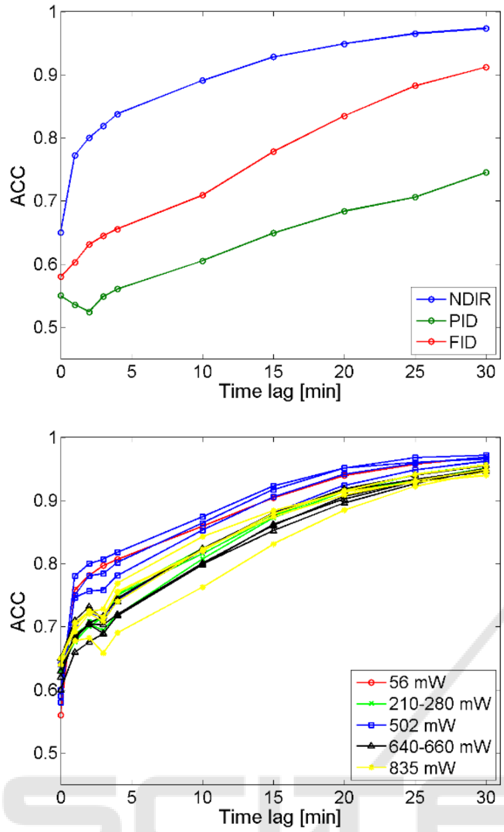


Figure 3: Accuracy of occupancy detection based on individual sensor responses recorded prior to the moment of detection. The following sets of features were considered: A1={$X_n$}, A2=A1∪{$X_{n-1}$}, A3=A2∪{$X_{n-2}$}, A4=A3∪{$X_{n-3}$}, A5= A4∪{$X_{n-4}$}, A10=A5∪{$X_{n-10}$}, A15=A10∪{$X_{n-15}$}, A20=A15∪{$X_{n-20}$}, A25=A20∪{$X_{n-25}$}, A30=A25∪{$X_{n-30}$}. The lowercase subtrahend {0, 1, 2, 3, 4, 10, 15, 20, 25, 30} is the time lag associated with a particular feature set. Bottom panel refers to semiconductor gas sensors, which are grouped according to energy consumption.

Based on results displayed in Fig. 3 to Fig. 5, the most accurate occupancy detection was attained when applying the sequence of sensor responses recorded prior to the moment of detection (Fig. 3). Time series of changes of sensor response were informative as well (Fig. 4), but the accuracy of detection was weaker when using features of this kind. In both cases, increasing the length of the time series resulted in the improved occupancy detection. We demonstrated that in case of some sensors the time lag of 30 min was sufficient for achieving high accuracy (NDIR, TGSs), but when using other sensors longer lags should be involved (PID, FID). Interestingly (Fig. 5), combining values of sensor responses and their changes in one feature set did not improve occupancy detection as compared to values of sensor responses only.

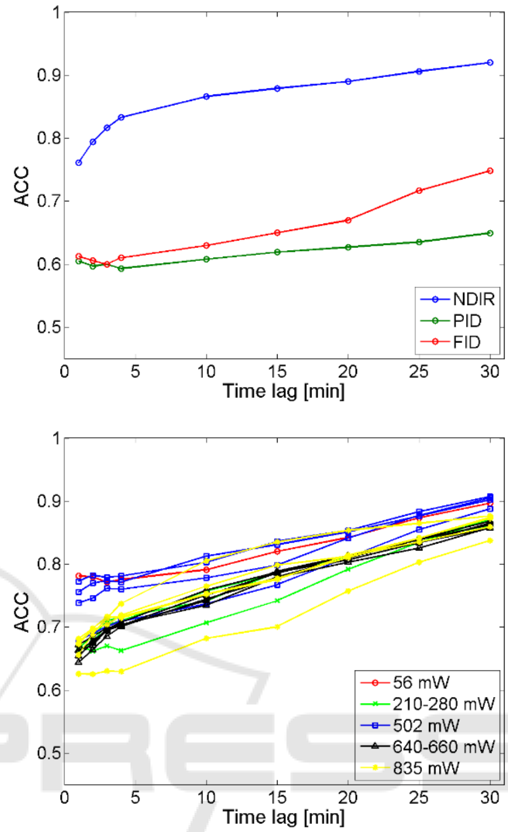


Figure 4: Accuracy of occupancy detection based on changes of individual sensor responses recorded prior to the moment of detection. The following sets of features were considered: B1={$\Delta X_n$}, B2=B1∪{$\Delta X_{n-1}$}, B3=B2∪{$\Delta X_{n-2}$}, B4=B3∪{$\Delta X_{n-3}$}, B5= B4∪{$\Delta X_{n-4}$}, B10=B5∪{$\Delta X_{n-10}$}, B15=B10∪{$\Delta X_{n-15}$}, B20=B15∪{$X_{n-20}$}, B25=B20∪{$\Delta X_{n-25}$}, B30=B25∪$\Delta X_{n-30}$}. The lowercase subtrahend {0, 1, 2, 3, 4, 10, 15, 20, 25, 30} is the time lag associated with a particular feature set. Bottom panel refers to semiconductor gas sensors, which are grouped according to energy consumption.

Although NDIR sensor performed best in occupancy detection (97.36 %), attention shall be payed to the fact that highly competitive accuracy was achieved with semiconductor gas sensors. A number of sensors of this kind were only by a fraction of percent weaker in occupancy detection accuracy than NDIR sensor. These were TGS2201g2 (97.16 %), TGS2201g1 (96.86 %), TGS2444 (96.86 %), TGS2201d2 (96.59%). Moreover, all semiconductor gas sensors involved in the study offered high performance. In general ACC in this group exceeded 93.99 %. Surprisingly, PID sensor demonstrated lowest suitability for occupancy detection (74.51%).

FID sensor performed much better (91.22%) compared with PID, but still it was not as good as semiconductor gas sensors.

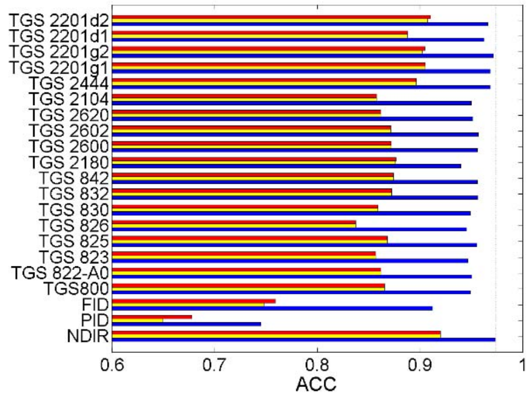


Figure 5: Accuracy of occupancy detection based on feature sets A30 (blue), B30 (red) and A30 ∪ B30 (yellow).

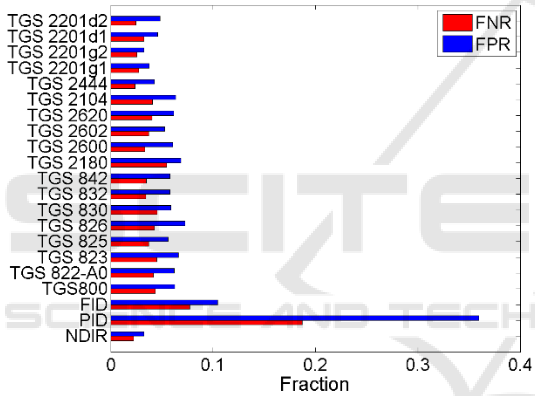


Figure 6: False positive rate (FPR) and false negative rate (FNR) occupancy detections using various sensors.

In Fig. 6 we analyse cases of room occupancy misdetection. False positive rate and false negative rate were applied for this purpose. As shown, for all sensors, false positive rate was greater compared with false negative rate. The smallest number of cases when the empty room was wrongly classified as occupied occurred with NDIR sensor (FPR=3.25%) and with TGS2201g2 (FPR=3.25%). The smallest number of cases when the occupied room was wrongly classified as empty occurred with NDIR sensor (FNR=2.23%) and with TGS2444 (FPR=2.39%). From the point of view of securing proper conditions for people who stay indoors false positive detections would be preferred to false negative ones. Multiple false negative detections could prevent maintaining human comfort by stopping the work of supporting installations while their operation is needed. Unfortunately, false positive detections are not indifferent as well. They make the supporting installations operate in vain and cause unjustified energy consumption.

# 5 DISCUSSION

In this work we studied occupancy detection using gas sensors: NDIR sensor, PID sensor, FID sensor and semiconductor gas sensors. They characterize indoor air from chemical point of view. It is known that human presence indoors influences air composition. This justifies the usefulness of gas sensors for occupancy detection.

Our results confirm best detectability of people presence indoors when applying NDIR sensor (ACC=97.36 %). High performance of the device which measures carbon dioxide concentration is in line with earlier findings of other researchers (Labeodan et al., 2015; Candanedo and Feldheim, 2016; Jiang et al., 2016).

The major achievement of this work is the demonstration that there are other sensors, which offer comparable accuracy of occupancy detection.

The competitive alternative to NDIR are semiconductor gas sensors. With the best of them we achieved 97.16% accurate detection. Some of these sensors are already commercialized as indoor air sensors. However, their use is not widespread yet. To our knowledge, this is the first work which demonstrated high performance of semiconductor gas sensors in the application to occupancy detection.

Tendencies in indoor air monitoring instrumentation incline toward PID sensor. Roughly, it addresses the same aspect of indoor air as semiconductor gas sensors. But, as we showed, PID sensor is practically useless from the point of view of occupancy detection (ACC= 74.51%). This fact actually raises a concern about the ability of PID sensor to follow human borne impact on indoor air.

In view of our results, semiconductor gas sensors are very interesting candidates for sensing elements in sensor nets for occupancy detection. As compared to NDIR sensor, these devices are several times cheaper. They are also smaller, and the miniaturization is constantly in progress. Additionally, their power consumption is competitive. NDIR sensors typically consume 600 mW while semiconductor gas sensors, which we selected as best consume, 502 mW (TGS2201g2) or 56 mW (TGS2444).

It shall be mentioned that occupancy detection presented in this work engaged raw measurement data. Some authors report advantages of initial data filtration or data smoothing techniques when estimating occupancy level (Wang, 1999; Jiang et al., 2016). In case of detection exclusively, the added value resulting from this kind of pre-processing is not obvious. However, the issue shall not be overlooked.

The drawback of the proposed approach to occupancy detection is related to the use of classifier. It causes that the detection model has to be tuned to the space in which it is supposed to operate. However, so far, solutions which do not involve classifier offer considerably worse performance in terms of detection accuracy.

# 6 CONCLUSIONS

This work focussed on occupancy detection in an indoor space. The basis for detection were responses of gas sensor. We considered NDIR sensor, PID sensor, FID sensor and wide range of semiconductor gas sensors.

Occupancy was detected in an exemplary lecture room. In occupancy periods this space was populated by 9 to 43 people. The detection was done with time resolution of 1 min.

Our results showed that best sources of information about presence of people in the room were NDIR sensor (ACC = 97.36 %) and semiconductor gas sensors, in particular TGS2201g2 (ACC = 97.16 %), TGS2201g1 (ACC = 96.86 %), TGS2444 (ACC = 96.86 %) and TGS2201d2 (ACC = 96.59%). Interestingly, the source of least informative data was PID sensor. The best achieved accuracy of detection was very high, considering that responses of individual sensors were used.

We demonstrated that time series of sensor responses, recorded prior to the moment of occupancy detection, are very useful for realizing this task. The relevant information was available within the time lag of at least 30 min. Changes of sensor responses were considerably less informative that their values.

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