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UltraSense: A Self-Calibrating Ultrasound-Based Room Occupancy Sensing System

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Abstract

Smart sensing technologies play a key role in the core of smart systems, which form the rapidly evolving internet of things. In this context, buildings' occupancy information is an important input that allows smart systems to be seamlessly aware of and responsive to the inhabitants, thus ensuring their comfort. In this paper we present **UltraSense**, an ultrasound-based room occupancy sensing system that relies on unsupervised learning, to automatically calibrate its parameters according to the room's environment. This ability avoids the need for manual calibration of the sensing system for each new environment. While commonly available occupancy detection technologies are limited to line-of-sight (LOS) conditions, UltraSense also operates in non line-of-sight (NLOS) scenarios. The proposed system was implemented and tested in order to characterize its performance. UltraSense was developed for the European research project SmartHeat in the frame of ambient assisted living.

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Keywords: occupancy sensing; ultrasound; unsupervised learning.

1. Introduction

In the recent years, the internet of things is rapidly evolving with the aim to radically improve the performance and quality of services of smart systems, and promote the comfort, health and well-being of people. Hence, the need is increasing for smart sensing technologies which constitute an important element of these systems. Buildings' occupancy information is an important input that paves the way for numerous applications. Example applications include Heating, Ventilating, and Air Conditioning (HVAC), lighting control, security systems and others. Occupancy detection systems are desired to be reliable, robust under different conditions, and non-intrusive to ensure user comfort. The required accuracy level of occupancy detection varies according to the need of the controlling systems. While home presence is sufficient for some systems, room-level presence accuracy is essential for some others.

The problem of occupancy detection has attracted increasing attention, and has been the subject of many research works. Occupancy information is mainly obtained through dedicated hardware. Passive infrared (PIR) sensors are widely used for occupancy detection[1,2]. These sensors, which rely on the differential of the reflected radiations to

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detect motions, provide a good accuracy and are generally appealing because of their low power consumption. A limitation of PIR sensors is the fact that they only operate in LOS condition, and they are sensitive to changes in the environment (sunlight, heating effect, etc.), which imposes some constraints on installation, and may require on-site calibration. Computer vision was also proposed[3] to observe occupants' presence. However, continuous monitoring using cameras might become intrusive for users' sense of privacy. The occupancy detection problem could also be solved through traditional localization techniques. In this context, proposed technologies include Bluetooth low energy[4,5,6], WiFi[7,8], ultra wide-band[9], and ultrasound[10]. Although a high accuracy can be achieved with indoor localization systems, they do not necessarily ensure user comfort, as they require carrying a smartphone or a dedicated device all the time. Occupancy information could also be inferred based on power monitoring, using smart electricity meters[11,12,13]. However, a dense deployment might be required to obtain accurate room-level occupancy information.

Ultrasound signals are suited for occupancy detection on a room-level scale, since they are inherently limited by walls separating rooms. We take a look at some of the state-of-the-art works in this domain. Caicedo *et al.*[14] use ultrasonic arrays to sense the presence and determine the location of a person inside a room. In their designed system, they consider the case of multipath propagation, but assume, however, that LOS is one of the multipath components, which may not be always the case. Some research works[15,16,17] have considered the presence at a particular location in the room, like the presence of a worker at his desk. The first mentioned paper[15] considers sound-based sensors among others and relies on decision trees to process sensors' information, in order to detect the presence. Similarly, the second work mentioned[16] uses ultrasonic sensors combined with stochastic recognition models, whereas the last paper[17] suggests a hidden Markov model. While these systems can achieve a good accuracy, they are generally designed assuming a direct LOS with the user, causing the performance to deteriorate otherwise, thus they are not suitable for scenarios with NLOS conditions.

In this paper we present UltraSense, a self-calibrating ultrasound-based room occupancy sensing system. UltraSense uses active ultrasound to discover persons' movements, based on the Doppler effect. It leverages unsupervised learning to self-calibrate in a seamless way, according to the surrounding environment in which it is installed. This characteristic makes the system operate regardless of the specific room environment, and whether it is in LOS or NLOS conditions. A working prototype was implemented to test the proposed system, and the results show that the system achieves high detection rates in different scenarios. UltraSense was developed to provide room occupancy information to the European research project SmartHeat, which aims to improve the heating conditions of inhabitants and reduce energy costs, in the frame of ambient assisted living.

In the rest of the paper, Section 2 shows the design aspects of UltraSense, then Section 3 explains the methodology used for occupancy detection. Section 4 presents the system calibration method, and the experimental evaluation is shown in Section 5. Finally, Section 6 concludes the paper and presents future work directions.

2. System Design

The requirements for the occupancy detection system we aim to design, are to have a high accuracy, to operate on a room-scale, and to have an automatic calibration. This feature allows the system to operate regardless of the specific settings of the environment in which it is installed, and whether it is in LOS or NLOS.

UltraSense uses active ultrasound to discover movements inside a room. It transmits periodically an ultrasonic signal, and observes the corresponding reflected signal. Doppler shifts in the signal frequency will indicate the detection of a movement. Room occupancy is then inferred based on motion detection. Acoustic signals emitted inside a room are generally confined to that same room, and hence, alterations to these signals are assumed to happen due to moving objects inside the room. Figure 1 shows how the transmitted signal would propagate: as the signal reflects on walls and objects, a person A who is moving inside will cause some alterations to the frequency of the signal, whereas moving person B who is outside will not alter the signal, since the latter does not propagate through the wall.

UltraSense requires one module per room. Each module is composed of a transmitter, a receiver, and a control/processing unit, as shown in Figure 2. The transmitter and receiver shall support the transmission of ultrasonic signals. As ultrasonic transducers which operate at around 40kHz are generally characterized by a narrow beam, we favor the use of commodity speakers and microphones since they have a larger directionality. These in general can support up to 22kHz, as their commonly used sample rate is 44.1kHz. UltraSense system uses the frequency range of 20-22kHz, which is non-audible and at the same time supported by commodity hardware. The control/processing unit

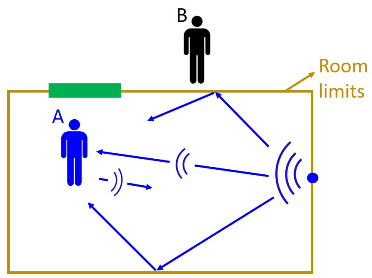

Figure 1: Acoustic signals are generally confined to the room in which they are emitted.

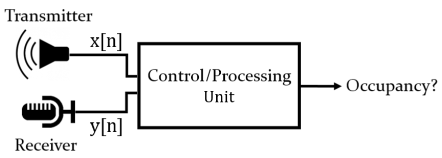

Figure 2: Architecture of the occupancy sensing module.

is used to trigger the signal transmission, record and process the received signal, and indicate whether the the room is occupied or not. This unit also implements the self-calibration method, as described in Section 4, and sends the occupancy results to a central system.

The transmitted signal is a finite sinusoidal pulse of frequency f_c, represented in discrete time as:

$$x[n] = \sin 2\pi n(f_c/f_s) \quad for\ n = 0, 1, \dots, T_{signal} \times f_s \tag{1}$$

where f_s and T_{signal} are the sampling frequency and the signal duration, respectively.

3. Occupancy Detection

A *frame* is defined as one transmission/reception of the ultrasonic signal. The receiver records the received signal $y[n]$ for each frame, and computes the magnitude $\{|Y[k]|\}$ of its discrete time Fourier transform (DFT), which represents its frequency spectrum:

$$|Y[k]| = |\mathcal{F}\{y[n]\}|_k = |\sum_{n=0}^{N-1} y[n]e^{-j\frac{2\pi}{N}nk}| \qquad for\ k = 0, 1, \dots, N-1 \tag{2}$$

The discrete sequence $\{|Y[k]|\}$ can be efficiently calculated using the Fast Fourier Transform (FFT). A *still frame* is one in which the room is unoccupied, and hence no movements occur inside. We denote its frequency spectrum by $\{|Y_{still}[k]|\}$. To detect any movements inside the room, the system compares the frequency spectrum of the current frame, to that of the known still frame. The *motion score* is a parameter calculated by the system for a given frame to quantify the movements, and hence infer the presence of people inside a room. It reflects the variations that took place to the spectrum as compared to a still frame, in order to detect Doppler shifts in the signal. In the general cases of multiple-person occupancy, or when a person is not necessarily moving with a constant speed in a steady direction, which is commonly the case, the Doppler shift will not consist of one well-defined frequency, but rather of multiple frequency shifts around the central frequency f_c. Figure 3 shows the frequency spectrum which reflects the Doppler shifts in the ultrasonic signal caused by a moving person, as compared to a still frame. To account for all cases, we take into consideration the total amount of frequency shifts around f_c, rather than the value of each one individually. The motion score that reflects the variations in the frequency spectrum, as compared to a still frame, is given by:

$$motion\ score = \sum_{k \in I} |\, |Y[k]| - |Y_{still}[k]|\, | \qquad where\ I = [f_c - \Delta_{f(max)}, f_c) \cup (f_c, f_c + \Delta_{f(max)}] \tag{3}$$

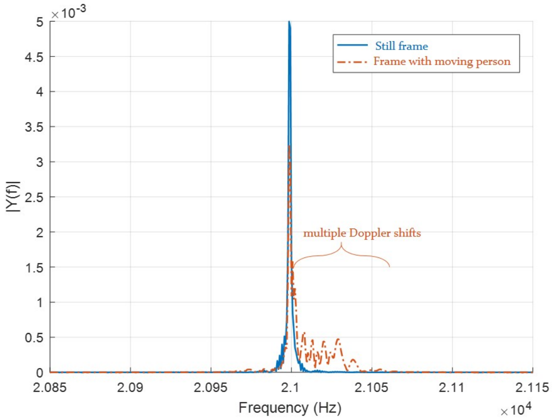

Figure 3: Difference in frequency spectrum between a still frame (blue) and a frame with a moving person (red).

The maximum Doppler frequency shift $\Delta_{f(max)}$ to be detected is a desgin choice, and is determined by the maximum possible velocity of a person's motion v_{max}:

$$\Delta_{f(max)} = \frac{2v_{max}}{c} f_c \tag{4}$$

When the room is unoccupied, the frequency spectrum of the recorded signal will be similar to the still one, and the motion score in Equation 3 should reduce to zero. However, due to possible noise, tiny differences between the two still spectra will yield a motion score that is close, but not equal, to zero. On the other hand, when there is a movement, the spectrum of the frame will include some Doppler shifts with respect to the still frame. The differences between the two compared spectra will add up to some value, yielding a score that is larger than the one corresponding to a still frame. In a more formal way, a *threshold* value should be carefully set in order to better differentiate between the two cases. If the motion score of a certain frame exceeds the threshold, it will indicate that some movements occurred in the room, while a score below the threshold value is assumed to correspond to a still frame.

The still frequency spectrum $|Y_{still}[k]|$ should be known to the system beforehand. At still conditions, when there are no movements inside the room, the signal frequency is not altered. Due to multipath propagation, the received signal will be composed of multiple copies of the transmitted ultrasonic signal $x[n]$. Assuming that M different multipath exist, the received signal, which is a summation of the multipath signals, can be represented in discrete time as:

$$y[n] = \sum_{m=0}^{M-1} \rho_m e^{j\phi_m} x[n - \tau_m] + v[n] \tag{5}$$

where ρ_m, ϕ_m, and τ_m represent respectively the signal attenuation, phase difference and time delay, of each of the multipath signals. $v[n]$ represents the noise. The values of ρ_m, ϕ_m, and τ_m are specific for each room setting, and depend on different parameters like room dimensions, and objects' positions. Since they are unknown to the system, the still frequency spectrum cannot be inferred at design time.

4. System Calibration

Both the *still frequency spectrum* $\{|Y_{still}[k]|\}$ and the value of the *threshold* constitute the system's required parameters for motion detection. When the system is installed, it needs to learn these parameters that correspond to its surrounding environment. Afterwards, the system uses the learned parameters in order to detect movements.

4.1. Manual Calibration

A simple and straight-forward approach for calibration, would be to have the room empty once the system is installed. The system will then trigger a series of transmissions and recordings. The collected frames would be used

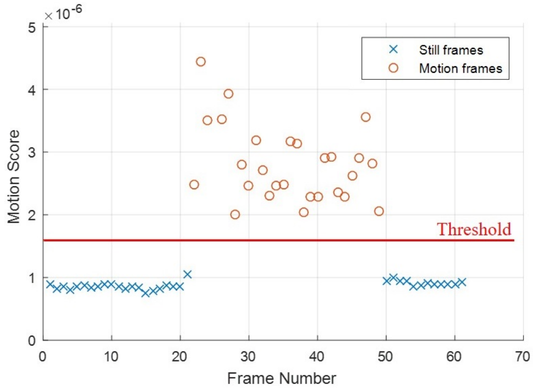

Figure 4: Frames clustering into *still* and *motion* frames, based on their corresponding motion scores.

afterwards to get the still frequency spectrum, and set the threshold value accordingly. Typical number of collected frames would be 10, with the still frequency spectrum being their average, and the threshold value set slightly above the maximum of motion scores, calculated for the collected frames. However, this way might be tedious and time consuming, especially because the user needs to install one module in each room. Therefore, and in order to ensure user comfort and seamless calibration, we propose a self-calibration method for our system.

4.2. *Self-Calibration*

The idea of the self-calibration is that the system senses the medium for a given duration, and collects a certain number of frames, to form a training set. Afterwards, the system uses unsupervised learning to classify the frames into *still* and *motion* frames. The system uses the information to get the still frequency spectrum and set the threshold value, according to the given room environment. The system would run the self-calibration process at installation time. The sensing duration should be long enough such that we are sure that there are moments when the room is occupied, and some others when it is vacant. The system keeps the frequency spectra of the collected frames. If N frames are collected, we denote their corresponding spectra respectively by: $\{|Y_0[k]|\}, \{|Y_1[k]|\}, \ldots, \{|Y_{N-1}[k]|\}$.

4.2.1. *Obtaining the Still Spectrum*

The still spectrum contains no Doppler shifts, and hence it has the lowest amplitude of frequency components. It can be obtained directly from the collected frames, even if we don't know the type of each frame yet. By just selecting the absolute minimum among all the frames, for each of the frequency components of the interval of interest I (Equation 3), we are sure to have picked the lowest frequency components, which correspond to the still spectrum $\{|Y_{still}[k]|\}$:

$$|Y_{still}[k]| = \min(|Y_0[k]|, |Y_1[k]|, \ldots, |Y_{N-1}[k]|) \quad \forall k \in I \tag{6}$$

4.2.2. *Frames Clustering*

The collected frames need to be divided into *still* and *motion* frames. The feature used to classify the frames is the motion score (Equation 3) calculated for each of them, using the obtained still frequency spectrum $\{|Y_{still}[k]|\}$. To cluster the frames, we use the k-means clustering method. To initialize the algorithm, the frame having the lowest motion score, is used as a starting point for still frames, since it is the closest to the minimum still frequency spectrum. Similarly, the most deviated frame from the still frequency spectrum, having the maximum motion score, is used as a starting point for motion frames. The rest of the training frames are then clustered into one of the two clusters. Once all frames are clustered to their correct type, a value of the threshold can be inferred. We define the threshold as the decision boundary given by the k-means clustering method.

Figure 4 shows the concept of frames clustering according to their motion scores, along with the threshold value. After the system has learned the necessary parameters through self-calibration, it becomes able to detect movements inside the room. The system may run the self-calibration process occasionally, in order to cope with potential changes

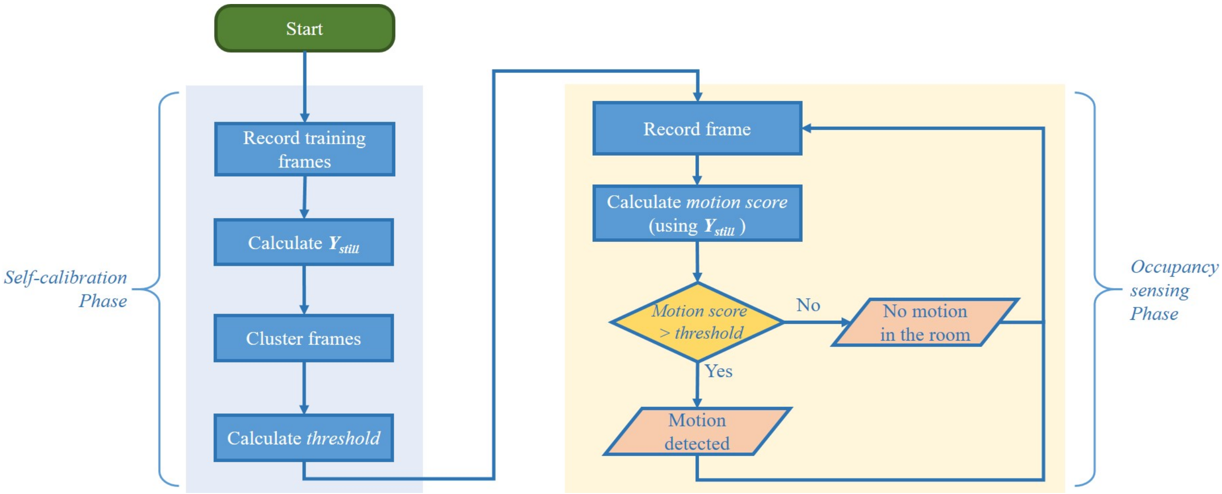

Figure 5: Diagram showing the self-calibration process and the occupancy sensing algorithm.

in the environment. In this case, the system continuously computes the still frequency spectrum and triggers the self-calibration when the change is major. Since this process is seamless to the users, the system can continue to operate without stop, while calibrating its parameters. Finally, we depict the self-calibration process and the occupancy sensing algorithm in the diagram of Figure 5.

4.2.3. Memory Usage

We briefly examine the memory requirement of the system. As for the self-calibration process, N frames need to be recorded in order to form the training set. We denote by T_{frame} the duration of one frame. The DFT of each frame is calculated and only the frequency spectrum of the interval of interest I (Equation 3) is retained, thus the number of samples needed for each frame is:

$$n_{samples/frame} = 2\Delta_{f(max)} \times T_{frame} \tag{7}$$

As N frames need to be stored during the self-calibration phase, the total required memory size is:

$$Required\ memory = N \times n_{bytes/sample} \times 2\Delta_{f(max)} \times T_{frame} \tag{8}$$

where $n_{bytes/sample}$ is the number of bytes needed to represent one sample.

Numerically, given a training set of size $N = 100$, a frame duration $T_{frame} = 3sec$, a sampling frequency $f_s = 44.1kHz$, a maximum Doppler frequency shift $\Delta_{f(max)} = 1kHz$, and assuming that $n_{bytes/sample} = 4$, the total required memory size would be around $2.3MB$. Once the self-calibration process is completed, this allocated memory can be freed, and only the threshold value and the still frequency spectrum Y_{still} need to be stored, requiring only $(1 + n_{samples/frame})$ samples, or $23.44kB$.

5. Experimental Evaluation

We have implemented a working prototype to test the functionality of the proposed system. The prototype, shown in Figure 6, comprises a low power commodity speaker, a commodity microphone, both connected to a Raspberry Pi board[18]. This board acts as the control/processing unit, and implements the calibration and occupancy detection algorithms described above. The prototype sends the occupancy results to a server via WiFi. The central frequency used is $f_c = 21kHz$, and $\Delta_{f(max)} = 1kHz$. The objective of this prototype is to examine the performance and capabilities of the proposed system, rather than creating a final product. However, once the design is validated, transforming the prototype into a more compact model should be straightforward.

To characterize the performance of UltraSense, we proceed with the following methodology: the prototype is placed inside the room. It is first calibrated manually as described in Section 4.1. Then, it runs the self-calibration

Figure 6: The implemented prototype comprises a commodity speaker and a microphone connected to a Raspberry Pi board.

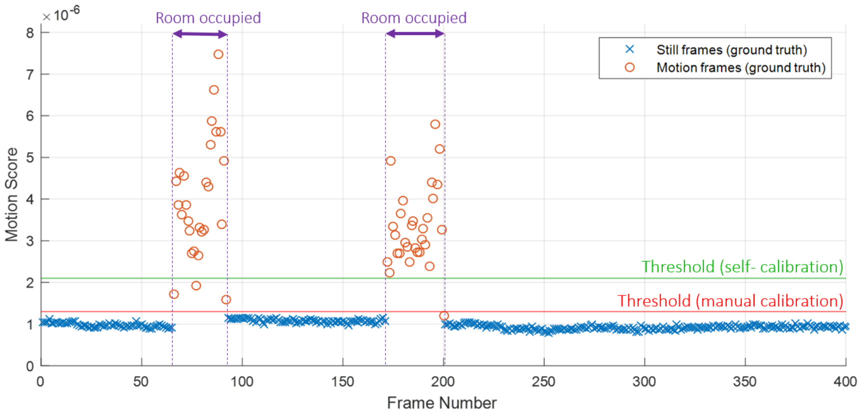

Figure 7: Comparison of motion detection using results obtained from manual and self-calibration, for a portion of the test set.

method as described in Section 4.2, using around 100 frames as a training set to obtain the motion detection parameters. Then, a large set of frames (1000) is recorded to form the test set. The collected frames include some still periods when the room is vacant, in addition to some movements when the room is occupied. During occupancy periods, people were going inside the room, walking around, then going out. Since we know at what moments the room was occupied, we label the frames into *still* and *motion* frames, so that this information is used to form the ground truth. Motion detection is applied to the test set, using the parameters obtained from manual calibration first, then using those obtained from self-calibration. The results are noted for comparison.

Aiming to cover different scenarios, the previous testing process is repeated for 4 different scenarios: in the first two, the prototype is placed in a small room ($6\times3.9m$) with clear LOS and NLOS (prototype placed behind a furniture), respectively. While the other two correspond to a large room ($6\times7.8m$), with clear LOS and NLOS, respectively. This way allows us to evaluate the system for different room sizes, and also to simulate the case when the sensing module is placed behind an obstacle. Figure 7 shows a portion of the testing set, as an example to illustrate how we evaluate the performance. The *detection rate* represents the true positives for occupancy detection results. The detection rates and false positives of both manual and self-calibration, are presented in Table 1.

Table 1: Results of detection rates for manual and self-calibration.

Scenario	Manual calibration: (detection rate — false positives)	Self-calibration: (detection rate — false positives)
#1: small room, LOS	98.2% — 1.0%	97.5% — 0.9%
#2: small room, NLOS	93.4% — 0.8%	91.8% — 1.2%
#3: large room, LOS	97.8% — 1.1%	96.1% — 1.3%
#4: large room, NLOS	89.2% — 0.7%	87.0% — 0.8%

Interpretation: The manual calibration uses solid conditions to infer the values of the detection parameters, and hence it yields the finest detection that the system is capable of. This explains the high detection rates accomplished by

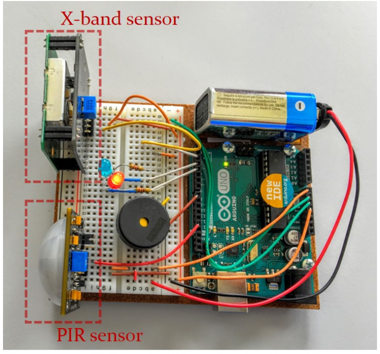

Figure 8: Circuit used to test the PIR and the X-band sensors.

manual calibration. On the other hand, the self-calibration uses unsupervised learning to get the detection parameters, which may still deviate from the perfect ones. Nonetheless, the self-calibration is still able to achieve high detection rates, though they are slightly inferior to those of manual calibration. However, given the fact that self-calibration is seamless to the users and promotes their comfort, and assuming that its high detection rates are satisfactory for the purpose of occupancy detection, we decide to integrate the self-calibration, rather than the manual one, in UltraSense system. We also note that the system still works with acceptable detection rates with NLOS, though it is more sensitive to movements in LOS conditions. The few false positives are due to random noises in the environment, however a simple sliding time window algorithm should be capable of filtering them out. The maximum range of the system is determined by the transmission power. With the used hardware, our system was able to detect movements within a range of around $8m$. However, multiple modules may be needed to cover larger areas.

Finally, we compare qualitatively the characteristics and capabilities of the UltraSense system with other occupancy sensing technologies, namely the PIR sensor, and the X-band motion detector. To do so, we implemented these sensors on an Arduino board, as shown in Figure 8, to verify their mode of operation. For the PIR, we used a model with a wide angle motion detection (model Parallax 28032[19]), and for the X-band motion detector we used the following model (Parallax 32213[20]). Table 2 shows an overview of the capabilities of each technology. The PIR sensor works only in LOS and is suitable for room scale applications. The X-band sensor has the capability to operate in NLOS, however it is not suitable for room granularity applications as it detects movements behind walls, leading to false positive detections. The sensitivity of both PIR and X-band sensors needs to be manually calibrated. Finally, UltraSense system is best suited for occupancy detection on a room scale, and when the system is desired to work equally under LOS and NLOS, with automatic calibration.

Table 2: Overview of the capabilities of different occupancy detection technologies

Occupancy Detection System	Works under LOS	Works under NLOS	Room Granularity	Self-Calibrating
PIR	YES	NO	YES	NO
X-band	YES	YES	NO	NO
UltraSense	**YES**	**YES**	**YES**	**YES**

6. Conclusion and future Work

In this work, we have presented UltraSense, an ultrasound-based room occupancy sensing system, which relies on unsupervised learning to self-calibrate according to the environment in which it is installed. UltraSense is non intrusive, and is able to work in different conditions, including LOS and NLOS. The proposed system was validated through a working prototype, and evaluated in different scenarios. The results show high accuracy of motion detection.

UltraSense system is limited to detect motions inside the room and uses this information to infer the presence of persons. However, it cannot detect the presence of a person standing still without moving. A future plan is to address this issue, and enhance the system to detect such persons by exploiting the room acoustic response under different conditions. Moreover, as kindly suggested by the anonymous reviewers, the possibility of occupants' counting is an interesting direction to explore. The system is also intended to be deployed and assessed in real world scenarios, and potential enhancements are to be suggested accordingly.

Acknowledgements

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