Enhanced Still Presence Sensing with Supervised Learning over Segmented Ultrasonic Reflections

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***Abstract*—Sensing the presence of people in indoor spaces allows smart systems to be aware of and responsive to the occupants, and paves the way for a wide range of applications. In this paper, we show how the reflection patterns of ultrasonic signals can be leveraged to detect the presence of still persons. We propose the use of supervised learning over segmented reflection patterns, and prove that this method is capable of detecting minute variations in the environment's response. The experimental evaluation of the proposed method in an office and a residential environment shows that it achieves a high presence sensing accuracy in the case of low signal-to-noise ratio (SNR), and a perfect accuracy in the case of high SNR, even in the case of non line-of-sight. Among the different tested classifiers, we found that the linear Support Vector Machine (SVM) achieves the best performance, yielding a presence detection accuracy of 84.3%-98.4% for low SNR, and 100% for high SNR, in the tested environments.**

***Keywords*—Ultrasound; presence sensing; supervised learning; reflection pattern**

I. Introduction

Sensing the presence of people represents an important input of smart systems, allowing them to be seamlessly aware of the occupants and responsive to their needs, thus promoting their comfort. Knowing the occupancy state of indoor spaces provides useful context information that paves the way for numerous applications, ranging from lighting control, Heating, Ventilation, Air Conditioning (HVAC) systems, to assisted living and security systems.

Presence information could be obtained using mobile localization techniques. With this approach, people would be asked to carry on a mobile device all the time, while a central system keeps track of the location of each user. Many possible technologies could be used for indoor mobile localization, which have been extensively studied and characterized in the literature. In this context, localization technologies include among others the use of WiFi infrastructure [1], [2], Bluetooth low energy beacons [3], [4], ultrasound systems [5], [6], [7], ultra-wide-band technology [8], [9], etc. Mobile localization techniques are able to achieve a high precision, and would allow the systems to know the exact number and location of occupants, assuming that each one of them is equipped with a mobile device. However, requiring the occupants to carry a mobile device all the time might become inconvenient, presenting a source of discomfort. Also, people could avoid carrying the mobile device, making some systems purposeless, like in the case of security systems for example.

Motion sensing is another way of inferring the presence of people in indoor environments. While several technologies are used for developing motion sensors, Passive Infrared (PIR) and ultrasound motion sensors remain the most prevalent [10]. PIR sensors are widely used to detect human motion, by responding to a change in the temperature pattern across the field of view of the sensor [11]. Different works have focused on algorithms to enhance the performance of PIR sensors and the processing of their output [12], [13], [14]. PIR sensors are attractive because of their low power consumption. However, the main drawbacks of PIR sensors are their limited accuracy and sensitivity to changes in the environment (sunlight, heating effect, etc.), as well as their limitation to work only in line-of-sight (LOS) conditions. On the other hand, ultrasonic motion sensors are based on non-audible acoustic signals, and sense human motions inside a certain area based on the Doppler effect principle [15], [16], [17]. These sensors are helpful to obtain fine information about the direction of movements and speed of occupants. They are more accurate than PIR sensors [10], and they are capable of sensing motions even from behind obstacles, due to the inherent nature of ultrasonic signals propagation. Human motions can also be detected with the use of RF-signals. In their work, Adib *et al.* [18] use WiFi signals to track human motions behind a wall and locate his position using a MIMO antenna array. However, a major limitation of motion sensors is the fact that they only detect persons when they are moving, while a person who remains still (sitting, sleeping, etc.) cannot be detected.

In this work, we exploit the use of reflection patterns of ultrasonic signals in order to infer the presence of still persons in indoor spaces. The reflection pattern is compared against a reference one in order to determine a similarity index. We argue that the similarity index evaluated over the whole reflection pattern may not be the best factor to differentiate the case of an occupied space from that of a vacant one.

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To cope with this issue, we propose evaluating the similarity indices over segments of the reflection patterns, so that a set of features characterizing a certain frame is formed. Supervised learning is used to train a classification model that is valid for mapping an unknown frame into a vacant or occupied state. We have tested the proposed method in an office and a residential environment, and the results show a high presence sensing accuracy in case of low signal-to-noise ratio (SNR), and a perfect accuracy in case of high SNR, even in the case of non line-of-sight. Among the different tested classifiers, we found that the linear SVM achieves the best performance.

The rest of this paper is organized as follows. First, Section II presents a review of the related work in the literature. Section III explains in detail our proposed method for presence sensing. In Section IV we present the experimental evaluation of the method. Finally, we state the conclusion and future work in Sections V and VI respectively.

II. Related Work

Some previous works suggested the use of ultrasonic ranging sensors for presence sensing [19], [20], [21]. These sensors use the time-of-flight of ultrasonic signals to determine the distance to a given target. Commercial models of these sensors are characterized in general by a narrow beam angle. In [19], an ultrasonic array is used along with PIR sensors to track people in a multi-residential home. The ultrasonic array consists of ultrasonic ranging sensors which track a person's height, using this feature as a unique bio-feature. Another work [20] proposes the use of a hidden Markov model based on the output of ultrasonic ranging sensors, in order to determine the presence of a user. In a similar work [21], these sensors are used to sense the presence of a person at his desk with a high accuracy.

Caicedo *et al.* [22] used the angle-of-arrival of a transmitted ultrasonic signal to locate a person inside a room. In their designed system, they consider the case of multipath propagation, but assume, however, that there is direct LOS between the system and the subject person, which may not be always the case. Bordoy *et al.* [23] locate a person using a single ultrasonic transceiver, based on the assumption that a human body moves slightly due to his breathing. They achieve a low error localization in a 2-dimensional space, but require a direct LOS with the located person as well.

The main contribution of our paper, is the proposed method in which the reflection patterns of the ultrasonic signals are used to sense the presence of still persons. The method is based on segmenting the reflection patterns and evaluating similarity indices over these segments to form feature vectors which can be used for classification. By segmenting the reflection patterns, the proposed method ensures a better perception of the environment as seen by the system, hence achieving a finer accuracy especially in the case of weak received signals. This way, the position of the occupant and the obstruction level in the environment have little impact over the presence detection rate.

III. Proposed Presence Sensing Method

A. Concept

Detecting the presence of a person in the indoor environment is based on emitting an ultrasonic signal and observing the reflected signals. A co-located transmitter and receiver take care of the transmission and recording of the ultrasonic signals, while a processor is responsible for the signal processing part and determines the presence state.

The method is based on the concept that each environment is characterized by a specific response to the emitted ultrasonic signal. When a person is present in this environment, she will cause some variations to the environment's response which will be reflected in the received ultrasonic signal. The aim of our method is to spot any variations in the environment's response with a high accuracy.

The emitted ultrasound is a short-time signal in the non-audible frequency range (above 20kHz). We have investigated different signal types, and preliminary tests showed that a chirp signal is more immune to interference, as compared to a sinusoidal signal. Therefore, the emitted ultrasonic signal $x[n]$ which we use in our presence sensing method is a chirp signal, whose discrete-time representation is:

$$x[n] = \sin\left(2\pi(\frac{f_0}{f_s})n + \frac{q}{2}(\frac{n}{f_s})^2\right) \text{ for } 0 \leq n \leq \lfloor f_s \times T_{chirp} \rfloor \tag{1}$$

where f_s is the sampling rate, T_{chirp} is the chirp duration, $q = {}^{(f_1 - f_0)}/_{2}$, f_0 and f_1 are the lower and upper frequency limits of the chirp respectively.

B. Reflection Pattern

Each indoor environment is characterized by a given response. This response depends on several parameters, like the environment's dimensions, boundaries, the position of obstacles, furniture, etc. We denote the environment's impulse response by $h[n]$, which defines the multipath propagation of the emitted signal's reflections, caused by the obstacles and environment's boundaries. It can be written as:

$$h[n] = \sum_{m=0}^{M-1} a_m e^{j\phi_m} \delta(n - \tau_m) \tag{2}$$

where a_m, ϕ_m, and τ_m represent the signal attenuation, phase difference, and time delay of the m^{th} multipath signal respectively. Note that $m = 0$ is the direct propagation of the emitted signal, between the transmitter and receiver.

We call a *reflection pattern*, the result of the environment's response to the emitted ultrasonic signal. When the ultrasonic signal $x[n]$ is emitted in the environment, the received signal $y[n]$ is the convolution of the transmitted signal $x[n]$ with the discrete-time version of the room impulse response $h[n]$, plus an additive noise $\nu[n]$ assumed to be white Gaussian:

$$y[n] = x[n] * h[n] + \nu[n] \tag{3}$$

The assumed noise is used to model the random noise caused by uncontrolled sources (ambient noise in the environment, noise introduced by the receiver, etc.).

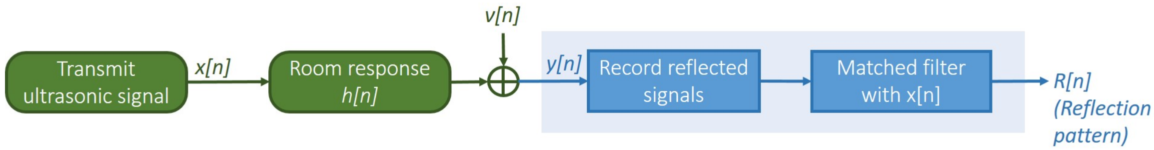


Figure 1. Obtaining the reflection pattern.

The reflection pattern $R[n]$ is obtained by applying a matched filter to the received signal $y[n]$, as depicted in Figure 1.

C. Comparing Reflection Patterns

The presence of a person in an indoor environment causes a modification in its response, as compared to the case where this environment is vacant. Instead of calculating a numerical expression of the environment's response for each frame, we statistically process the reflection patterns in order to spot the variations in the environment response.

We call $R_{ref}[n]$ the reference reflection pattern, which corresponds to the case where the environment is vacant. A certain reflection pattern $R[n]$ with unknown occupancy state is compared to the reference $R_{ref}[n]$ in order to infer whether the indoor environment is vacant or occupied by a person. The comparison of two reflection patterns is achieved by cross-correlation, to determine the similarity between them. We denote by *similarity index*, the maximum value of the cross-correlation result in absolute value:

$$similarity\ index = max|cross\text{-}correlation(\boldsymbol{R_{ref}}, \boldsymbol{R})| \quad (4)$$

The similarity index is a value ranging between 0 and 1. A high index (close to 1) shows high similarity of the compared reflection patterns meaning that the environment is vacant. On the other hand, a low similarity index indicates some variations in the environment response, and therefore the environment has been occupied.

The reference reflection pattern $R_{ref}[n]$ is obtained when the environment is vacant. To reduce the effect of noise when calculating $R_{ref}[n]$, we use multiple recorded frames instead of a single one. Assuming that the noise is additive zero-mean Gaussian, it can be mitigated by taking the average of a relatively large number L of reflection patterns:

$$R_{ref}[n] = \frac{1}{L}\sum_{k=1}^{L} R_{ref,k}[n] \quad (5)$$

D. Signal Propagation

When the ultrasonic signal $x[n]$ is emitted in the indoor environment, it propagates in a semispherical pattern. The direct line-of-sight copy of the signal is the first one to be picked up by the receiver as it travels the shortest distance. Subsequent multipath copies of the signal scattered by different objects, obstacles, and enivronment's boundaries are received at later time instants. After a certain time duration T_{total}, the propagated signal vanishes (becomes too weak to be picked up by the receiver). In Figure 2, we show an indicative example of the signal propagation in the case where the environment is vacant, and when it is occupied. This example aims to show only the concept of diversity of multipath propagation, rather than the actual exact propagation obeying physics laws.

The transmitted ultrasonic signal follows a pathloss model, which means that the more distance it travels, the lower its amplitude becomes. Therefore, the reflected copies of the signal caused by close objects are stronger than those caused by farther ones. If we denote by $m = 0$ the direct propagation of the emitted signal, between the transmitter and receiver (corresponding to propagation time τ_0), by $m = 1$ the first received multipath copy (scattered from the closest object), and so on, the last detected multipath signal corresponds to $m = M$. Since the traveled distance is directly proportional to the propagation time, if:

$$\tau_0 < \tau_1 < ... < \tau_M \quad (6)$$

then the corresponding amplitudes of the received multipath copies observed in the reflection pattern $R[n]$ are such that:

$$a_0 > a_1 > ... > a_M \quad (7)$$

E. Segmented Reflection Patterns

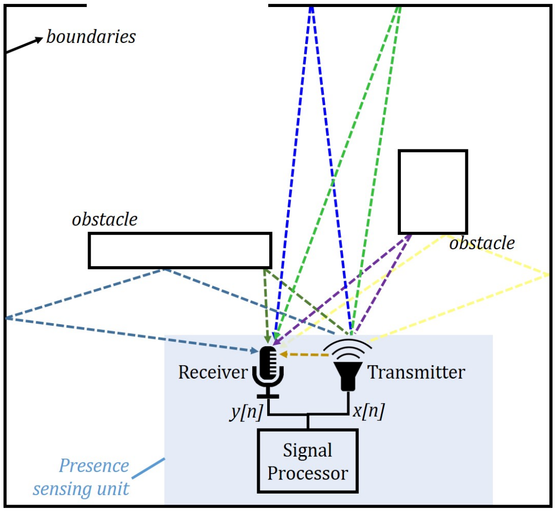
In the case where the environment is vacant, the impulse response is:

$$\begin{aligned} h_{ref}[n] &= \sum_{m=0}^{M-1} a_m e^{j\phi_m}\delta(n-\tau_m) \\ &= a_0 e^{j\phi_0}\delta(n-\tau_0) + a_1 e^{j\phi_1}\delta(n-\tau_1) + \ldots + \\ &\quad a_M e^{j\phi_{M-1}}\delta(n-\tau_{M-1}) \end{aligned} \quad (8)$$

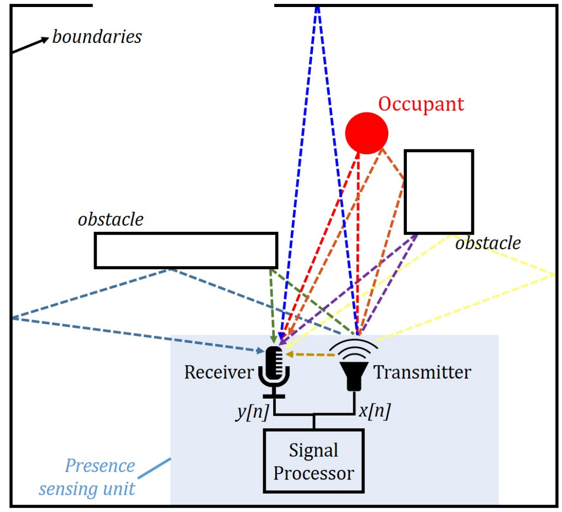
On the other hand, when the environment is occupied, the impulse response will be altered:

$$\begin{aligned} h_{occupied}[n] &= \sum_{m=0}^{M'-1} a'_m e^{j\phi'_m}\delta(n-\tau'_m) \\ &= a'_0 e^{j\phi'_0}\delta(n-\tau'_0) + \ldots + a'_{M'} e^{j\phi'_{M'-1}}\delta(n-\tau'_{M'-1}) \end{aligned} \quad (9)$$

While the multipath signals scattered from close objects and obstacles will not be altered, the occupant will cause some disturbance in the subsequent multipaths. If p corresponds to the first multipath copy that is affected by the presence of the occupant, then the first multipath signals $(m = 0, \ldots, p-1)$ are unchanged as they do not reach the body of the occupant.



(a) Vacant environment



(b) Occupied environment

Figure 2. Indicative example showing the difference of the emitted signal's multipath propagation, in the cases of (a) vacant and (b) occupied environments.

Therefore the impulse response of the occupied environment can be written as:

$$\begin{aligned} h_{occupied}[n] &= \sum_{m=0}^{M'-1} a_m e^{j\phi_m}\delta(n-\tau_m) \\ &= a_0 e^{j\phi_0}\delta(n-\tau_0) + \ldots + a_{p-1}e^{j\phi_{p-1}}\delta(n-\tau_{p-1}) \\ &+ a'_p e^{j\phi'_p}\delta(n-\tau'_p) + \ldots + a'_{M'} e^{j\phi'_{M'-1}}\delta(n-\tau_{M'-1}) \end{aligned} \tag{10}$$

The first unaltered multipath copies ($m = 0, \ldots, p-1$) of the signal are much stronger in amplitude than the subsequent copies ($m = p, \ldots, M' - 1$), as explained in the previous subsection. Therefore, the strong reflections from close objects and obstacles might mask the presence of the occupant, especially when he is not too close to the transmitter, or when she is been camouflaged by the furniture. In this case, the occupant will cause little variation to the reflection pattern, which will be masked by the strong reflections in the calculation of the similarity index (Equation 4). Hence, relying on the single similarity index evaluated over the whole reflection pattern, may not be decisive to detect presence, especially when the SNR is not high enough.

To illustrate the problem, we show in Figure 3 the values of the similarity index evaluated for some frames corresponding to a vacant environment, then for some other frames with the presence of an occupant. One can observe that differentiating the two classes of frames cannot be achieved by a simple threshold-based boundary.

To cope with this problem, we propose to extend the evaluation of the similarity index of Equation 4, and calculate it iteratively over segments of the reflection pattern. By discarding a certain segment from the beginning of the vector, corresponding to a duration of $T_{segment}$, all the reflections caused by the obstacles in the range of a propagation distance equivalent to $T_{segment}$ are ignored. In this case, if the little

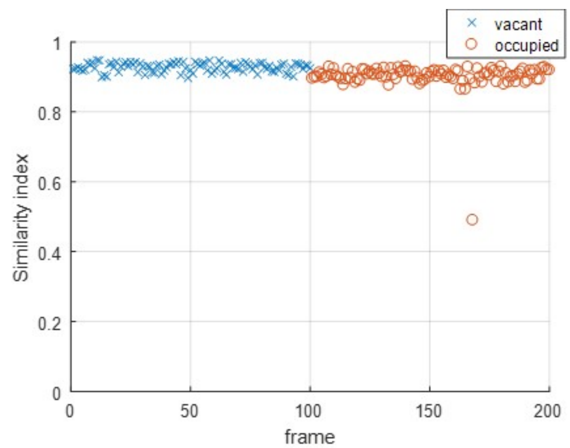


Figure 3. Similarity indices of frames corresponding respectively to vacant and occupied environment.

variations caused by the occupant are detected in the remaining vector, they will not be masked by the stronger reflected signals. Following this segmentation method, the similarity index is evaluated subsequently over multiple segmented reflection patterns, until the end of the reflection pattern vector is reached. This way, the i^{th} similarity index is obtained by discarding i segments from the reflection pattern vectors:

$$similarity\ index\ [i] = max|cross\text{-}correlation(\boldsymbol{R_{ref,i}}\ , \boldsymbol{R_i})| \tag{11}$$

where $\boldsymbol{R_i}$ (respectively $\boldsymbol{R_{ref,i}}$) is the reflection pattern vector $\boldsymbol{R}$ (respectively $\boldsymbol{R_{ref}}$) with i segments discarded:

$$\boldsymbol{R_i} = \boldsymbol{R}\{k, k+1, \ldots, N\} \tag{12}$$

with $k = \lceil i \times T_{segment} \times f_s \rceil$, and N is the total length of $\boldsymbol{R}$.

Figure 4 illustrates the evaluation of the similarity indices over segmented reflection patterns. In our design we use a

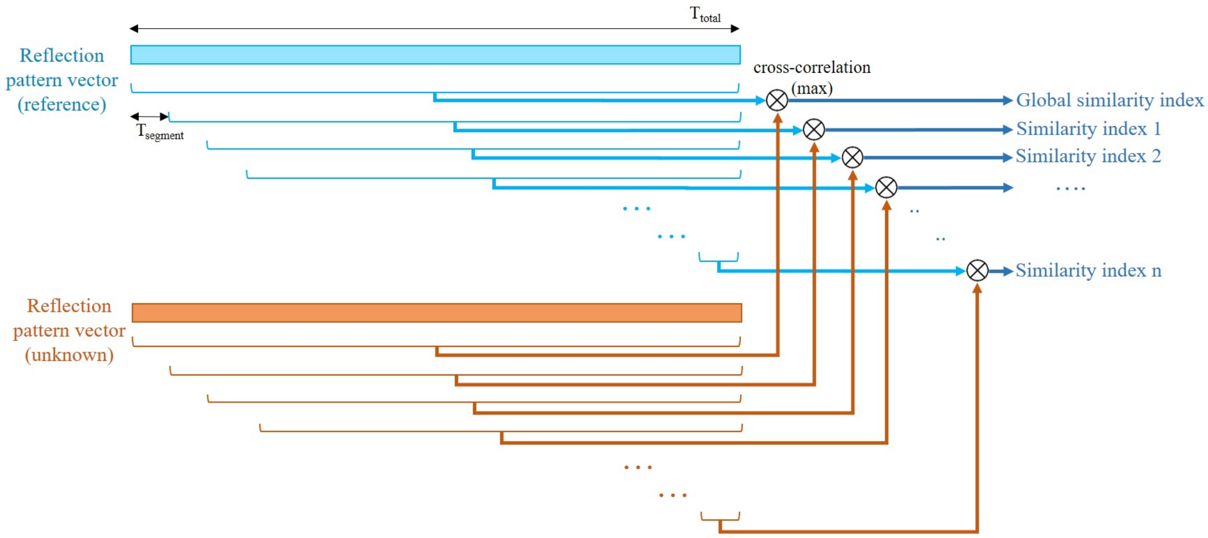


Figure 4. Similarity indices evaluated over segmented reflection patterns.

Figure 5. Segmenting the reflection pattern is equivalent to dividing the environment into segmented spaces (iteratively discarding the first i segments).

segment length $T_{segment}$=1.5ms, which approximately corresponds to a propagation distance of 0.5m.

Segmenting the reflection pattern into smaller chunks is equivalent to dividing the environment into segmented spaces, thus ensuring a finer perception of the environment, as seen by the system. Figure 5 illustrates this concept. However, due to the nature of multipath propagation, the segmented spaces in reality are not as uniform as shown in the figure, but rather have more complex shapes.

F. Classification

The similarity indices evaluated over segmented reflection patterns, as described in the previous section, are used as features to form a feature vector used for classification. For each frame, the global similarity index is evaluated as in Equation 4, and the rest of similarity indices as in Equation 11. The feature vector is then formed as follows:

$$\boldsymbol{V_{features}} = \begin{bmatrix} global\ similarity\ index \\ similarity\ index\ [1] \\ similarity\ index\ [2] \\ \vdots \\ similarity\ index\ [N_{segments}] \end{bmatrix} \tag{13}$$

where $N_{segments} = {}^{T_{total}}/_{T_{segment}}$.

Supervised learning is used in order to classify the feature vectors. The pattern classification model is trained using a set of labeled frames. These frames correspond to cases where the environment is *vacant* and where it is *occupied* by a person. Once the correct model is obtained, it can be used to classify any frame with unknown occupancy state, in order to determine whether the environment is vacant or occupied.

IV. Experimental Evaluation

In this section, we present the experimental evaluation of our proposed method. We start by showing the set-up used, then we explain the followed procedure to obtain the dataset and finally we present the results.

A. Set-up

The transmitter and receiver shall support ultrasonic frequencies. Commercial speakers and microphones are manufactured to support audible sounds, but they also support a tiny frequency bandwidth in the non-audible range. At a sampling frequency of 44.1kHz, commercial speakers and microphones support frequencies up to 22.05kHz according to Nyquist criterion, therefore the ultrasonic interval 20-22kHz is covered. In our tests, we use one commercial speaker as ultrasonic transmitter and a microphone as receiver (both of Logitech brand), which are connected to a PC used for the signal processing. While we opted for such components to complete the tests with convenience, it is worth noting that the same procedure could be reproduced using dedicated ultrasonic

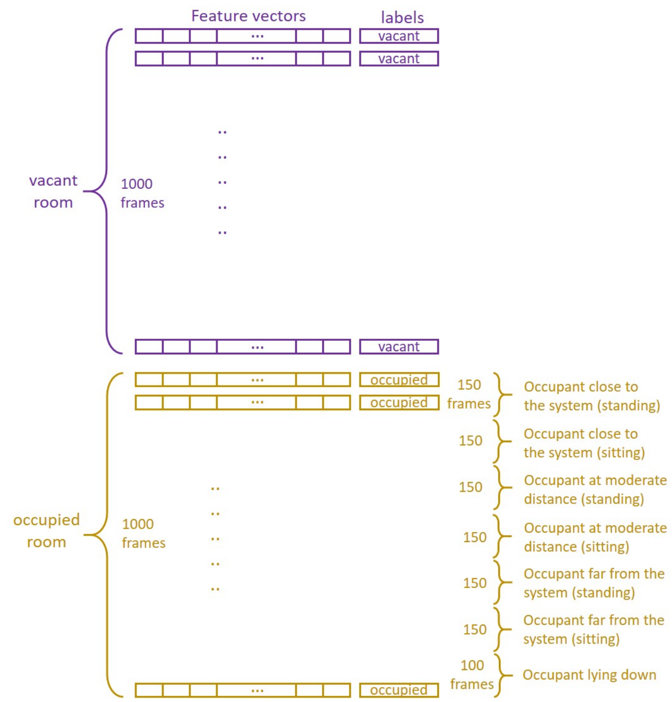


Figure 6. Dataset's frames distribution.

transducers, connected to a microprocessor that implements the signal processing algorithms.

The transmitted ultrasonic signal is a 10ms chirp signal with limit frequencies of 20-21kHz. The received signal is recorded with a total duration of T_{total}=0.3sec, corresponding to maximum propagation distance of around 100m.

B. Dataset

The system is placed inside an indoor environment and the reference reflection pattern is obtained from the average of $L = 100$ frames. In order to form the dataset, a large number of reflection patterns is collected. These reflection patterns correspond to frames where the environment is *vacant*, and others where it is *occupied* by a person. The occupied environment frames are recorded with different occupancy states, trying to cover the maximum number of different cases: person close to the system ($<$1m), person at a moderate distance (few meters), person far from the system ($\sim$10m where applicable), and person lying down. In all the cases except from the last one, the person was asked to sit down for half of the recordings, and stand up for the rest.

For each frame, the feature vector comprising the similarity indices with respect to the reference reflection pattern, is calculated as described in the previous subsection. All the feature vectors, along with the corresponding labels, are then combined to form the dataset. The dataset is formed from 1000 frames for the *vacant* case, and another 1000 frames for the *occupied* one. Figure 6 shows the distribution of the frames forming the dataset.

The described procedure is repeated for the following environments:

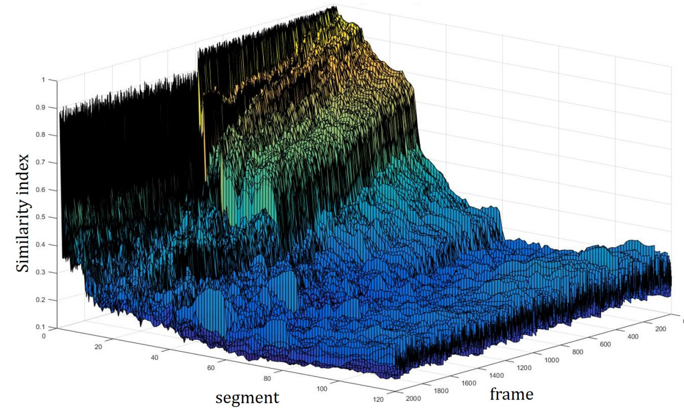


Figure 8. Similarity indices over segmented reflection patterns for vacant (frames 1-1000) and occupied environment (frames 1001-2000), case of high SNR, Room A, LOS.

- Room A: An office room of dimensions 7.8×6m. The first time the system was placed with a clear LOS, and the second time it was placed behind an obstacle, blocking the LOS.
- Room B: A residential room of dimensions 5.2×3.6m. The process was also repeated for LOS and NLOS.

In Figure 7, we show a map of the tests' environments and different positions of the occupant during the recordings.

In order to investigate the effect of the SNR over the performance. We repeat the procedure for low and high ultrasound amplitude level, resulting in two different SNR values for the received signal. The SNR is calculated by taking the ratio of the amplitude of the first received signal copy to the maximum noise level:

- Low SNR: The measured SNR is around 3dB.
- High SNR: The measured SNR is around 10dB.

In Figure 8, we consider one of the test cases, and we visualize the evaluated similarity indices over segmented reflection patterns, which form the feature vectors.

C. Classification Results

The pattern classification model is trained and validated using a 5-fold cross validation over the dataset. We compare the results of several machine learning algorithms, namely complex decision tree, Linear Discriminant Analysis (LDA), logistic regression, linear Support Vector Machine (SVM), and weighted K-Nearest Neighbors (KNN).

We assess the performance of each of the models using the detection accuracy, which is the rate of true positives (occupied frames correctly classified), and the false positive rate (vacant frames classified as occupied). Table I shows the performance of each of the models in the case of low SNR, and Table II shows the performance for the case of high SNR.

In the case of low SNR, we observe that overall the SVM classification model has the best performance considering the detection accuracy and false positive rate together. Nonetheless, the decision tree and logistic regression models achieve also a comparable performance to that of SVM. However, it

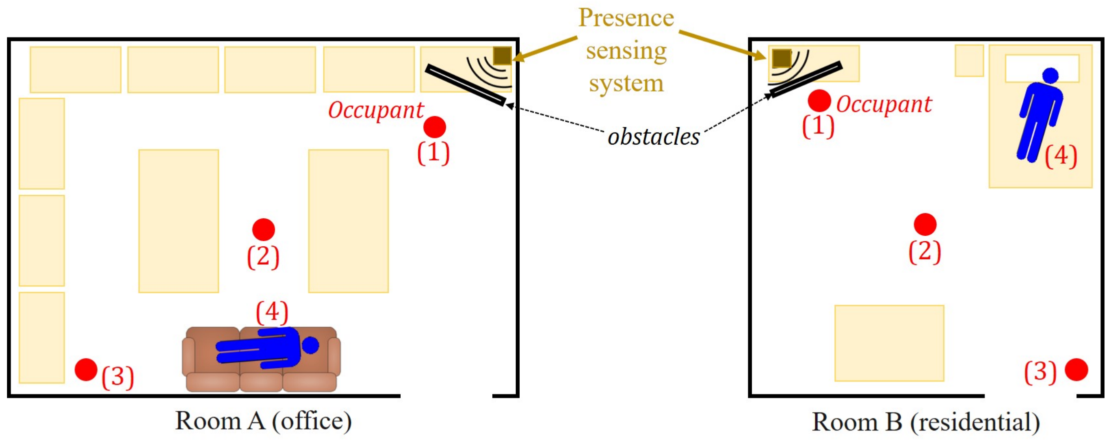


Figure 7. Tests' scenarios showing the occupant's position for the *occupied* frames: (1) close to the transmitter (standing/sitting), (2) at moderate distance (standing/sitting), (3) far from the system (standing/sitting), and (4) lying down. Obstacles are placed to simulate the NLOS case, and removed for LOS case

Table I. Performance **(Detection accuracy — False positives)** of the proposed method in the case of **low SNR**

Indoor Environment	Decision Tree	LDA	Logistic Regression	SVM	KNN
#1: Room A, LOS	94% — 6.5 %	91% — 21.3%	93.4% — 7.4%	**94.4% — 4.9%**	83.1% — 28.1%
#2: Room A, NLOS	78% — 21.4%	71.8% — 35%	84.2% — 14.7%	**84.3% — 10%**	69.7% — 31.1%
#3: Room B, LOS	98.5% — 1.8%	82.2% — 13.3%	98.4% — 0.6%	**98.4% — 1.3%**	74% — 11.7%
#4: Room B, NLOS	89.1% — 9.6%	76.6% — 19%	90.7% — 12.9%	**85.9% — 3.1**%	63.7% — 25.6%

Table II. Performance **(Detection accuracy — False positives)** of the proposed method in the case of **high SNR**

Indoor Environment	Decision Tree	LDA	Logistic Regression	SVM	KNN
#1: Room A, LOS	100% — 0%	100% — 0%	100% — 0%	**100% — 0%**	100% — 0%
#2: Room A, NLOS	100% — 0%	100% — 0%	100% — 0%	**100% — 0%**	100% — 0%
#3: Room B, LOS	100% — 0%	100% — 0%	100% — 0%	**100% — 0%**	100% — 0%
#4: Room B, NLOS	99.8% — 0.3%	98.4% — 0%	100% — 0%	**100% — 0%**	99.8% — 0.1%

can be deduced that the LDA and KNN are not valid models for the considered problem, since they result in a low accuracy and/or high false positive rate. In general, it can be seen that the proposed method works with non line-of-sight settings, though the performance is slightly inferior to that of the clear line-of-sight.

Finally, in the case of high SNR, our proposed method impressively achieves a perfect accuracy with a zero false positive rate in almost all classification models. This can be explained by the fact that a high SNR allows the detection of minute variations in the environment's response, while the proposed method guarantees that these variations are fairly spotted.

D. Remarks

During the experiments we focused on still presence detection. The user was asked to remain still during the recordings. However, similar results are expected to be obtained in case she were moving, since in this case she will also cause variations to the environment's response. But since the case of detecting a moving person was already addressed in our previous work [15], we limited our experiments to the case of still person sensing.

Given the inherent nature of ultrasonic signals, they are mostly limited by boundaries of indoor spaces (walls, doors, etc.), hence the presented system can sense the presence on a room-scale. In order to cover a complete indoor space, like the whole house or an office building, it is sufficient to place one sensing unit in each room.

V. Conclusion

In this paper, we showed how the reflection patterns of ultrasonic signals can be leveraged to infer the presence of still persons in indoor spaces. We propose to evaluate similarity indices over segmented reflection patterns, in order to form a set of features that can be used for classification into vacant and occupied cases. This method allows to detect the presence of people even when they are completely still, while the absence of line-of-sight and the occupant's position have little impact over the system's performance. The proposed method was tested and proved to achieve a remarkable accuracy with low SNR, and perfect accuracy with high SNR. The linear SVM is found to achieve the best performance among the different tested classifiers.

Since our proposed method performs well for low levels of SNR, it is suitable to use for applications with low power consumption requirements. A sensor developed to use this method could operate for an extended time using a limited energy source.

VI. Future Work

The reference reflection pattern was obtained manually by making sure the environment is vacant before recording. A future plan is to develop a method to make this process automatic, so that the system detects automatically when the environment is vacant, and calculates the reference reflection pattern accordingly. A possible way to accomplish this, is to observe the environment for over given duration, say one or several hours, and check if an activity is detected. Since a person is unlikely to remain still for several hours, the absence of activity would represent the condition for the system to re-calibrate. Additional measures are to be investigated in order to rapidly adapt to small changes in the environment (like moving furniture for example).

The presented system is capable of detecting the binary occupancy state (vacant or occupied). As a future step, we intend to examine the possibility of determining the exact location of the occupant especially in non line-of-sight based on the reflection pattern. Also, one could think of using the reflection pattern to determine the occupant's posture and activity (standing, sitting, sleeping). This way, the delivered services could be customized accordingly, like for example switching the lights off when the person goes to sleep, or changing the heating level when the person gets up.

While in our experiments the occupancy condition of the environment was considered with one occupant, the method can also detect if the environment is occupied in the presence of multiple occupants, since they would alter the environment's response. However, a future step is to investigate whether the reflection patterns of the signals could be used to infer the people's count in a certain area.

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