Indoor Occupancy Sensing with Ultrasounds

THÈSE

présentée à la Faculté d'Economie et de Management
de l'Université de Genève

par

Abbass Hammoud

sous la direction de

Dr. Michel Deriaz et
Prof. Dimitri Konstantas

pour l'obtention du grade de

Docteur ès Économie et Management
mention Systèmes d'Information

Membres du jury de thèse:

M. Dimitri KONSTANTAS, Professeur, GSEM - CUI
M. Michel DERIAZ, Docteur, GSEM - CUI
M. Gilles FALQUET, Professeur, GSEM – CUI, Président du jury
M. Jean-Henry MORIN, Professeur, SdS - CUI
M. Pedram PAD, Docteur, CSEM
M. Serge GRISARD, CEO, DomoSafety

Thèse no xx
Genève, 23 Nov 2018

knowledge is better than wealth; for knowledge guards you, while you have to guard wealth; and wealth is diminished when spent, while knowledge grows and increases when put in use.

— Imam Ali ibn Abi Taleb (AS)

Acknowledgements

I would like here, first of all, to acknowledge Prof. Dimitri Konstantas, and Dr. Michel Deriaz, the co-directors of this PhD thesis. I would like to thank them for giving me the opportunity to pursue my PhD at the University of Geneva, for their guidance and continuous support throughout the past years, up to the completion of the thesis. I would like also to thank the respected jury members: Prof. Gilles Falquet (president of the jury), Prof. Jean-Henry Morin (faculty of social sciences), Dr. Pedram Pad (CSEM), and M. Serge Grisard (CEO of Domosafety), for taking the time to evaluate the contents of the thesis, and for their valuable feedback, comments, and recommendations. I would like also to acknowledge the funding agencies for my research work: the State Secretariat for Education, Research and Innovation of the Swiss federal government and the European Union, in the frame of the EU AAL projects SmartHeat (aal-2014-153) and Many-Me (aal-2016-063), as well as the Commission for Technology and Innovation CTI, of the Swiss federal government, in the frame of the CTI project IDDASS (18877.1 PFES-ES).

I would like also to extend my thanks to the current and previous members of our lab, who became long-life friends. Specifically, I would like to thank Athanasios and Grigorios for helping me in my reasearch work, preparing and performing the experiments, and for being always supportive colleagues and friends throughout my PhD. Alberto and Maher were both successful and talented project leaders of the project SmartHeat, and helped me shape my ideas into working systems. Carlos, Tiago, Kevin, and Panagiotis also helped me in reviewing some of my work and publications, their comments and feedback were always useful and helpful.

Additionally, I want to express my gratefulness to all my friends in Geneva, Lausanne, Bern and Zurich, who made my life in Switzerland an enjoyable and rewarding experience. I thank them for staying next to me throughout those years, their support played an extremely important role in arriving to this life-milestone. Thank you Hamza, Dia, Rida, Beydoun, Mahmoud, Tarek, Ayoub, and all others.

Lastly, I would like to express my deepest thanks to my parents, Fatima and Hassan, for the life they gave me, for their sacrifices and for everything I learned from them. Thanks also for the two princesses in our family Hawraa and Ghaydaa, and for my brothers Mohammad Jawad, Ali Hadi, and Mohammad Hussein. May God bless them and keep us always together. This thesis is especially dedicated to my mother Fatima, the reason for my success, and the source of my happiness. Without you this journey would not have been possible.

Geneva, 23 November 2018 Abbass Hammoud

Abstract

As human beings, we rely on audible sounds as one way to communicate between each other and to infer information about our surrounding environment. Similarly, ultrasounds are used by some species in the animal kingdom to sense objects around them and get relevant information about their environment. In this thesis, we build on the inherent characteristics of ultrasounds and explore their application in occupancy sensing of indoor spaces, as ultrasounds exhibit interesting advantages compared to other technologies. Specifically, we design methods and algorithms to generate and process ultrasonic signals and infer the room occupancy, and we develop systems to evaluate their performance. Throughout the work, we address the implementation of our methods using commodity hardware, we pay attention to design algorithms that are computationally efficient, and we evaluate their time and space complexity. We focus on the reusability aspects in our designs, with the aim of bringing the technology to a wide range of existing and potential commercial devices, that would be able to implement our methods and algorithms seamlessly, and offer insights for new applications (like improving users' experience, enhancing home automation, etc.).

This thesis brings four main contributions. We start off by presenting our solution for a device-based occupancy detection system, in which the room occupancy is determined using people's smartphones. The system wouldn't be robust, unless the problem of signal interference and packet collision is mitigated. Therefore, we show how collisions could be detected, and propose a solution to reduce their occurrence probability.

Then, we move on to address device-free occupancy sensing, where we sense the presence of persons without requiring them to carry or wear any devices. In this regard, our contribution is a self-calibrating motion sensing system that is based on the Doppler effect. We show how unsupervised learning can be used to auto-calibrate the parameters of the system without prior information of the installation environment.

While active ultrasonic motion sensing offers a higher accuracy, it generally consumes more energy than traditional passive sensing technologies (like passive infrared sensors). To alleviate this limitation, our third contribution is a novel automatic power switching method that can reduce the energy consumption of the sensors. The method, which we call “power hopping”, allows a motion sensor to optimize its transmit power in function of the surrounding environment's conditions, and is automatically triggered every time the layout of the environment is detected to have changed.

In our last contribution, we address the sensing of still persons. For this, we explore the use of reflection patterns of ultrasonic signals. We show how we can process the signals and make use of supervised learning techniques, to accurately detect the presence of still persons, even in low signal-to-noise ratio conditions.

All of the presented methods and algorithms were experimentally evaluated using working prototypes. To summarize this dissertation, we discuss how our proposed methods and algorithms can be applied to make devices and appliances smarter, more aware and responsive to their users. These include smartphones, digital speaker assistants, PCs, smart TVs, and virtually any devices equipped with sound speakers and microphones.

Keywords: Ultrasound, Occupancy sensing, Persons detection, Indoor localization, Frequency/Time analysis, Machine learning, Smart Environments, Environment sensing, Motion sensors, Power switching

Résumé

En tant qu'êtres humains, nous utilisons les sons audibles comme moyen de communiquer entre nous et pour en inférer des informations sur notre environnement ambiant. D'une façon similaire, les ultrasons sont utilisés par certaines espèces animales pour détecter les objets qui les entourent et obtenir des informations pertinentes sur leur environnement.

Dans cette thèse, en partant des caractéristiques intrinsèques des ultrasons, nous explorons leur application dans la détection de présence dans les espaces intérieurs. En effet, les ultrasons présentent des avantages intéressants par rapport aux autres technologies. Plus précisément, nous créonsdes méthodes et des algorithmes pour générer et traiter les signaux ultrasonores et déduire la présence des personnes, tout en développant des systèmes pour évaluer leur performance. Tout au long de ce travail, nous abordons la mise en œuvre de nos méthodes à l'aide de matériel de base, nous mettons l'accent sur la conception d'algorithmes efficaces, et nous évaluons leur complexité temporelle et spatiale. De plus, en ce qui concerne nos conceptions, nous nous concentrons sur les aspects de réutilisabilité dans le but d'apporter la technologie à un large éventail de produits commerciaux existants et potentiels, qui seraient capables d'intégrer nos méthodes et algorithmes d'une façon transparente, et d'ouvrir la porte pour de nouvelles applications (comme améliorer l'expérience des utilisateurs, l'automation domestique...)

Cette thèse présente quatre contributions principales. Tout d'abord, nous commençons par présenter notre solution pour un système de détection d'occupation basé sur un appareil, dans lequel l'occupation de la pièce est déterminée à l'aide des smartphones des gens. Le système ne serait pas robuste, sauf si le problème d'interférence de signal et de collision de paquets est résolu.

Par conséquent, nous montrons comment les collisions peuvent être détectées et proposons une solution pour réduire leur probabilité d'occurrence.

Ensuite, nous abordons la question de la détection de présence sans appareil. Ici, nous détectons la présence de personnes sans qu'elles aient à porter d'appareil. À cet égard, notre contribution est un système de détection de mouvement auto-calibrant basé sur l'effet Doppler. Nous montrons comment l'apprentissage non supervisé peut être utilisé pour auto-calibrer les paramètres du système sans information préalable sur l'environnement d'installation.

Bien que la détection active de mouvement par ultrasons offre une plus grande précision, elle consomme généralement plus d'énergie que les technologies traditionnelles de détection passive (comme les capteurs infrarouges passifs). Pour remédier à cette limitation, notre troisième contribution est une nouvelle méthode de changement automatique de puissance qui peut réduire la consommation d'énergie des capteurs. La méthode, que nous appelons "power hopping", permet à un capteur de mouvement d'optimiser sa puissance d'émission en fonction des conditions de l'environnement, et se déclenche automatiquement chaque fois que la disposition de l'environnement est détectée comme ayant changé.

Dans notre dernière contribution, nous abordons la perception des personnes immobiles. Pour cela, nous explorons l'utilisation de modèles de réflexion de signaux ultrasonores. Nous montrons comment nous pouvons traiter les signaux et utiliser des techniques d'apprentissage supervisées afin de détecter avec précision la présence de personnes immobiles, même dans des conditions de faible rapport signal/bruit.

Tous les méthodes et algorithmes présentés ont été évalués expérimentalement à l'aide de prototypes fonctionnels. Pour résumer cette thèse, nous discutons comment ces méthodes et algorithmes proposés peuvent être appliqués pour rendre les dispositifs et appareils plus intelligents, plus conscients et plus réactifs à leurs utilisateurs. Il s'agit notamment des smartphones, des assistants haut-parleurs numériques, des PC, des téléviseurs intelligents et pratiquement tous les appareils équipés de haut-parleurs et de microphones.

mots clés: Ultrasons, Détection de présence, Localisation intérieure, Analyse de fréquence/temporaire, Apprentissage automatique, Environnements intelligents, Détecteurs de mouvement, Changement de puissance

Contents

1 Introduction

1.1 Everything Is Getting Smart

Smart buildings, systems, and appliances continue to flourish nowadays, driving a rapidly evolving internet-of-things (IoT) that promises to radically improve the quality of life of people, and promote their comfort, health and well-being. With this, the need is increasing for smart sensing solutions that serve as the eyes, ears and skin for the various systems, feeding them with useful context information about their surrounding environment. As smart systems are built around the needs of their users, sensing their presence and inferring the occupancy state of the indoor environments remain one of the most vital information for these systems. People spend most of their time indoors, it is estimated that the average person stays indoors approximately 90% of his time [1]. Inside their homes, office buildings, shopping malls, etc. people interact with a wide range of systems and appliances. Occupancy information make the systems seamlessly aware of and responsive to the inhabitants, and allow the systems to customize their operation to satisfy users' needs.

1.2 Anyone There?

In our everyday life, we need to tell the systems we interact with about our presence, every time the occupancy sensors are missing or are not adequate. You walk into a room where the lights are off and it is dark, if the lights do not recognize your presence themselves, then you need to look for the switch manually and turn them on. You like your home to be warm during winter and cool in summer when you and your family are inside, but if you care about your heating or cooling costs, you would like the systems to shut down when no one is there. If the systems can not sense your presence, you need to switch them off manually every time you are away, then switch them on again when you are back. So on and so forth. Instead of having to communicate our presence manually to the systems, smart occupancy sensing solutions were established with the aim of offering an automated and seamless means of detecting the presence of people in indoor spaces, and allowing them to customize their operation accordingly.

When it comes to examples of the applications of occupancy sensing, the list goes endlessly: When you are on vacation, you need to know when someone enters your home while you don't expect guests. You may like your noisy washing machine to run only when you leave your apartment. When the oven is overheating and nobody is there to watch, you want it to analyze the situation and switch off automatically. In your company, you have a business meeting with some clients, and would like to check directly if any of the meeting rooms is available, without the need to go and knock on each one of them. If you can think of similar applications in your daily routines, then scale this up by the countless possibilities that are triggered by an increasing population, and a rapidly evolving IoT, to get an idea of how essential occupancy sensors are becoming to our everyday life.

1.3 The Applications

Occupancy sensing is becoming a crucial part of our nowadays systems, especially with the increasing interest in smart systems and buildings, and the continuous growth of IoT. Indoor occupancy information paves the way for a wide range of applications and services. Here are some fields of applications where occupancy information is essential:

- HVAC systems: Heating, Ventilation, and Air Conditioning (HVAC) systems are designed to guarantee thermal comfort for the occupants and air quality in indoor spaces. Therefore, occupancy information of these spaces allows the systems to adjust their performance to satisfy the occupants.

- Energy efficiency: Heating and cooling systems account for a large fraction of buildings' energy consumption [2, 3]. In addition to the comfort, occupancy information allows these systems to shut down or reduce their performance when there are no occupants, in order to save energy costs. This also applies to electric appliances that can be turned off when no person is there, like a TV, a PC, or a voice digital assistant.

- Lighting control: Lights are generally needed when the corresponding places are occupied, and they can be dimmed or switched off when these places are vacant, to save energy and extend their lifetime.

- Emergency response: In the case of emergencies, occupancy information is crucial to guarantee efficient evacuation, or to timely locate any persons in need of help, and guide the first responders towards them.

- Security: Occupancy sensing allows the detection of unwanted intruders in prohibited access places, or to guarantee the safety of persons in hazardous zones (like factories, construction sites, etc.).

- Assisted living: Some segments of the population need assistance in their everyday life, especially elder adults, dementia patients, and impaired persons. Occupancy sensing solutions can enhance a smart home, where these persons can enjoy their autonomy, while benefiting from adequate assistance (personal or digital).

1.4 Ultrasounds

Ultrasounds are sound waves above the human hearing limit, and share similar physical properties with the audible acoustic waves. The human hearing capability is limited to a certain frequency range, considered to be between 20Hz and 20kHz [4]. Sound waves above 20kHz are non-audible and are called ultrasound. Figure 1.1 shows the frequency ranges of sound waves, which can be categorized into infrasound, audible sound, and ultrasound.

Figure 1.1: Frequency ranges of acoustic signals

The ultrasound technology has long been employed in different fields of applications due to their unique characteristics. Applications include:

- Ranging: accurate distance measurements.
- Medical imagery: diagnostic sonography.
- Non-destructive testing: quality of industrial products.
- Fluids characteristics: flow of fluids inside pipes, blood flow in veins.

The use of ultrasound technology for occupancy sensing offers some interesting advantages. So what are the main ones?

Room-level occupancy: Because of their nature, ultrasonic waves are inherently limited by walls and doors, which makes them an excellent choice to achieve room-level granularity, as compared to other RF-based technologies (WiFi, Bluetooth, X-band, etc).

Beyond line-of-sight: While many sensing technologies need a line-of-sight (LOS) with the occupants (like infrared-based, video cameras), ultrasounds propagate around objects and can cover what is behind LOS.

Commercial hardware support: Another interesting fact is that most commercial devices (speakers, microphones, smartphones) support a certain frequency range of ultrasound, namely that of 20-22kHz. The common sampling rate used in sound cards is 44.1kHz, while some use an even higher rate (48, 96, or 192kHz). This rate determines the Nyquist frequency, which is the maximum frequency that speakers and microphones can support, and is equal to half of the sampling rate, or 22.05kHz.

Signal processing: A certain custom ultrasonic signal can be synthesized and played by an unmodified sound speaker. Similarly, the received raw signals can be recorded by a microphone and later processed in software. Hence, the complete processing loop from transmission to reception can be completed using software-defined methods only, without the need to modify the hardware. This advantage of low-level signal processing is not offered by other technologies, say WiFi for example. Works that use WiFi technology for occupancy sensing, either rely on high level processing of received signals and have no control over the form and characteristics of the transmitted signals, or use modified hardware to allow unsupported signal types and modulations, which limits the methods' reusability and the seamless integration with existing commercial hardware and devices.

Effects on humans: As we mentioned previously, the human hearing capability is limited to a maximum of 20kHz, and this limit diminishes with age. Therefore, even babies or young children will not be disturbed by the ultrasonic signals we consider, which are limited to the frequency range of 20-22kHz. Up to this date, and to the best of our knowledge, there is no sufficient evidence to characterize any negative effects that may result from the exposure to the ultrasonic signals.

Unlike humans, pets are able to hear some frequencies of the ultrasonic range, like dogs (64Hz-44kHz) and cats (55Hz-77kHz) [5]. However, it is not clear whether this would have any negative impact on their behaviors, compared to other ambient sonic noises. In our tests, we do not involve any pets to check this issue, since our aim is to benefit from the existing hardware to validate and test our methods and algorithms for 20-22kHz. However, since the same methods can be employed with higher ultrasonic frequencies, not audible to pets, future improvements in the manufacturing of hardware components would allow to support these frequencies, and alleviate this limitation.

1.5 Occupancy Sensing Approaches

A variety of methods and technologies have been employed to sense the presence of people in indoor spaces. We can differentiate between two main approaches in this regard: The first approach assumes or requires the occupants to carry or wear a device on them, we refer to this approach as *device-based*. Whereas the second approach senses the presence of persons without the need for a carried device, referred to as *device-free*. We present here the aspects of each of the approaches.

1.5.1 Device-Based Approach

The device-based presence sensing approach leverages the localization of mobile devices and maps them to their holders, in order to infer the occupancy of indoor spaces. This field is known as indoor localization, and has been gaining increasing attention, research, commercial and standardization efforts in the recent years. In a typical scenario, a central system or server locates the devices in the area of interest, or each device would infer its own location and communicate it to the system.

While the technologies for indoor localization span a wide spectrum, the mobile device to be located depends on the underlying technology. Most of these technologies target the use of existing devices which users already possess, or can acquire with a reasonable cost or effort. Typically, such devices are of general purpose type like a smartphone or a bracelet. Some technologies supported with general purpose devices include WiFi, Bluetooth, low frequency ultrasound (20-22kHz). In other cases, a custom device developed specifically to support a certain localization technology is used, which an average user doesn't necessarily have. Examples include an Ultra-Wideband (UWB) enabled device, a device equipped with an RFID tag, or a device to support high frequency ultrasound (above 22kHz), etc. This would be usually the case when the underlying technology is not supported by a generic device.

By mapping located devices to their holders, one can obtain comprehensive information about the occupancy state, people count, their movements and activity (time spent at different locations, paths followed, etc.). This information may be used later not only to feed occupancy-driven systems and to customize their services, but also to gain relevant insights about people preferences, behaviors, and their overall experience.

One advantage of this approach is the high accuracy that could be achieved through indoor localization techniques, with the most promising of them offering an accuracy within a few centimeters [6]. Another advantage is the ability to know the exact occupancy, people count, and possibly people identity which are inside the areas of interest. Depending on the desired application this approach can be very useful. Let us consider this example: A large shopping center, an exhibition, or a museum wants to collect statistics about its customers or visitors, in order to study their interests, and assess their overall experience. This would not be possible without obtaining exact occupancy information, not only which locations were occupied or not at different times, but also how many people visited a certain spot, what these people were also interested in during their visit, and how long they stayed overall.

On the other side, the main disadvantage is the need for the occupants to wear or carry a device that supports the localization system being used, which cannot be always available or guaranteed. The device to be located needs to be configured to support the localization system. Moreover, requiring the occupants to carry the mobile device all the time might become inconvenient in some cases, presenting a source of discomfort. For example, it might not be convenient to use a device-based occupancy sensing system in a smart home, as this will require the inhabitants to carry the mobile device all the time. Furthermore, some systems may lose their whole purpose if people could just avoid carrying the mobile device, this could be the case of security systems for example.

1.5.2 Device-Free Approach

The device-free approach is based on using a sensing module to detect the presence of people in indoor spaces. The sensor usually detects one or more characteristic of a human body in order to infer the occupancy. This goes around answering the question: What characterizes a human body, as compared to other objects (walls, structures, furniture, etc.)? The sensing technology then relies on the answer to the question. This can be related to:

- Heat: A human body's temperature can be used to distinguish it from its surroundings. This heat manifests as emitted infrared radiations [7].
- Motion: A human being can change position or move parts of his body, unlike static objects (wall, chair, table, etc.) [8].
- Signal reflection: When a person is present in a certain environment, he or she will alter any mechanical or electromagnetic signals that propagate in the environment and reach his body, through reflection and scattering [9].
- Breathing: The human body breaths normally with a rate of 12 to 20 breaths per minute. When he does so, he consumes oxygen (O_2) and generates carbon dioxide (CO_2) [10], and his chest moves periodically to allow cycles of inhaling and exhaling [11].
- Appearance: A person's image and shape can be used to recognize his presence [12, 13].

In addition to the mentioned characteristics, any other feature that physically identifies a person's presence can be leveraged (like talking, pressure on ground or chairs, etc.), and used with an appropriate detection technology.

As a comparison to the device-based approach, an advantage of device-free is the unnecessity for people to have a device on them all the time. This allows more comfort for the users, and offers more flexibility for the potential applications. Moreover, with this approach the privacy of the occupants is preserved, as their identity is not linked with the devices (with the exception of technologies that can still identify people, like video cameras). Additionally, setting up and using occupancy sensing systems becomes more convenient with this approach, as there is no need for pre-configured devices to be carried or worn by the target users.

However, the major drawback of the device-free approach, is the limitation of information about the occupants' behaviors, which can be used for statistical analysis. This is due to the lack of identification of the occupants.

In general, the choice of the approach is governed by the application of the occupancy information. When exact data and details about the occupants are sought, then a device-based approach is necessary. On the contrary, if only general occupancy information is required, like to know which spaces are currently occupied by someone and which are vacant, then a device-free approach is more suitable. In Chapter 2, we elaborate more on the two approaches, by presenting the different technologies and methods that are used for each of them.

1.6 Thesis Scope

The scope of this PhD thesis is to come up, study, analyze, develop and implement novel methods and algorithms for occupancy sensing using ultrasounds, and to obtain a thorough knowledge of the capabilities and limitations of this technology.

Occupancy sensing is a broad field that spans different dimensions of resolution, whether it is spatial, temporal, or information about occupants. In order to define the exact scope of this thesis, we refer to the occupancy resolution models described in the literature, which categorize the resolution levels.

In their paper [14], Melfi *et al.* summarize the different occupancy resolution levels in the decomposition shown in Figure 1.2. In their model, the authors categorize

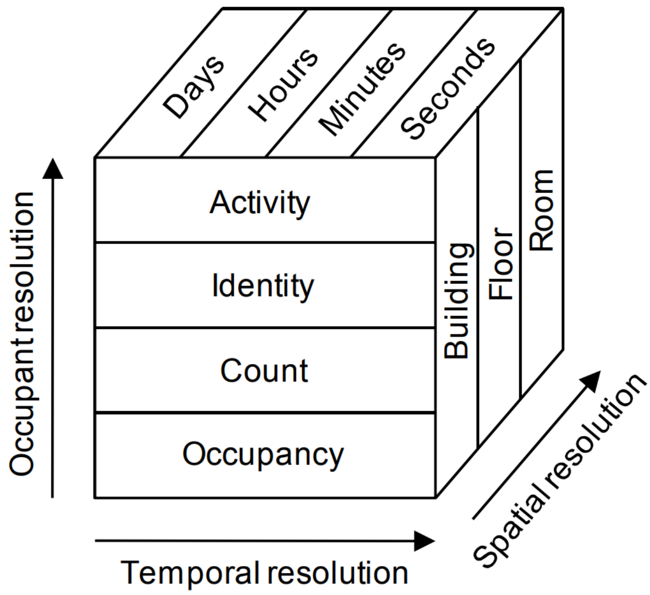


Figure 1.2: Occupancy resolution as described in [14]

the occupancy resolution problem using three dimensions:

- The spatial resolution, which includes the building, floor, or room resolution.

- The occupant resolution, composed of the occupancy (binary case: occupied or not), count, identity, and activity.
- The temporal resolution, whether it is in days, hours, minutes, or seconds.

Each level of occupancy resolution has its own set of applications, and may require different methods and techniques. For example, general binary occupancy detection is different from specific presence identification. The general occupancy sensing concerns knowing whether the indoor spaces are occupied by some persons or not, regardless of the identity of these occupants. This type of information is useful for applications like lighting control, heating and cooling, emergency response, etc. where only the presence of the occupants, and not their identity, affects the provided services. Presence identification consists of knowing who is present in a certain indoor space at a given time. This can be handy in applications like intrusion identification, or can be used to collect statistics about the occupants and their activity. With the exception of video cameras, identifying the presence is mainly possible through device-based methods. The same concept applies to other dimensions like space and time. For example, building or floor occupancy may be used for intrusion detection and requires less infrastructure, whereas room occupancy can be used for lighting or heating control and requires a different deployment of sensors. Similarly, a resolution of hours may be used for collecting some statistics about the occupancy, whereas a resolution of seconds is useful in real-time applications.

The previous model of occupancy resolution was later refined by Palipana *et al.* [15] (Figure 1.3). The refined model categorizes the occupancy resolution by space (building, floor, room, point), occupants (presence, head count, tracks, activity, identity), and time (offline, hours, minutes, real-time). Given these models, we define the target scope of this dissertation. Following Melfi *et al.*'s model, the scope falls in the occupancy resolution of room (spatial resolution), binary occupancy (occupant resolution), seconds (temporal resolution). Similarly,

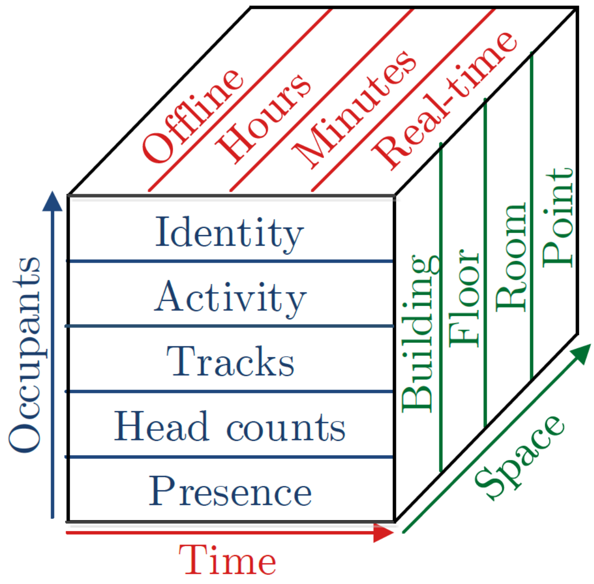


Figure 1.3: Refined occupancy resolution in [15]

if we follow Palipana *et al.*'s model, we can define the scope as room resolution (space resolution), presence (occupants resolution), and real-time (time resolution).

1.7 Thesis Contributions

My thesis brings four main contributions:

- I present my design of a device-based occupancy sensing system using ultrasounds, in which a user's smartphone locates the room it is inside using ultrasonic packets. We show how we can turn commodity sound speakers into ultrasonic beacons, and describe our solution for a reduced complexity packet decoding, using a two-step process comprising a coarse detection and a fine decoding methods. We prove that, under the discussed conditions, packet collision cannot be fully eliminated. Rather, we describe how these collisions can be detected, and reduce their probability by a careful choice of emission periods. We present our implementation of the described methods using commodity sound speakers and smartphones. For this purpose, an Android application was developed to decode the ultrasonic packets and locate the subject device. In order to assess the performance of the system, we test it experimentally in an office environment including two adjacent rooms of different sizes, connected with a hallway. Under ambient noise conditions, the system achieves a room localization accuracy of 98%, despite packet collision.
- As for device-free occupancy sensing, I present a self-calibration method for an ultrasound-based motion detection system, called UltraSense. The method allows the system to auto-calibrate its parameters using unsupervised learning techniques, without a prior knowledge of its installation environment. This avoids the need for manual calibration of the sensing modules, as it is the case with conventional sensors in use. I implement a prototype of the proposed system using a Raspberry Pi board[1] and commodity speaker and microphone. The system is proved to achieve a high accuracy in different scenarios, including non line-of-sight

[1] Raspberry Pi 3 Model B: https://www.raspberrypi.org/products/raspberry-pi-3-model-b/

conditions, a challenge that current occupancy sensors fail to overcome. We have tested the system in rooms with different sizes, and with varying conditions (LOS and NLOS), and the results show an accuracy between 87 and 98%, with a false positive rate between 0.7 and 1.3%.

- To solve the problem of higher power consumption associated with ultrasonic motion sensors, as compared to passive ones like infared, I introduce an automatic power switching method, which I call power hopping. The method's objective is to optimize the transmit power level, by calculating automatically the optimal value for a given environment. I also design an algorithm to automatically detect any changes in the environment layout. The proposed method and algorithms are implemented, tested, and the results validate the assumption of the possibility to reduce the energy consumption, which reaches up to 78% in our tests.
- I propose a method for sensing the presence of still persons with ultrasounds. We start by discussing how the presence of persons affect the propagation of ultrasonic signals through reflection and scattering, and that by observing the reflection patterns of the signals one can theoretically infer the occupancy state. We explain the limitation of masked presence especially in poor SNR (signal-to-noise ratio) conditions. To solve this challenge, I propose the use of segmented reflection patterns, and show that the application of supervised learning over features extracted from these patterns can result in a very high accuracy, even in low SNR conditions. We evaluate the performance of the system in office and residential environments, under LOS and NLOS conditions, and with different positions and postures of the occupants. With the best tested classifier (SVM), we were able to achieve an accuracy of 86-98%.

By addressing the use of commodity hardware to prove the designed methods, I aim to offer a solution that can work across different existing and potential commercial devices, which will open the door for new applications of smart homes, systems, and devices.

1.8 New Potential Applications

We envision that our presented algorithms and solutions can be used in various domains. Here are some possible applications that can be enabled through our work:

- A shopping center, a hospital, an airport, or a museum that uses installed loudspeakers for broadcasting announcements, or playing music, can turn them directly into ultrasonic transmitters that can be used for localization of occupants, using our proposed system (Figure 1.4). The transmission of ultrasonic signals can co-operate seamlessly with traditional loudspeakers'functions. With their consent, the occupants use an application on their smartphones for localization, and share their indoor location with the management system to customize a certain set of services. An example of these services would be to redirect the occupants to exit doors in a balanced way in case of an emergency, achieving an efficient and safe evacuation (Figure 1.5).

- With its speaker and microphone, a PC can use our ultrasonic motion detection method to detect when the user walks away (Figure 1.6). In this case, the PC may go to lock mode in order to avoid unwanted access from other persons.

- A TV screen can similarly detects when the user walks in (Figure 1.7). In his home, the TV can play an excerpt of the users' preferred news or programs when he returns home, or pause on a movie when he moves out of the room. In a hotel room, it can be used to play a welcome message for the guests and show them a video of the top attractions in the region. In a museum or exhibition, it can display information for people when they enter a room or a section.

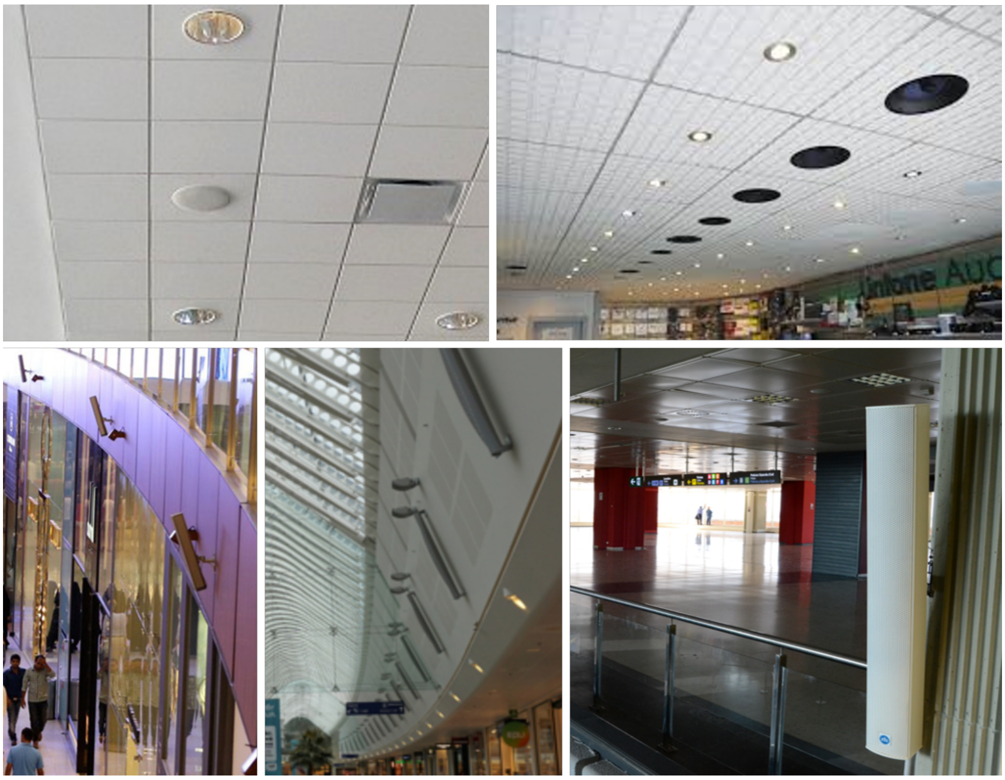


Figure 1.4: Ceiling and wall-mounted loudspeakers already installed in buildings like shopping malls and airports, can be used as ultrasonic transmitters for occupancy sensing.

Source: *https://www.prosoundweb.com/images/uploads/LargeEVNewAirport.jpg - https://www.lintone.co.uk/media/wysiwyg/CEILING_SPEAKERS_2_.JPG - https://meyersound.com/wp-content/uploads/2014/05/mall_feature1.jpg - https://www.prosoundweb.com/wp-content/uploads/2015/09/20150929harman.jpg - https://www.renkus-heinz.com/upload/dsc_0925-2-thumbnail.jpg*

Figure 1.5: In case of an emergency evacuation of a crowded place, the management system should be able to quickly estimate the occupancy of different spaces, in order to guide people to safe exit doors in a balanced and efficient way

Source: *https://static1.st8fm.com/en_US/content_pages/1/pages/simple-insights/img/80-for-black-friday-shopping-list-wide.jpg*

Figure 1.6: A PC can use ultrasonic signals to detect that his user is walking away, in order to switch to lock mode

Source: *https://s3.envato.com/files/aae12db7-a45f-4397-b693-d35057a4ae5b/inline_image_preview.jpg*

Figure 1.7: Smart TVs in homes, hotels, or museums can use ultrasonic signals to sense the occupancy of their environments, and customize their displays accordingly

Source: *https://ntmresizer.azureedge.net/sized/780/437/www.cfmedia.vfmleonardo.com/imageRepo/4/0/64/854/122/43422x_P.jpg - https://www-static.operacdn.com/static-heap/67/67ee871aaed2eaddcb62b91e7d6f0aa210717989/opera-tv-livingroom.jpg - https://t-ec.bstatic.com/images/hotel/max1024x768/134/134728303.jpg - https://static1.squarespace.com/static/574ef83b4d088e84c523b0e8/57505dd39f726601674e874f/57505dd4555986cfe502ba74/1465494032646/empathics_2.jpg?format=1500w*

Figure 1.8: A smartphone can use ultrasounds to sense if the user is in the vicinity or not, and adjust the ringing volume accordingly

Source:
https://austinlchurch.com/wp-content/uploads/2016/02/sell-what-people-are-buying-1024x683.jpg

- A smartphone can use its built-in speakers and microphones to sense motions in its vicinity and infer if the user is nearby (Figure 1.8). The smartphone can therefore adjust the ringing volume according to the scenario: the phone will ring with a low volume when the user is detected in the vicinity, and when the user is not detected to be around, the phone can either ring with a high volume or reply with a custom automated message.

- In the same way, a smart speaker assistant can sense motions around to help the virtual assistant customize the delivered services, or improve the communication with the user (Figure 1.9).

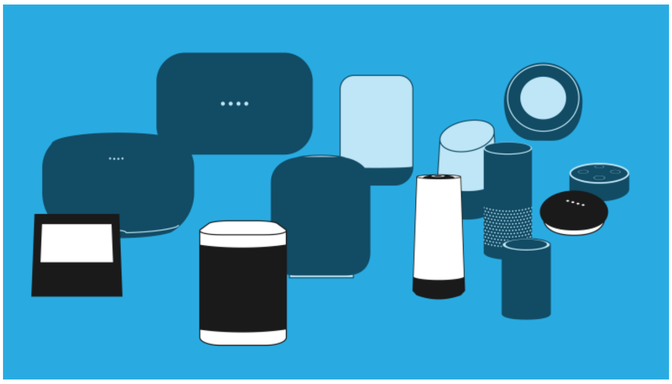


Figure 1.9: Our proposed methods can enhance the capabilities of smart speaker assistants, and their response to the user

Source: *https://techcrunch.com/wp-content/uploads/2017/10/voice-assistants.png?w=1390&crop=1*

1.9 Thesis Frame

The work presented by this dissertation was mainly completed in the frame of the European project SmartHeat[2]. The project is part of the Active Assisted Living (AAL) Programme, and consists of developing an intelligent heating management system, especially targeting the elderly population. The aim of my work is to provide a robust and reliable solution for presence sensing inside residential buildings. The occupancy information obtained by my solution is fed to the smart system, so that it can learn the users' habits and behaviors. Accordingly, the system can improve the heating conditions of inhabitants and reduce energy costs.

Here follow the main desired characteristics that our work aims to fulfill in the frame of the project. These characteristics emerged from the requirements set by the needs of the project's end-users. Nevertheless, the generic nature of these requirements allows the re-usability in other types of applications as well. In addition to the basic requirements, like the reliability, robustness, and accuracy, here are the main targeted ones:

[2]AAL SmartHeat Project: http://www.smartheat-aal.eu/

- Non-intrusiveness: It is desired for the solution to ensure user's comfort, and be non-invasive for his privacy.
- Non line-of-sight operation: The sensing solution should be able to operate in both LOS and non-LOS conditions, allowing for continuous sensing if the system is obstructed by objects or furniture. This is also useful since elderly people might be reluctant to accept visible sensing modules.
- Convenience of use: The solution should be convenient to use, seamless, and not requiring heavy infrastructure or equipment to be deployed. Moreover, it desired to be easily scalable.
- Room-level operation: The presence sensing solution is required to have a room granularity, and hence our work focuses on room-level occupancy detection. We define a room as a space enclosed within four walls, with possible entry through a door that connects it to a hallway or another room. The typical size of a room we consider is in the order of few to tens squared meters, nonetheless the coverage of the sensing system can be enhanced, if need be, with a higher transmitted signal power using suitable hardware components.

SmartHeat project was run through a consortium of 8 European partners, some of which are focusing on technical aspects, and others focusing on end-users. The technical aspects include the core system that learns the habits of the users and controls the heating through smart valves, the design of the smart valves, and the occupancy sensing solution. The end-users partners focus on all other aspects, like getting the requirements desired by the end-users, assessing the acceptability of the used technologies, the evaluation of the developed systems, addressing the security and privacy concerns, and checking the compliance with European regulations and standards.

Within the frame of the thesis, the proposed methods and techniques were implemented and evaluated using functional prototypes. We have built these prototypes by integrating mainly COTS components and some custom-made modules using our expertise, and with the help of our technical partners, namely the Spanish-based SME ModoSmart, and the Italian-based company Sensor ID. The developed prototypes were tested and characterized in realistic environments (details follow in the corresponding experimental evaluations). The next step is for our industrial partners to miniaturize the prototype in a small-size sensing module, implement the communication protocol through Bluetooth or Zigbee, and integrate it into the complete SmartHeat system. The leading of the commercialization, ModoSmart, will have up to 2 years as a time-to-market after the project's end, in order to have the system ready for the market, according to the AAL committee's instructions.

As we mentioned previously, some pets may be able to hear ultrasonic waves. However, studying the effect of the used ultrasounds on pets was beyond the scope of the thesis. Nonetheless, our developed methods and algorithms make it possible to use low-power signals, which will reduce the chance of them being a source of annoyance for pets.

While the main application that drove our work was related to energy efficiency in terms of improving the comfort and reducing heating costs, our developed solutions and algorithms are valid to be used in other applications that are based on occupancy information. Nonetheless, the choice of the specific parameters might need to be customized to better suit the target application. Some of these parameters include the signal frequency selection, sampling rates, transmitted signals characteristics, frames duration, frames acquisition rate, training set size, classification models, etc. The choice of the parameters is mostly subject to trade-offs and can have an impact on the detection accuracy, false positives rate, immunity to noise and interference, processing time, power consumption, training time, etc.

1.10 Thesis Structure

The rest of this thesis is organized as follows. In Chapter 2, we review the general state-of-the-art in occupancy sensing, in addition to the related works in the literature. We detail the technologies that have been employed in device-based and device-free occupancy sensing, and discuss the pros and cons of each of them. We also review the scientific works that address the problem, and present the contributions they bring, their aspects, and their limitations if any.

In Chapter 3, we present our solution for a robust device-based occupancy sensing system, which localizes smartphones on a room-level scale using ultrasounds. We describe the design aspects, the decoding algorithm, collision detection and avoidance. Then we show the implementation and the experimental evaluation of the system, and discusses the obtained results. This chapter revises a previous publication [16]: Abbass Hammoud, Michel Deriaz, and Dimitri Konstantas. **Ultrasound-based Room-level Localization System Using COTS Components.** UPINLBS 2016.

Starting with Chapter 4, we address device-free occupancy sensing. In this chapter, we present the self-calibration method for an ultrasound-based motion detection system, called UltraSense. We implement the proposed method on a prototype using commodity hardware, and show the results from the experimental evaluation. The chapter revises a previous publication [17]: Abbass Hammoud, Michel Deriaz, and Dimitri Konstantas. **UltraSense: A Self-Calibrating Ultrasound-Based Room Occupancy Sensing System.** ANT 2017.

In Chapter 5, we present the power hopping method. We describe the theory behind the algorithm, and its time complexity. Then we show the method which automatically detect changes in the environment, and finish by testing the proposed methods. This chapter revises two previous publications [18]: Abbass Hammoud, Grigorios Anagnostopoulos, Athanasios Kyritsis, Michel Deriaz, and

Dimitri Konstantas. **Power Hopping: An Automatic Power Optimization Method For Ultrasonic Motion Sensors.** UIC 2017. And [19]: Abbass Hammoud, Michel Deriaz, and Dimitri Konstantas. **Adaptive Power Switching Technique For Ultrasonic Motion Sensors.** Journal of Ambient Intelligence and Humanized Computing 2018.

We dedicate Chapter 6 to address the sensing of still persons with ultrasounds. We show how such people can be masked by the other structures escpecially in poor SNR conditions, and discuss our method to overcome this challenge. The method and algorithms are also implemented, tested, and analyzed. The chapter revises a previous publication [20]: Abbass Hammoud, Athanasios Kyritsis, Michel Deriaz, and Dimitri Konstantas. **Enhanced Still Presence Sensing with Supervised Learning over Segmented Ultrasonic Reflections.** IPIN 2017.

Lastly, Chapter 7 summarizes all the conclusions drawn from designing the methods and algorithms, developing and implementing the described systems, testing and assessing their performance. We also discuss the new insights that our contributions bring to the field of occupancy sensing.

2 State-Of-The-Art Overview

With the importance of occupancy information and its implication in various applications, the problem of occupancy sensing has attracted efforts from the scientific community, as well as commercial-oriented engineering solutions. This chapter gives an overview on the technologies, methods, and works that address the occupancy sensing up to this date, before proceeding to present our own work. While the presented literature review focuses on the scope defined in the introduction chapter (Section 1.6), it is worth to mention that some of the mentioned technologies, methods, and works, may be valid for different resolution levels.

2.1 Device-Based Technologies

As mentioned earlier, the device-based occupancy sensing approach relies on determining the presence of a device, which is held or worn by the occupant. This field of indoor localization has been triggered in the recent years, with the increasing popularity of mobile devices. The located mobile device may be a smartphone, a bracelet, or a custom-made tag. Outdoor localization is mainly governed by the use of GNSS systems (like GPS [21], Glonass [22], etc.). However, this technology cannot be used indoors as the signals are obstructed.

Therefore, several technologies and methods have been suggested and investigated for indoor localization [23–25]. We present in the following subsections, the most relevant technologies for occupancy detection.

2.1.1 WiFi

WiFi access points can be used to locate compatible devices and estimate the occupancy. By mapping the mobile device to one or more closest access points, an estimate of his location can be obtained. The accuracy of the location depends on the distribution of the access points and the localization technique in use, and is typically in the range of few meters error [26]. One technique is to use the high-level WiFi data, and observe the MAC and IP addresses of the WiFi packets exchanged between the mobile device and the access point, to infer the zone in which the located device is inside. For instance, [27] and [14] use this technique for occupancy estimation.

Another technique is to examine the Received Signal Strength Indicator (RSSI) of WiFi signals, and then use methods like trilateration combined with a chosen propagation model, in order to locate the device. However in indoor environments, the propagation of RF signals like WiFi can exhibit some randomness due to the complex structures and their multipath effects. Hence, the location estimate might deviate from the actual location when using models like the Log-distance pathloss, and one should opt out for a more representative and suitable propagation model.

Fingerprinting can also be used [28]. It relies on a training phase where RSSI measurements are collected and mapped to the corresponding locations. On the real time phase, the received RSSI of WiFi signals are compared against the RSSI maps in order to infer the device's current location. In [29] for example, WiFi fingerprinting is used for lighting control. One drawback of this method is the need for a manual training phase for each new environment, which makes it tedious and time consuming for large scale deployments. Moreover, several locations might have similar fingerprints, leading to errors in the location estimation [30].

Overall, the advantage of using WiFi for occupancy sensing is that the majority of commercial and residential buildings are already equipped with WiFi access points, which can be leveraged directly without the need for additional hardware deployment. On the other side, the coverage and distribution of WiFi access points may not be optimized to fit the purpose of occupancy detection, affecting the accuracy of the location estimates.

2.1.2 Bluetooth

Bluetooth technology can also be employed in occupancy sensing. In this case, Bluetooth-compatible devices like smartphones and bracelets scan for Bluetooth packets, which are periodically emitted by the Bluetooth beacons [31]. Typical beacons use Bluetooth low energy (BLE), and operate for several months or few years on a single battery. Figure 2.1 shows some commercial models of Bluetooth beacons.

Similar to WiFi, the RSSI or fingerprinting techniques can be used. Athanasios *et al.* [33] propose an algorithm combining RSSI measurements with the room geometry information, to achieve room-level occupancy sensing. An RSSI-based algorithm is similarly proposed in [34] and [35]. Whereas in [36], a fingerprinting technique is presented with the use of supervised learning over the collected data. In general, Bluetooth can be similar to WiFi in the pros and cons, except that the deployment of Bluetooth beacons, which is more dense than WiFi access points, allows a better achieved accuracy, typically of 1-2m [26].

Figure 2.1: Different models of Bluetooth beacons (adopted from [32])

Source: *http://www.seillc.com/images/blog-beacons.gif*

2.1.3 UWB

Ultra-Wideband (UWB) technology uses high-bandwidth radio signals which offer a better accuracy for range estimation. UWB has been used by [37] to determine the occupancy and manage the energy consumption. While this technology offers a better accuracy compared to other RF-based ones (like WiFi and Bluetooth), its use is mainly restricted by the need for special equipment and receivers, limiting its wide-scale adoption.

2.1.4 RFID

An RFID (Radio Frequency IDentification) system consists of a reader that identifies nearby tags, which can be passive or active transceivers (Figure 2.2). The range is typically 1 to 2 meters for battery-less passive tags, and can reach up to 30 meters with active battery-powered tags [38]. Li *et al.* [39] use RFID tags to estimate the occupancy and control HVAC operations. Their results report a higher accuracy for stationary occupants (88%) than mobile ones (62%). In [40], RFID data is fused with PIR sensors to improve the accuracy, in the application of lighting control. [41] uses active RFID tags to determine the room-level occupancy and adjusts heating efficiently. In general, the accuracy achieved with RFID technology is satisfactory for occupancy detection, however the need for special deployment and the necessity to equip all occupants with the special tags, are the main drawbacks.

Figure 2.2: RFID tags and reader (adopted from [42])

2.1.5 Ultrasound

While the previous technologies are based on RF signals which are electromagnetic waves, ultrasounds are mechanical waves by nature. The use of ultrasounds offers some interesting advantages over the other technologies as described earlier. For instance, ultrasounds are inherently limited by walls and structures allowing to achieve the required room-level occupancy detection. Additionally, the support of commercial hardware avoids the need for a dedicated infrastructure to be deployed. Since Chapter 3 is dedicated for device-based occupancy detection with ultrasounds, we keep the discussion of the related works to the corresponding section in the chapter.

2.2 Device-Free Technologies

When device-based occupancy detection solutions become inconvenient or uncomfortable for the occupants, the device-free approach aims to find the alternative. As described earlier, this approach relies on sensing modules placed in the indoor areas, which sense the presence of persons without their explicit participation or interaction. So what are the relevant technologies and methods that are found in the literature?

2.2.1 PIR

A passive infrared (PIR) sensor detects the infrared radiations from the surrounding objects (Figure 2.3). By responding to the change in temperature pattern across the field of view, a PIR sensor can sense persons' motions and infer the occupancy [43]. This sensor is considered passive as it does not emit any energy itself, but rather relies on the pattern of the received infrared radiation in the environment [44].

In [45], PIR sensors are used to achieve 10 to 15% in energy saving. Dodier *et al.* [46] enhance the occupancy accuracy using a Bayesian network with PIR sensors' data, and similar works use a Naive Bayes algorithm [47] and a Kalman Filter [48]. In [49], a network of PIR sensors is used to count visitors in a given building. Raykov *et al.* [50] use a hidden Markov model with a single sensor to estimate the occupancy count in a room. And instead of using PIR to obtain binary motion information, Narayana *et al.* [51] propose to process analog signals from the sensors to get a more fine information about the moving object, its speed, range, etc.

PIR sensors have been widely used commercially for various applications. They are generally attractive due to their low cost and power consumption. However, the main drawbacks of PIR sensors are their limitation to work only in

Figure 2.3: PIR sensors

Source: *https://i.ytimg.com/vi/DJ2JjirBw1o/maxresdefault.jpg*

line-of-sight (LOS) conditions, as well as their sensitivity to changes in the environment (sunlight, heating effect, etc.), which imposes some constraints on installation, and usually require on-site calibration (Figure 2.4). Moreover, the

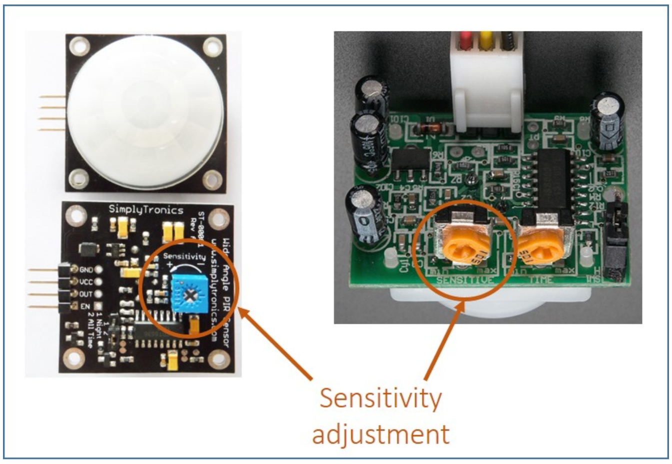


Figure 2.4: PIR sensors usually require manual calibration

Source: *https://cdn-learn.adafruit.com/assets/assets/000/013/839/medium800/proximity_189bottom_LRG.jpg?1390948358* sensitivity decreases sharply as the range increases leaving some dead points (Figure 2.5), and a dense deployment [52] may be needed to overcome this limitation, like placing four sensors per room as suggested.

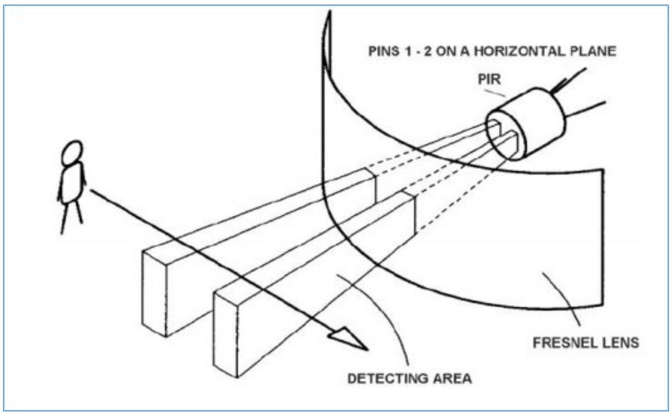


Figure 2.5: PIR detection zones leave some dead points as the range increases

Source:
https://www.researchgate.net/profile/Syeda_Puspita_Mouri/publication/303314563/figure/fig4/AS:363150974177281@1463593347035/Working-principle-of-PIR.png

2.2.2 RF-based technologies

RF signals can be leveraged to detect human motions or the presence of persons in a certain area, without requiring the occupants to wear a device. Doppler-based micro radars represent one means to sense persons' motions. An example is the X-band motion sensor (Figure 2.6). The frequency range of X-band is specified by IEEE at 8 to 12GHz. UWB can also be used. [53] combines the use of a UWB radar with a power monitoring software to increase the robustness of occupancy detection.

Some works propose the use of modified WiFi access points. Depatla *et al.* [54] are able to estimate the occupancy count between a WiFi transmitter and a receiver, placed opposite to each other. They report a high accuracy (88%) with directional antennas (modified hardware), and a lower one (63%) with omnidirectional antennas (unmodified routers), in an indoor environment. Also

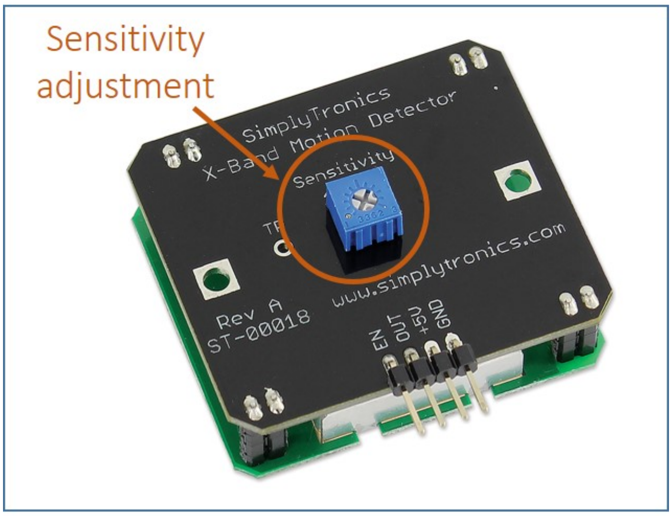


Figure 2.6: An X-band motion sensor

Source: *https://www.parallax.com/sites/default/files/styles/full-size-product/public/32213_0.png?itok=Ar_9M9SJ*

in their work, Adib *et al.* [55] use WiFi signals to track persons behind a wall and locate their positions using a MIMO antenna array.

However, one disadvantage of using RF signals for occupancy, is the fact that as electromagnetic waves, they propagate through walls and doors, and hence they are not suitable for determining the occupancy at the room-level. Since in this case, persons in adjacent rooms will alter the propagated RF signals, and lead to errors in the occupancy state results in the subject room. Accordingly, if we were to consider a scenario where the system in [55] is being used, then to detect the occupancy state in a room X, a sensing unit (modified WiFi router in this case) is to be placed in an adjacent room Y pointing towards the room of interest (X). A similar unit would need to be placed in room X (or adjacent) to detect the occupancy state of room Y for example, and so on.

2.2.3 Computer vision

Computer vision is traditionally used to allow devices and computers to see and analyze their environment, as humans naturally do. By installing cameras in indoor spaces and processing the acquired frames, the presence of occupants can be detected. Example works that use computer vision for occupancy is [56] where a network of cameras is used along with PIR sensors to sense occupants' presence, and similarly [57] uses cameras with PIR and other environmental sensors. [58] determines the presence of persons by detecting human heads, using a three-level classification algorithm.

Computer vision can offer a very high accuracy of occupancy sensing, especially with advanced classification algorithms. Additionally, it is possible to determine the activities of the occupants, which can be useful to customize services. On the other hand, image processing algorithms require a high computational load. Moreover, people are generally sensitive about being continuously filmed, and reluctant to accept to be monitored with cameras, which they consider intrusive to their sense of privacy [59].

2.2.4 Power meters

By monitoring the power consumption of different electric appliances, it is possible to obtain occupancy information. Algorithms that describe the use of smart electricity meters in occupancy information can be found in [60–63]. This technology is usually more useful for post-processing analysis rather than real time occupancy sensing, since it relies on processing of data recorded over a certain period of time, or training a model during an initial phase. Moreover, a dense deployment is generally required to obtain accurate room-level occupancy information.

2.2.5 CO_2 Sensors

When a person is present in an indoor environment, the CO_2 level increases due to his breath. A CO_2 sensor detects this change to identify if a person is present. For isntance, [64] and [65] leverage CO_2 sensors to infer the occupancy, reporting an accuracy of 96% and 94% respectively. The main limitation of this type of sensors is the time delay: When a person enters a room, the change in CO_2 level will only be detectable after a certain time duration. The same applies when a person leaves the area, where the CO_2 level will start to drop gradually. This is why CO_2 sensors are usually not used alone, but rather combined with other sensors to guarantee the robustness. For example to enhance the occupancy detection accuracy, [66] uses the combination of temperature, humidity, CO_2 concentration, and PIR sensors, where the collected data is fused using a radial basis function network. A similar approach can also be found in [67].

2.2.6 Ultrasound

When it comes to ultrasound, there are different types of methods and sensors used for device-free occupancy sensing. Compared to other technologies, and especially to the widely used PIR, one important advantage of ultrasounds is the ability to operate in NLOS conditions, in addition to other ones like the higher sensitivity, the support of commercial hardware, etc. Occupancy detection techniques using ultrasounds include the use of ranging techniques, motion detection, and still presence sensing. We elaborate more on these and we compare them to our work later in this thesis, namely in Chapters 4 and 6.

2.3 Summary

After discussing the different techniques involved in occupancy sensing, we provide an overview comparison of the presented technologies for the two approaches, with

Table 2.1: Summary of state-of-the-art technologies in occupancy sensing

	Technology	**Advantages**	**Limitations**
Device-Based Approach	WiFi	Widely Available - Use of existing infrastructure	Limited localization accuracy using RSSI - Not tailored for room level - Fingerprinting requires manual training phase
	Bluetooth	Easily deployed	Need a high density of beacons for a high accuracy - Fingerprinting requires manual training phase
	UWB	High localization accuracy	Need for specialized equipment and receivers
	RFID	Satisfactory accuracy for occupancy sensing	Need for specialized equipment and tags
Device-Free Approach	PIR motion sensors	Widely Available - Low cost - Low power	Sensitive to heat and sunlight - Manual calibration - reduced accuracy with distance
	RF-based technologies	High accuracy of motion detection	Not tailored for room-level
	Computer vision	High accuracy - occupancy count	Privacy concerns
	Power meters	Simple to place and use	Dense deployment for high accuracy
	CO_2 sensors	Simple and convenient	Limited accuracy - usually complemented with other technologies

the main pros and cons of each of them. We keep the discussion of advantages and limitations of ultrasounds to the subsequent chapters.

3 Ultrasound-Based Room-Level Localization Using Smartphones

3.1 Chapter Abstract [1]

In this chapter, we follow a device-based approach, and present a room-level localization system based on ultrasounds. Our aim is to offer a robust and accurate localization system for room-occupancy detection, using the least possible hardware deployment. The purpose is to guarantee the ease of deployment and scalability in different potential environments. In our system, smartphones locate in which room they are using commodity sound speakers as ultrasonic beacons. It was designed to be robust to noise, scalable, to have a low complexity on the receiver, and not requiring synchronization between the transmitters and receivers. We avoid the use of RF signals, and rely solely on ultrasounds. Additionally, we discuss the design of the ultrasonic packets, in a way that ensures the support of typical hardware and devices commercially available. Since distinct transmitters work independently, signal interference is a potential problem to be solved as it leads to packets collision. Therefore, we address the collision detection problem and present our solution for collision

[1] A shorter version of this chapter was published in: A. Hammoud, M. Deriaz and D. Konstantas, "Robust ultrasound-based room-level localization system using COTS components," 2016 Fourth International Conference on Ubiquitous Positioning, Indoor Navigation and Location Based Services (UPINLBS), Shanghai, 2016, pp. 11-19.

avoidance. In addition, we describe how our proposed system satisfies crucial characteristics that are desired for an indoor localization system, namely the accuracy, robustness, availability, scalability and ease of deployment. As for the system implementation, we show how the system can be assembled using different commercial off-the-shelf components. Our experimental evaluation of the system in realistic conditions shows that it is able to achieve a high accuracy (>98%) of room localization, despite ambient noise and packet collision.

3.2 Introduction and Related Work

Several technologies have been investigated, and many methods were developed for indoor localization. However, there is currently no standard for an indoor localization system, like it is the case for GPS outdoors. Some of the main reasons are the insufficient availability, and the need for extensive node deployment and maintenance, which prevent the widescale adoption of most systems' implementations [38]. Thus, a robust, reliable, and widely available indoor localization system would pave the way for a wide range of applications.

In the previous chapter, we presented the works that address device-based occupancy sensing. Here, we focus on the use of ultrasound technology. As we mentioned earlier, ultrasounds present some advantages that make them interesting to use, compared to other technologies. There are several ways for the employment of ultrasounds in the indoor localization of devices. One of them is using the time-of-flight (ToF) of the ultrasonic signals. With this technique, the transmitter should be synchronized with the receiver, for example through an RF technology. The time it takes for the signal to travel from the first to the latter is measured, and translated to a distance value. By measuring the distance to three or more transmitters, one can obtain an estimate of the receiver's position (device to be located) [68, 69]. Another technique is the TDOA, where three or more synchronized receivers send signals that are picked up by the receiver, who infers its position using hyperbolic geometry methods [70–74]. ToF and TDOA techniques are used for 3-D localization, and typically require extensive hardware deployment.

While 3-D accuracy level might not be necessary for occupancy information, less hardware can be used and deployed to obtain room-level accuracy. Our proposed system consists of one transmitter per room, periodically emitting a unique ultrasonic packet, where the user's smartphone decodes the received packets to locate itself at a given time instant. Since our system uses commercial off-the-shelf (COTS) components, it does not require special hardware or dense infrastructure to be deployed.

There are also several studies that explore the use of sound signals for localization, as we do in our work. SoundLoc [75] uses sound signals to infer unique impulse responses for different rooms, where the located device comprises both the transmitter and receiver. The mentioned system achieves a high accuracy for the tested set of rooms. The authors do not mention whether ultrasound is used, which suggests that audible sounds were employed. In this case, special attention should be given as to ensure that the chosen signals are not disturbing for the users or for people who are present around. Moreover, a limitation of this system is that it requires a training phase, which might become a burden for scalability. A similar work [76] uses ambient sound fingerprinting combined with WiFi to obtain a room-level localization. Shahid *et al.* [77] propose a system with dedicated ultrasound beacons operating at a frequency of 40kHz for room-level localization. A special ultrasonic receiver is worn by the user to support the ultrasound frequency used. This receiver decodes the ultrasonic signal to identify the corresponding beacon, and the authors state that the system achieves a good accuracy. However, the main limitation of their system is the fact that it requires special ultrasonic hardware for both transmitters and receivers, which limits the possibility for a widespread adoption. A similar work [78] uses an ultrasound array combined with RFID technology, it also requires special receivers for the ultrasonic signals. [79] locates smartphones using ultrasonic transmitters operating at 41kHz. As a smartphone doesn't inherently support this frequency, it is equipped with an external hardware to sample the received signals. However, although a good localization accuracy is reported by the proposed system, it's clear that the solution is not easily scalable, since all smartphones to be located need to be augmented by additional hardware components. Borriello *et al.* [80] used a combination of ultrasound and WiFi packets, generated by PCs to achieve room level accuracy. Nonetheless, the system requires having PCs in all the rooms, which may not be available on all environments.

3.3 Our Contribution

Our work presents a localization system in which smartphones locate the rooms they are inside using ultrasonic beacons. In differentiation to the previously mentioned works, it offers the following contributions:

1. Our proposed system uses ultrasound signals solely, without any RF signals. This ensures the localization method will only need a microphone available on the located device, and that it would still work even if other technologies like WiFi or Bluetooth are not available or disabled on the device.

2. Our system uses commercial off-the-shelf (COTS) components. Commercial sound speakers are used as transmitters, and any device with a typical microphone can be used as a receiver. Therefore, no expensive or heavy deployment of infrastructure is needed. The design of ultrasonic signals and the detection techniques we use allow the hardware to be used seamlessly, so that it can still be used for other applications simultaneously (a loudspeaker to broadcast messages, play music, or a smartphone to make a call).

3. We make sure that the different transmitters operate independently and do not require synchronization between themselves or with the receiver device. This is why signal interference leading to packet collisions is a potential problem. To solve this problem, we propose a method for collision detection and avoidance.

4. We derive a formula for the probability of collision under the implemented mechanism, as a function of the emission periods of transmitters.

5. We introduce the *confidence score*, as a measure of the reliability of the localization result. An application which uses the localization system, may benefit from this value as an indicator of the accuracy.

6. The system is robust to ambient noise and signal interference. It proves a high accuracy when experimentally tested in realistic conditions in order to characterize its performance.

The rest of this chapter is organized as follows. In Section 3.4, we mention the desired features we target for our device-based localization system. Then, Section 3.5 details the design aspects of our system, and Section 3.6 presents the packet collision detection and avoidance methods. The experimental setup and the testing results are shown in Section 3.7, and Section 3.8 shows how the system's characteristic features address the target ones. Finally, Section 3.9 concludes and summarizes this chapter.

3.4 Desired Characteristics

Before starting to discuss the design aspects of our system, we mention the most important characteristics that we target in our design of the localization system. Lacking some of these characteristics will represent a burden on the widescale adoption of the localization system. We summarize these characteristics in the following points. Later in this chapter, we show how our proposed localization system addresses each one of these points:

1. Accuracy: The indoor localization system is desired to be accurate, as to locate users reliably, in order to guarantee correct occupancy information.
2. Robustness: Operation under different conditions, and resistance to changes in the environment (ambient noise, change in structure/layout, etc.).
3. Availability: The technology used should be available to the public, and the equipment is preferred to be of low cost, without the need for expensive specialized hardware. Supported devices to be located should be accessible to the users.
4. Scalability: It is necessary to have a localization system that can be extended to new environments and still benefit from the same devices.
5. Ease of deployment: A system which is easy to deploy and maintain is favored over one that requires installing heavy infrastructure, and extensive node deployment.

3.5 System Design

3.5.1 Architecture

Our localization system is composed of one transmitter per room, and the receiver is the device that locates itself. We select the transmitter to be a commercial sound speaker. However, custom made ultrasound beacons can also be used instead. Each room needs to have one transmitter, which periodically emits an ultrasonic signal. The emitted signal contains information that associates it to the corresponding room. On the other side, the receiver is a mobile device that captures the ultrasonic signals and identifies the current room.

The receiver needs to have a microphone, it can be a smartphone, a tablet, a smartwatch, or even a robot equipped with a microphone.

Filonenko *et al.* [81] demonstrated the ability of mobile phones to support ultrasound at the frequency range of 20-22kHz. In our work, we have run additional tests to prove that it is also the case for other devices including commercial loudspeakers and microphones, in addition to mobile phones. The devices that we tested are the following: Samsung Galaxy S4 and S5, HTC One M7, Nexus 5X, Logitech and Creative loudspeakers, Logitech and Blue microphones. Although we have tested a limited number of devices, other ones should also enjoy the same capabilities, given that they use a sampling rate of 44.1kHz or above.

3.5.2 Ultrasound Signal Design

The design of the transmitted ultrasonic signal used for localization is critical. It should be supported by commercial sound speakers and microphones, and also be non-audible at the same time. Moreover, the signal should be detected and decoded robustly in noisy environments, and has to accommodate for multiple rooms. The previous requirements translate into the following points:

1. The signal frequency bandwidth should be picked from the frequency band 20-22kHz.
2. The signal form should ensure a good autocorrelation.
3. The signal modulation is to be carefully chosen so that it accommodates for any number of rooms.

Taking these constraints into consideration, we decided to use chirp signals, and design the ultrasound signal as a packet containing two parts, as shown in Figure 3.1: the first part is the *pilot signal*, common to all rooms, and the second part is the *identifier* represented by a binary sequence. Having the transmitted signal composed of two parts, instead of one, reduces the computational complexity at the receiver side, and makes the decoding process simpler, as will be discussed later in Section 3.8.

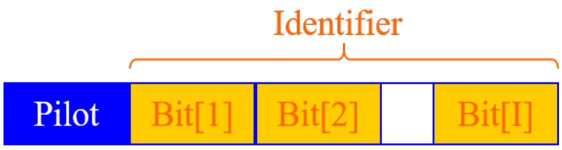


Figure 3.1: Design of the transmitted ultrasound packet

3.5.2.1 The Pilot Signal

The pilot signal is composed of one chirp pulse. Peng *et al.* [82] proposed the use of the linear chirp signal in ultrasound systems, as it has a good autocorrelation function. A linear chirp is a signal whose frequency increases linearly with time. During experimental tests, when the amplitude of the chirp signal was not properly scaled, we noticed that the sound speaker generates an unpleasant tick sound, due to the abrupt change in the amplitude of the audio signal. Therefore, to guarantee a smooth performance, we decided to scale the chirp pulse by a triangular function, so that its amplitude increases gradually at its start, and decreases similarly at its end. The continuous time domain representation of the chirp scaled by a triangular function is given by the following formula:

$$x(t) = \begin{cases} \frac{2t}{T_{chirp}} \sin(2\pi f_0 t + \frac{q}{2} t^2) & \text{for } 0 \leq t \leq \frac{T_{chirp}}{2} \\ (2 - \frac{2t}{T_{chirp}}) \sin(2\pi f_0 t + \frac{q}{2} t^2) & \text{for } \frac{T_{chirp}}{2} < t \leq T_{chirp} \end{cases}$$

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

In our system, we manipulate and process the ultrasonic signal in discrete-time domain. The discrete-time representation of the chirp then becomes:

$$x[n] = \begin{cases} \frac{2n}{N}\sin(2\pi(\frac{f_0}{f_s})n + \frac{q}{2}(\frac{n}{f_s})^2) & \text{for } 0 \leq n \leq \lfloor\frac{N}{2}\rfloor \\ (2-\frac{2n}{N})\sin(2\pi(\frac{f_0}{f_s})n + \frac{q}{2}(\frac{n}{f_s})^2) & \text{for } \lfloor\frac{N}{2}\rfloor < n \leq N \end{cases}$$

where f_s is the sampling frequency, and $N = f_s \times T_{chirp}$.

As a design choice, we select the lower and upper frequency limit of the chirp to be 20kHz and 20.5kHz respectively. The length of the chirp pulse is an important factor for accurate detection. The pulse needs to be long enough to be resistant to noise, and short enough to reduce computational complexity and power consumption on the receiver side. As a trade-off, we empirically chose the pulse duration to be 10ms. Figure 3.2 shows the time plot of the pilot signal, composed of a single chirp pulse.

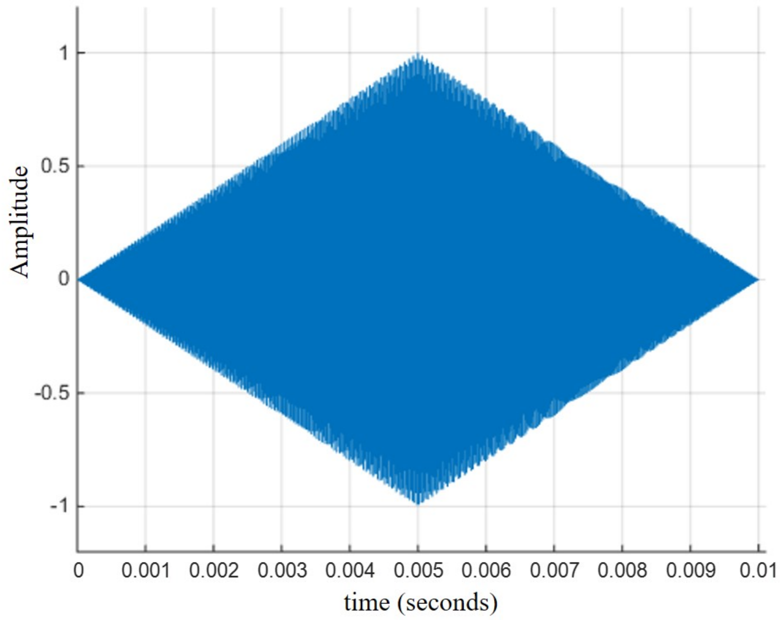


Figure 3.2: Time plot of the scaled pilot chirp signal

3.5.2.2 The Identifier

Our system is intended to rely only on ultrasound, without the need for RF signals like Bluetooth or WiFi. Therefore, the source's unique identifier should be embedded in the ultrasonic signal itself. To achieve this, we use frequency multiplexing as a modulation scheme, and we append additional chirp signals to the pilot. This way of signal modulation ensures flexibility and scalability of the system. The identifier is a unique binary sequence, represented by a train of chirp pulses. Bits 0 and 1 are assigned to two chirp signals with different frequencies. We choose to represent the bit 0 by a chirp whose frequency band is 20.5-21kHz, and the bit 1 by another chirp of 21-21.5kHz. Figure 3.3 shows the frequency allocation of the signals.

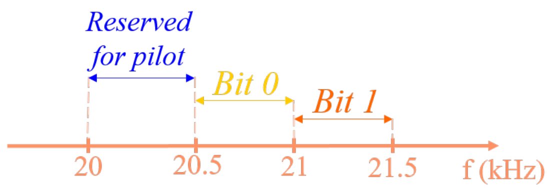


Figure 3.3: Frequency allocation of chirp signals

The number of rooms determines the length I of the identifier. As a rule, $I = \lceil \log_2 N \rceil$ bits are needed to represent N rooms. To give an example of the transmitted ultrasonic signal, and without loss of generality, we consider a scenario where we have 8 rooms, so that the identifier is composed of 3 bits. With 3 bits, the binary sequence identifiers are: $000_2, 001_2, \ldots, 111_2$. Each one of these unique identifiers is assigned to a room. Figure 3.4 shows four of the eight signals assigned to the rooms, while the remaining four are similar and go from 100_2 to 111_2. The period of emission T defines the update rate of the receiver, which should also be equal to the recording time.

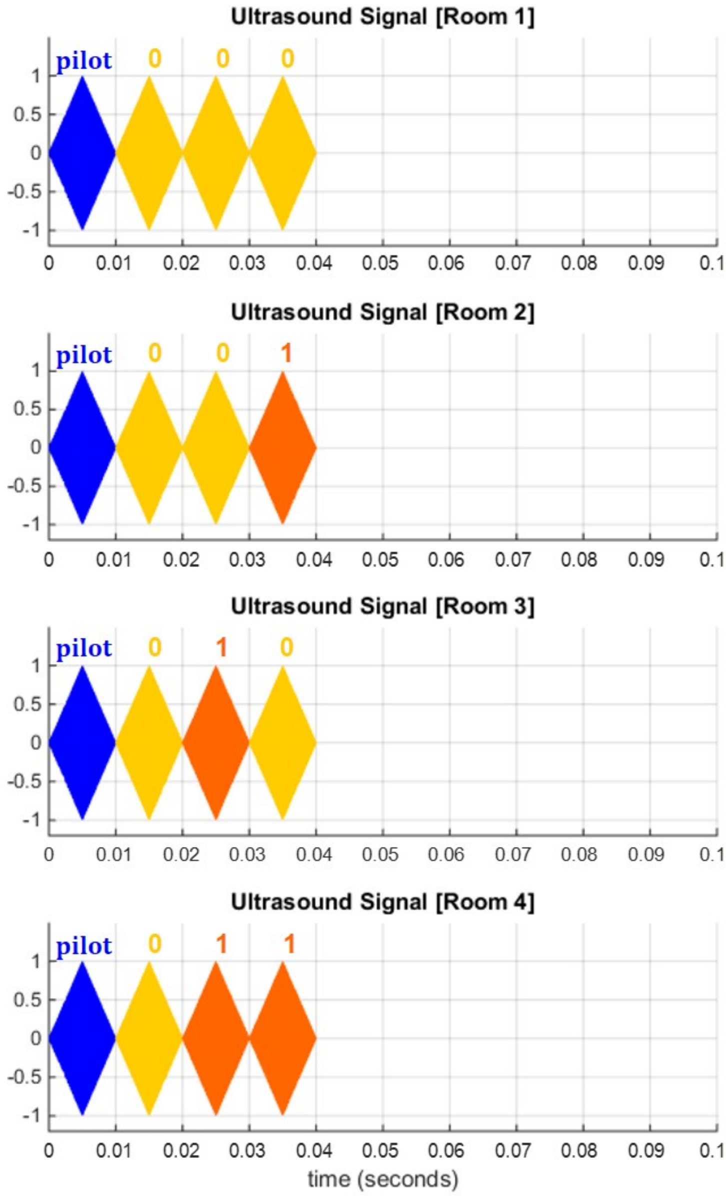


Figure 3.4: Transmitted ultrasonic signals for different rooms

3.5.3 Ultrasound Signal Decoding

The receiver is responsible for identifying the room it is inside. It continuously listens to the environment and records the received sound. To identify the correct room, the receiver processes the recorded signal to decode the ultrasonic component. The detection process is divided in three steps, in order to ensure its

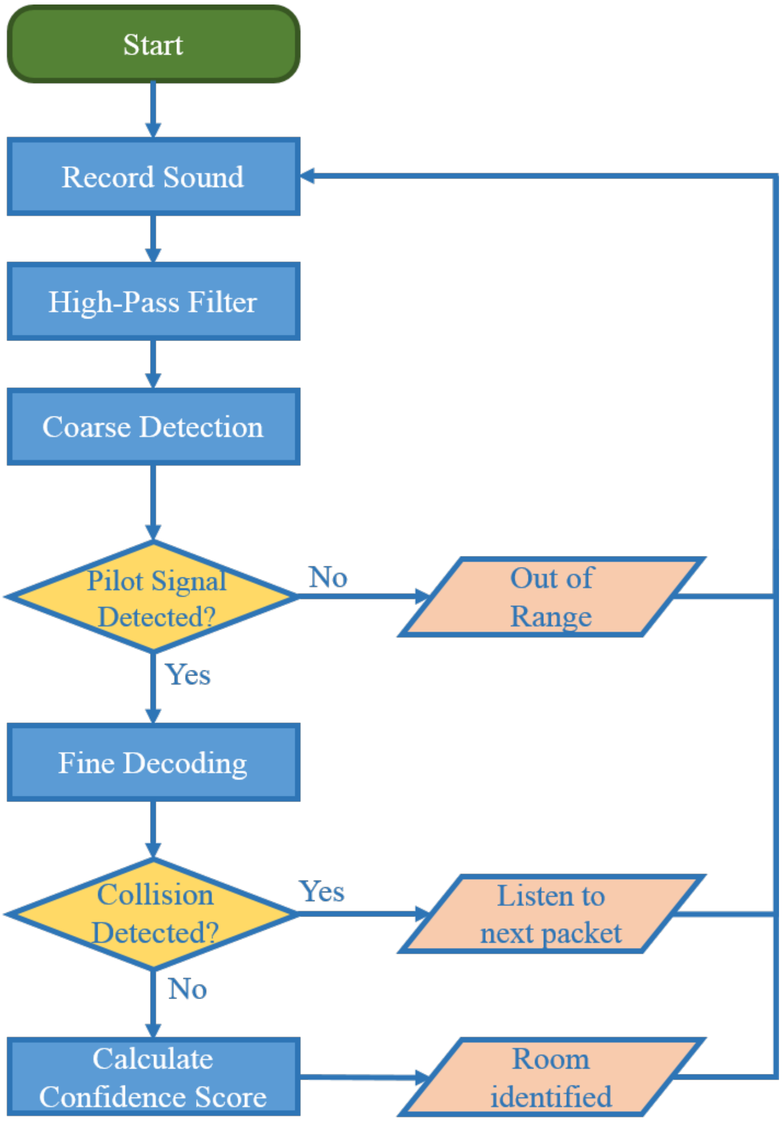


Figure 3.5: Flow chart of the localization process

robustness while keeping computations as low as possible. Decoding starts by filtering the recorded signal, then a coarse detection step locates the pilot signal, and finally a fine decoding step decodes the information embedded in the ultrasonic signal, and retrieves the identifier bit sequence. In case no collision is detected, the system computes a value indicating the reliability of the result, which we call the confidence score. As a summary, the flow chart of Figure 3.5 depicts the complete localization process.

3.5.3.1 High-Pass Filtering

The signal recorded by the microphone contains different frequencies ranging from low audible frequencies, up to high non audible ones. In order to filter out low frequencies and make the system immune to noise, the recorded signal is filtered using a discrete-time high-pass filter to keep only the ultrasonic components at 20-22kHz, before proceeding with the decoding process.

3.5.3.2 Coarse Detection

In this step, the receiver checks whether the ultrasonic signal was actually received, indicating that the device is in range of the localization system. The algorithm looks for the pilot signal in the whole recorded signal, and, if found, locates its position inside this signal. If the pilot signal is not found, the receiver is assumed to be out of range, and is not in any of the designated rooms. To detect the pilot signal, a matched filter is used by correlating the received signal with the known pilot signal. The matched filter was chosen as it is the one that maximizes the signal-to-noise ratio. The peak correlation result is compared against a certain threshold, which is empirically calculated and set. If the peak correlation value exceeds the threshold, the ultrasonic signal is considered to be received successfully, the mobile device is then assumed to be in one of the designated rooms, and the fine decoding step takes place. Otherwise, the mobile device is assumed to be out of range. The position of the peak correlation indicates the starting point of the pilot signal, as shown in Figure 3.6. The position of the pilot in the recorded signal is used to decode the subsequent bits.

Let the transmitted pilot signal be $X = [x_1, x_2, ..., x_N]$ and the recorded signal be $Y = [y_1, y_2, ..., y_L]$ where $L \gg N$. The peak correlation value is given by Equation 3.1:

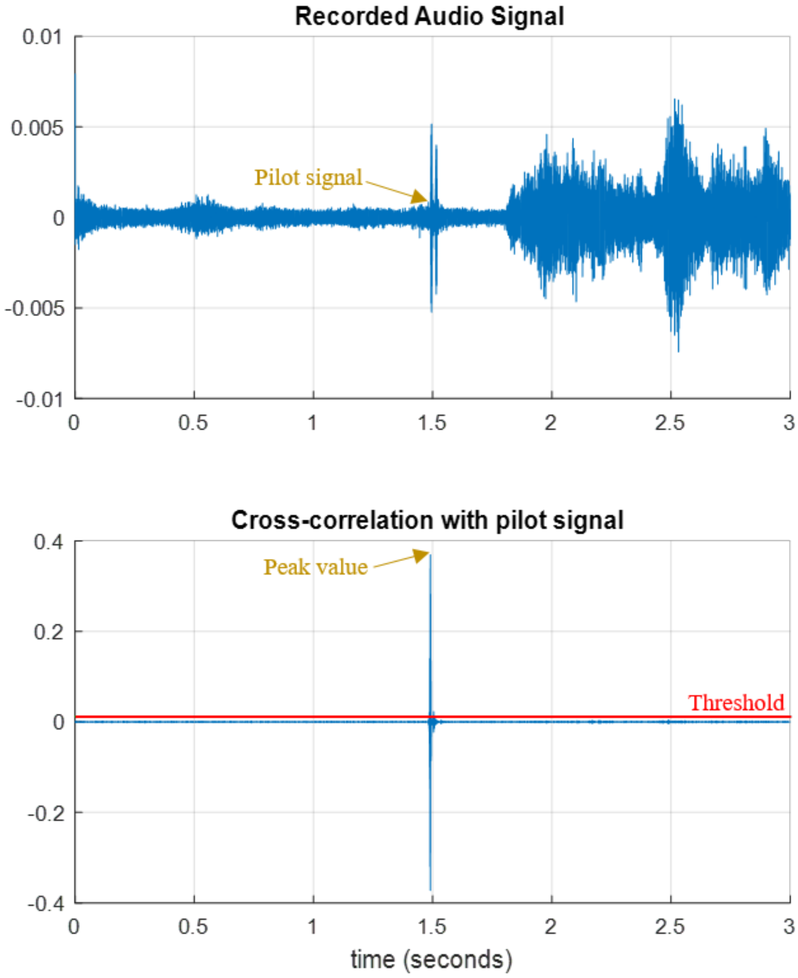


Figure 3.6: The first plot shows the recorded audio signal. The second plot shows the result of its cross-correlation with the known pilot signal

$$peak\ correlation = \max_{k} \sum_{n=1}^{N} x_n y_{(n+k)} \quad \text{for } 0 \leq k \leq L - N \tag{3.1}$$

The starting point of the pilot signal corresponds to the index of the peak correlation:

$$K^* = \arg\max_{k} \sum_{n=1}^{N} x_n y_{(n+k)} \quad \text{for } 0 \leq k \leq L - N \tag{3.2}$$

3.5.3.3 Fine Decoding

Once the pilot signal is located, the receiver proceeds to decode the identifier binary sequence, bit by bit. To decode one bit, the receiver correlates, in time domain, the corresponding signal with the two chirps that are used to represent the bits 0 and 1. Assuming the two chirps that modulate the bits 0 and 1 are respectively $A = [a_1, a_2, ..., a_N]$ and $B = [b_1, b_2, ..., b_N]$, the receiver calculates the following two quantities to decode the first bit that follows the pilot signal:

$$bitZeroCorrelation = \sum_{n=1}^{N} a_n y_{(n+N+K^*)} \tag{3.3}$$

$$bitOneCorrelation = \sum_{n=1}^{N} b_n y_{(n+N+K^*)} \tag{3.4}$$

where K^* is the index found in Equation 3.2. If the signal is successfully received, one of the two quantities resulting from Equations 3.3 and 3.4 will be positive and above the threshold. This quantity corresponds to the actual received bit, while the other one will be close to zero, as a result of correlating with the wrong bit. If the result of Equation 3.3 is the one that is positive, then the signal is decoded as 0, and if it is the second one that is positive, the signal is decoded as 1. However, if both quantities of Equations 3.3 and 3.4 are positive and above the threshold, this indicates that two different signals were superposed and that a collision took place between the ultrasonic packets of adjacent rooms. In Section 3.6, we will explain how the occurrence of such collisions is minimized.

Decoding the subsequent bits goes similarly. The receiver should know the length of the identifier beforehand. Once all bits are decoded and no collision is detected, the identifier binary sequence can be mapped to the correct room number, and the room is successfully identified.

3.5.4 Confidence Score

When looking for the pilot signal in the recorded sound, the receiver selects the highest peak of the correlation result. In case multiple packets from different rooms are received, this will yield the strongest signal among them, which will be used then to identify the corresponding room. However, this does not indicate how reliable the localization result is. Therefore, we introduce the *confidence score*, as a measure of the reliability of the result. Instead of considering just the highest peak value of the correlation, the receiver also locates all other peaks that are above the threshold, which indicate the signals that are received from the adjacent rooms. If M peaks are detected in total, we refer to the i^{th} peak as P_i, and to the maximum peak as P_{max}. Then, the following formula is used to compute the confidence level as a percentage:

$$confidence\ score = 100 \times \frac{P_{max}}{\sum_{i=1}^{M} P_i} \tag{3.5}$$

The previous formula can be interpreted as the following: if only one signal is detected, the confidence score of the result of room localization is 100%. Otherwise if multiple signals are received, although the strongest among them is used to identify the room, the confidence score in this case is penalized by an amount that is equivalent to the relative intensities of other received signals. Figure 3.7 shows an example where three different packets were received. The highest peak in this case (P_2) is used to identify the room, while the other two are considered to be received from the adjacent rooms, and are used to calculate the confidence score, which in this example is equal to around 60%.

3.6 Packet Collision

Transmitted signals from adjacent rooms may interfere, especially when the user is at a boundary point between rooms. Collided ultrasonic packets may lead to

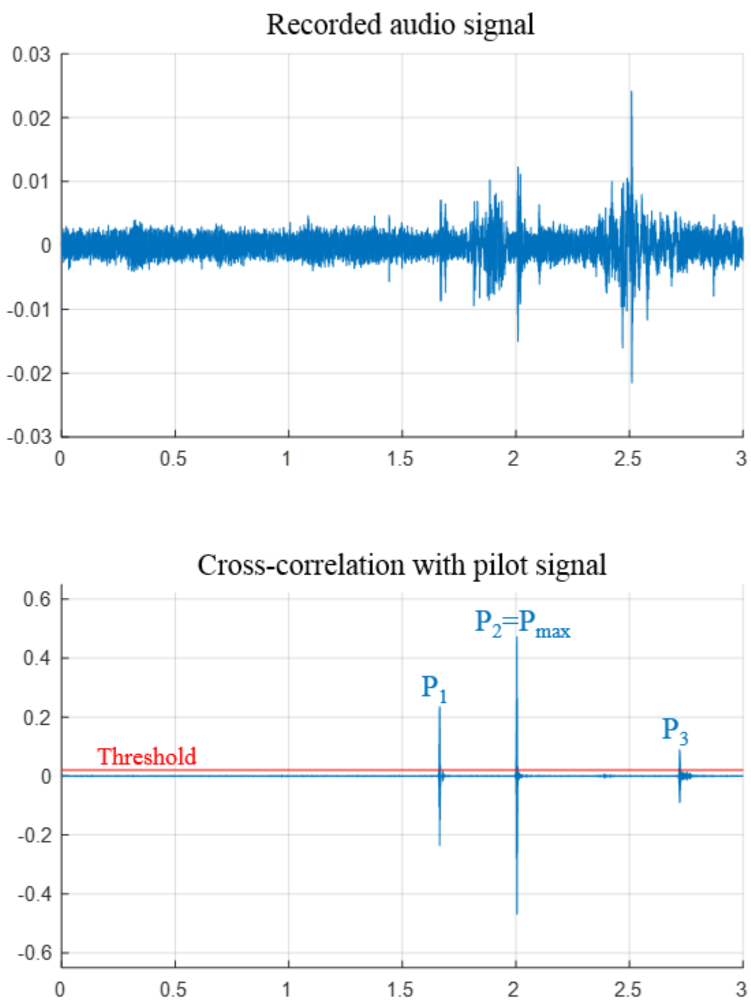


Figure 3.7: Three different signals received with different intensities

erroneous detection by the receiver. This section explains how such collisions could be detected, and also suggest a method to avoid collisions.

3.6.1 Collision Detection

A collision is assumed to take place at the receiver when the latter is not able to decode the received signal correctly. Failing to decode one or more bits in the identifier sequence will indicate a collision of two or more signals. As mentioned earlier, if the results of Equations 3.3 and 3.4 both yield positive values above the threshold, then this indicates that two different signals modulating bits 0 and 1 have interfered, and a collision of packets has occurred. In this case, the receiver cannot identify the correct room, and reports an error due to collision. Then, it listens to the next transmitted packet in order to identify the corresponding room.

3.6.2 Collision Elimination

Collisions are desired to be fully eliminated. In our system design, we start from the assumption that the transmitters are not synchronized, aiming for a system that has a low complexity and which does not require the deployment of extensive infrastructure. Hence, we assume that we do not have control over the emission time instants of different transmitters. Under this assumption, we show that packet collisions cannot be completely eliminated.

We consider the scenario depicted in Figure 3.8, where two transmitters are placed in two adjacent rooms. Each transmitter emits an ultrasonic packet periodically every T seconds. The two transmitters are not synchronized, we denote by Δ_t the time difference between their emission time instants:

$$-T < \Delta_t < T$$

The receiver Rx that needs to be located is somewhere in the boundary region between the two rooms, and can hear both emissions. Assume that the ultrasonic packet emitted by the first transmitter reaches the receiver at time t_1, and the one emitted by the second transmitter at time t_2. Taking into account the propagation time of the ultrasonic signal, t_1 and t_2 can be written as:

$$\begin{aligned} t_1 &= nT + \frac{d_1}{c_{air}} \\ t_2 &= nT + \Delta_t + \frac{d_2}{c_{air}} \end{aligned}$$

where c_{air} is the speed of sound in air.

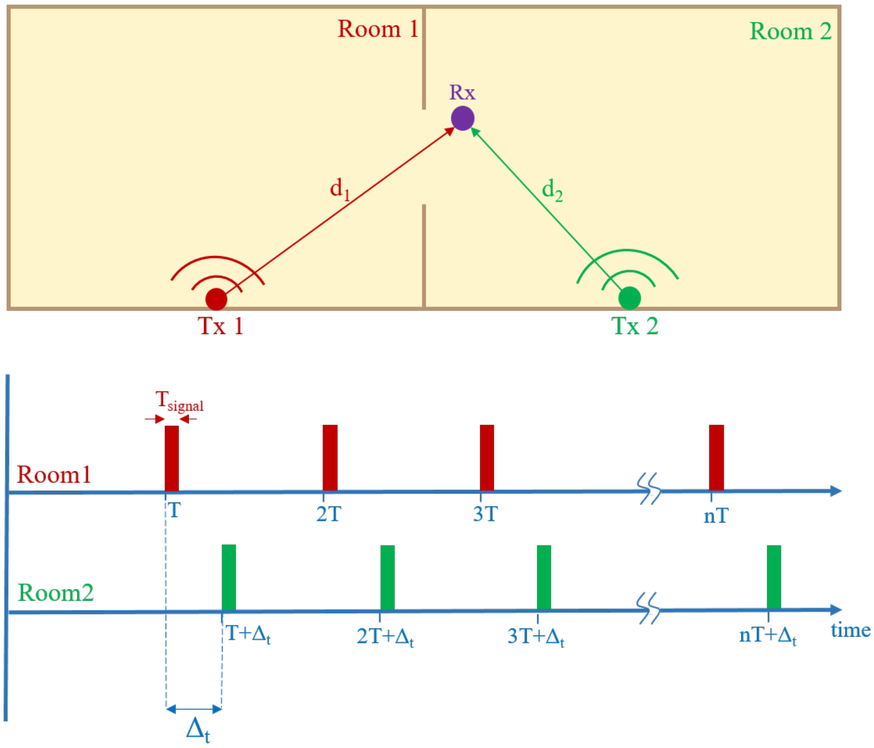


Figure 3.8: A scenario showing two transmitters of adjacent rooms, and the receiver in the boundary regions between them

Assuming that the signal duration is T_{signal}, the condition on t_1 and t_2 so that no packet collision occurs is such that:

$$|t_2 - t_1| > T_{signal}$$

which yields:

$$|\Delta_t + \frac{d_2 - d_1}{c_{air}}| > T_{signal} \tag{3.6}$$

This means that in order to guarantee no packet collision, Δ_t and the distance difference $(d_2 - d_1)$ should satisfy the condition in Equation 3.6. But since Δ_t can take any value in the interval $(-T, T)$, the aforementioned condition is not guaranteed to hold. An example that violates the condition is when Δ_t is very

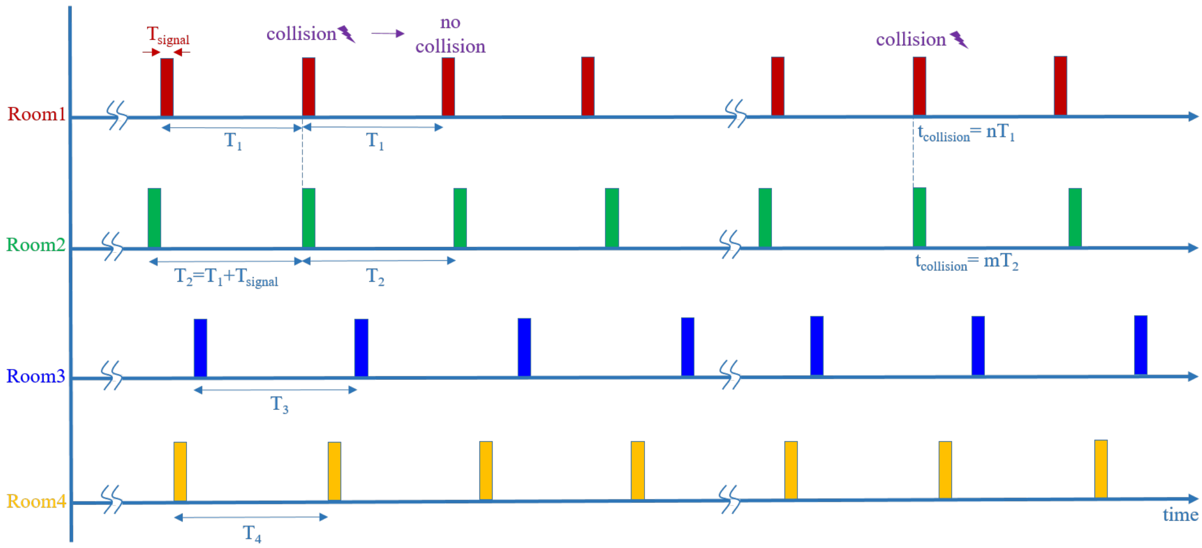


Figure 3.9: Adjacent rooms have slightly different periods of emissions: no successive collisions occur, and the time between two collisions is maximized

small (close to 0), and the values of d_1 and d_2 are very close to each other, making the result of $|\Delta_t + {}^{(d_2-d_1)}/_{c_{air}}|$ less than T_{signal}.

Moreover, if a collision happens at some point P, it will lead to infinite collisions at that point, because the values of T, T_{signal}, and Δ_t are constants.

3.6.3 Collision Avoidance

As collisions cannot be fully eliminated, we aim to reduce the probability of their occurrence. In other words, if a collision occurs at a certain time, we try to maximize the time that will elapse before another collision would occur again. We found that this is not possible if different transmitters have the same period of emission T. To reduce the probability of collisions between signals of adjacent rooms, we propose to assign different periods of emissions to the corresponding transmitters. We found that the best strategy to reduce the probability of collisions is to assign periods of emissions which differ exactly by T_{signal}. Figure 3.9 shows the emission time instants of transmitters of adjacent rooms.

With this technique, the chance of successive collisions is eliminated. Moreover, if a collision occurs at a certain time at some point P between signals of adjacent rooms 1 and 2, the next collision at point P will occur at $t_{collision}$, which in this case is:

$$t_{collision} = nT_1 = mT_2$$

where m and n are the number of emissions of transmitter 1 and 2 respectively, before the next collision occurs (as shown in Figure 3.9). Knowing that the first collision occurs when $m = n-1$, and replacing T_2 by $T_1 + T_{signal}$, we get:

$$t_{collision} = nT_1 = (n-1)(T_1 + T_{signal})$$

which yields:

$$n = 1 + \frac{T_1}{T_{signal}} \tag{3.7}$$

This means that one collision will happen every n transmissions, so the probability of collision is:

$$collision\ probability = \frac{1}{n} = \frac{T_{signal}}{T_1 + T_{signal}} \tag{3.8}$$

3.7 Experimental Evaluation

3.7.1 Experimental Setup

In order to test the system's functionality, we have implemented it in our lab, at the Battelle building of the University of Geneva. We used one fixed loudspeaker per room, which periodically transmits a unique ultrasonic packet. The chosen periods of emission are around 5sec. We focused the tests on two adjacent rooms with different dimensions, along with the corridor, as shown in Figure 3.10. The rooms were assigned distinct periods of emissions as described in Section 3.6. On the receiver side, an Android application was developed for room localization. This application receives the broadcasted ultrasonic signals, and implements the decoding process described in Section 3.5. It was installed on a Samsung Galaxy S5 smartphone.

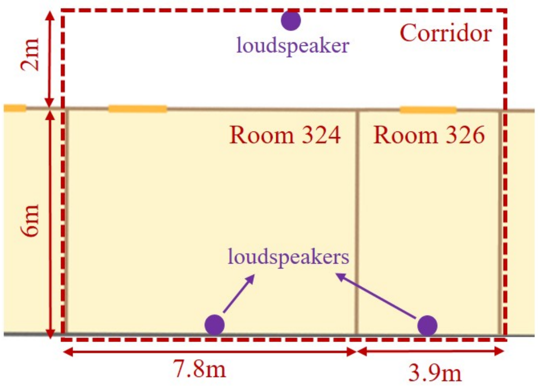


Figure 3.10: A map showing the rooms subject to testing

3.7.2 Tests and Results

We chose 20 different points to cover the selected area, as shown in Figure 3.11. At each of these points, 100 measurements were recorded consecutively, using the Android localization application, as Figure 3.12 shows, and under ambient noise conditions. The experiments were repeated twice: the first time with closed doors, and the second with open doors.

Tables 3.1 and 3.2 show the results for the case with closed doors, and that with open doors respectively. The tables show the percentage of the results that match the correct room in which the user is, and the average of the confidence scores of these results.

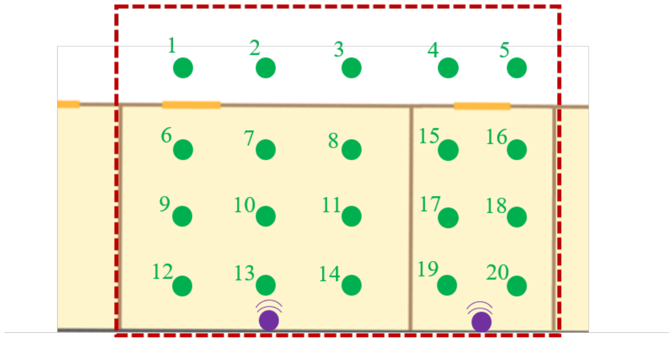


Figure 3.11: Points at which the tests were performed

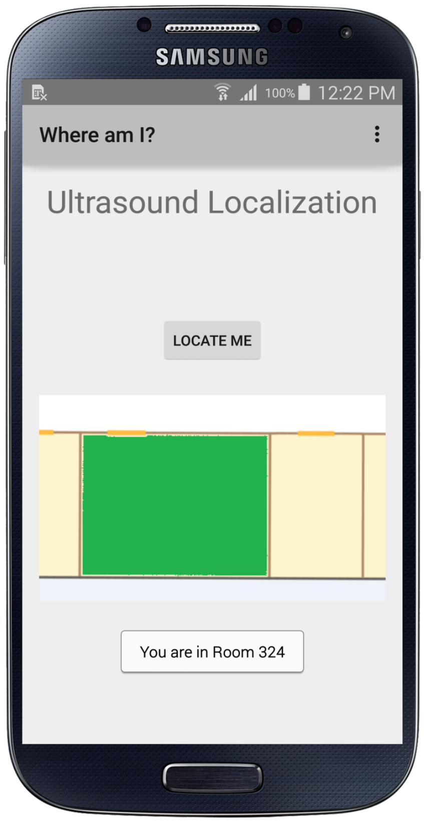


Figure 3.12: A snapshot of the Android localization application

Interpretation of Results

In the case of closed doors, the ultrasonic signals are confined to the room in which they are emitted, and the signals leaking from adjacent rooms are very

Table 3.1: Room Localization Results - Closed Doors

Point Number	Correct Room Results	Average Confidence Score
1	100%	94.8%
2	100%	95.2%
3	100%	96.7%
4	100%	95.1%
5	100%	94.5%
6	100%	94.6%
7	100%	95.1%
8	100%	94.5%
9	100%	95.3%
10	100%	96.2%
11	100%	95.1%
12	100%	95.6%
13	100%	97.7%
14	100%	96.5%
15	100%	95.1%
16	100%	94.8%
17	100%	96.0%
18	100%	95.9%
19	100%	98.2%
20	100%	97.7%

weak. This leads to perfect room localization results, with high confidence scores, and also causes the collisions to vanish. On the other hand, when the doors are open, the signals from adjacent rooms can interfere, leading to packet collisions. However, the probability of such collision is very low, thanks to our suggested method. This explains why we obtain very low false detection results, which correspond to collided packets.

The confidence score is affected by the strength of the signals received from adjacent rooms. Nonetheless, it is up to the application layer to use this score, in order to judge the reliability of the localization result, when multiple signals are received. It is also notable that the confidence score is high when the receiver is close to the transmitter, and decreases as we move away from it.

Table 3.2: Room Localization Results - Open Doors

Point Number	Correct Room Results	Average Confidence Score
1	99%	68.3%
2	99%	77.1%
3	100%	82.8%
4	99%	76.5%
5	99%	70.8%
6	99%	73.2%
7	99%	77.7%
8	100%	84.0%
9	99%	80.9%
10	99%	81.5%
11	100%	86.2%
12	100%	89.4%
13	100%	93.3%
14	100%	90.7%
15	99%	75.1%
16	99%	68.0%
17	100%	83.5%
18	99%	76.2%
19	100%	90.4%
20	100%	91.9%

3.8 System Characteristic Features

In our proposed room-level localization system, we make sure to address and satisfy the desired characteristics previously discussed in Section 3.4. As a result, here are the main characteristic features that our system offers:

- Accuracy: As proved in the experimental evaluation, the implemented system presents a high room presence accuracy, suitable for the purpose of occupancy detection.

- Robustness: the methods that are used for signal modulation and processing, like chirp signals, frequency multiplexing, and matched filters, make the system robust against ambient noise. Moreover, assigning distinct periods of emission guarantee low collision rates.

- Availability: as it is sufficient to have deployed sound speakers for our system to work, it is suitable to use in many environments, such as museums, hospitals, offices, and shopping malls, without the need to deploy additional infrastructure. As ultrasounds do not alter audible sounds, the same speakers can still be used to play music or to broadcast voice messages.
- Scalability: the system is easily scalable to accommodate any number of rooms.
- Ease of deployment: the system can be easily deployed and ready to use without the need for an offline training phase.
- Low complexity: by dividing the ultrasound signal into two parts, the decoding process becomes of low complexity in terms of number of operations, which guarantees a fast response time on the receiver side. Having the pilot signal as a common part for all rooms, requires the receiver to correlate the recorded signal with the pilot signal only, before proceeding to identify the corresponding room. If we did not have a common signal part, the receiver would have to match the recorded signal with all possible signals from different rooms, in order to identify the correct room. In that case, signal decoding becomes computationally expensive, especially when the system is scaled to accommodate a large number of rooms.

3.9 Summary

In this work, we have proposed a device-based room-level localization system using ultrasound, that can be built out of COTS components. The designed system is robust, scalable, and has a low computational complexity and collision rate. It was shown to have a very good performance in ambient noise environments. The system was designed for localization inside houses in the context of smart heating, however its characteristic features make it a suitable solution to use for other applications and in different environments, such as hospitals, museums, offices, shopping malls, etc. This is because many of these environments are traditionally equipped with loudspeakers, which can be used for occupancy detection.

4 UltraSense: Device-Free Motion Detection System

4.1 Chapter Abstract [1]

With this chapter, we open the part that follows a device-free approach for occupancy detection. We investigate the use of ultrasounds for sensing the presence of people in indoor environments. This chapter focuses on motion sensing as one means to infer the occupancy. We present a self-calibrating ultrasonic motion sensing system, which we call **UltraSense**. UltraSense uses active ultrasound to sense persons' movements, based on the Doppler effect. It leverages unsupervised learning to automatically calibrate its parameters in a seamless way, according to the surrounding environment in which it is installed. This ability avoids the need for manual calibration of the sensing system for each new environment. Additionally, it makes the system operate regardless of the specific room environment, and whether it is in LOS or NLOS conditions. UltraSense is non-intrusive, in the sense that neither does it need a physical contact, nor does it require the user to carry a device with her. A working

[1] A shorter version of this chapter was published in: A. Hammoud, M. Deriaz and D. Konstantas, "Ultrasense: A self-calibrating ultrasound-based room occupancy sensing system," Procedia Computer Science, vol. 109C, pp. 75–83, 2017, 8th International Conference on Ambient Systems, Networks and Technologies, ANT 2017, May 2017, Madeira, Portugal.

prototype was implemented to test the proposed system, and the results show that the system achieves high detection rates in different scenarios.

4.2 Introduction and Related Work

As we described previously, a device-free approach is based on using environmental sensors to sense the occupancy of persons, without requiring them to carry a device. One means of inferring the presence of persons in an indoor space is *motion detection*. Motion detection is based on the Doppler effect, which states that a moving object causes a frequency shift in the signal that bounces off this object [83]. This frequency shift, which is directly proportional to the velocity of the moving object that reflects the signal, is given by the following formula:

$$\Delta_{f(signal)} = \frac{2v_{object}}{c} f_{signal} \tag{4.1}$$

where v_{object} is positive if the object is approaching, and negative if it is receding from the signal source. c is the speed of propagation of the signal.

The Doppler effect principle is implied in different applications. Radars leverage this principle to monitor planes and ships using RF signals. Another application are the speed guns used by the police and law enforcement agencies to measure the velocity of cars on the roads (Figure 4.1). Additionally, the concept is used in medical fields to observe blood flow and velocity, and in industrial applications to monitor fluids inside tubes.

Ultrasonic signals can be used to sense human motions based on Doppler effect. Ultrasounds present some characteristic advantages over RF signals in this regard. From one side, commonly used ultrasounds have a much lower frequency range (typically 20kHz up to few MHz) when compared to X-band RF signals (in the range of 10GHz). Moreover, ultrasounds propagate much slower than RF signals. Therefore, a frequency shift caused by a moving person will be much higher and

Figure 4.1: A speed gun used by police to detect a car's speed.

Source: *https://i2-prod.leicestermercury.co.uk/news/article262755.ece/ALTERNATES/s615b/A-traffic-officer-using-a-laser-speed-gun.jpg*

hence more detectable for an ultrasonic signal as compared to an RF signal. For example, using Equation 4.1, a person who is moving at a speed of $0.5m/s$ will cause a frequency shift of 116 Hz for an ultrasonic signal whose frequency is 40kHz, but only a shift of 0.033 Hz for an RF signal whose frequency is 10GHz. The use of RF signals is also governed by regulations of frequency allocation [84], and hence some frequency bands are subject to license, whereas ultrasounds can be used without authorization. On the other side, since ultrasounds are mechanical waves, they are limited to walls in their propagation. This characteristic makes them better suited for occupancy detection and guarantees a finer granularity, since moving objects behind walls will not cause false positive detection.

Let us take a look at the related works in the literature. An early work by Geisheimer *et al.* [85] uses a continuous-wave (CW) RF radar operating near 10.5 GHz for human gait analysis. Since the movement of different body parts (arms, torso, legs) can cause multiple frequency shifts with different amplitudes to the reflected signals, processing the reflected signals could offer a lot of information and allows to extract various parameters of the human gait. A similar work [86] uses a micro-Doppler radar system for the acquisition of human gait signatures.

Ekimov *et al.* [87] use active ultrasound to analyze human motions by leveraging Doppler shifted signals. Similarly, Mehmood *et al.* [88, 89], they employ an ultrasonic sonar at 40kHz to measure the Doppler signature generated by the motion of body segments using different electronic and signal processing schemes. In [90], Raj *et al.* present their prototype that comprises an ultrasonic transmitter and receiver operating at 40kHz, which uses the Doppler effect principle for various applications, like motion detection, gesture recognition and speech recognition.

4.3 Our Contribution

Our work differentiate from the previous works in these main aspects:

1. Our motion detection system uses unsupervised learning to classify the collected data and infer the room occupancy. In this sense, there is no need for a manual labeling of the different frames. The system uses methods to automatically calibrate its parameters according to a each specific environment. This fact makes the system easily deployable and ready to use for every new installation environment.

2. The way we designed our system makes it work regardless of the specific installation, and whether it's in direct LOS or in NLOS with the occupants, whereas commonly available occupancy detection technologies are limited to LOS conditions.

3. We use commodity hardware (speaker, microphone) in our system with a frequency of 20kHz. This characteristic proves that it is possible to use such hardware, which can be easily available and deployed, for device-free occupancy sensing in different indoor environments.

In the rest of the chapter, Section 4.4 shows the design aspects of UltraSense, then Section 4.5 explains the methodology used for occupancy detection. Section 4.6 presents the system calibration method, and the experimental evaluation is shown in Section 4.7. Finally, Section 4.9 concludes this chapter.

4.4 System Design

While studying the use of ultrasound in motion sensing to infer the occupancy, we aim for a system that satisfies the following requirements:

1. High accuracy, so as to offer a reliable occupancy information for the prospective applications.
2. Operation on a room-scale, as it's the most common granularity level suitable for a wide range of applications (lighting, HVAC systems, intrusion detection, etc.)
3. To have an automatic calibration, as to reduce the deployment complexity and avoid the need for manual intervention for each new installation. This feature also 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.

Our designed system, UltraSense, uses active ultrasound to detect 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 4.2 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

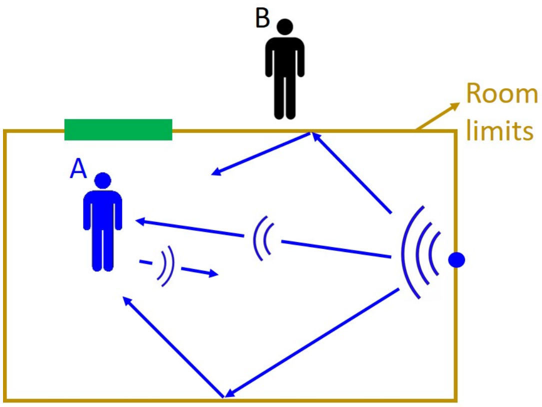


Figure 4.2: Acoustic signals are generally confined to the room in which they are emitted.

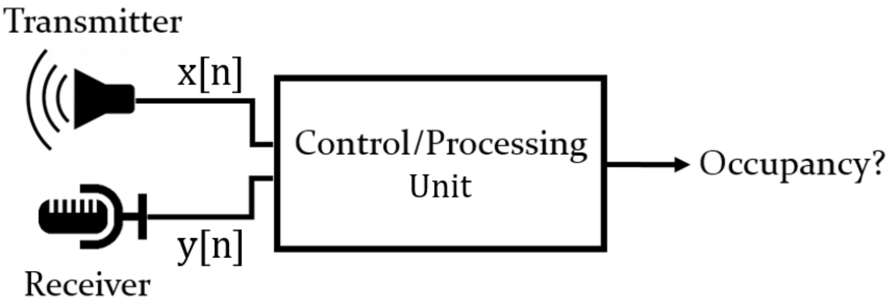


Figure 4.3: Architecture of the occupancy sensing module.

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 4.3.

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 wider directionality. These in general can support up to around 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 is used to trigger the signal transmission, record and process the received signal,

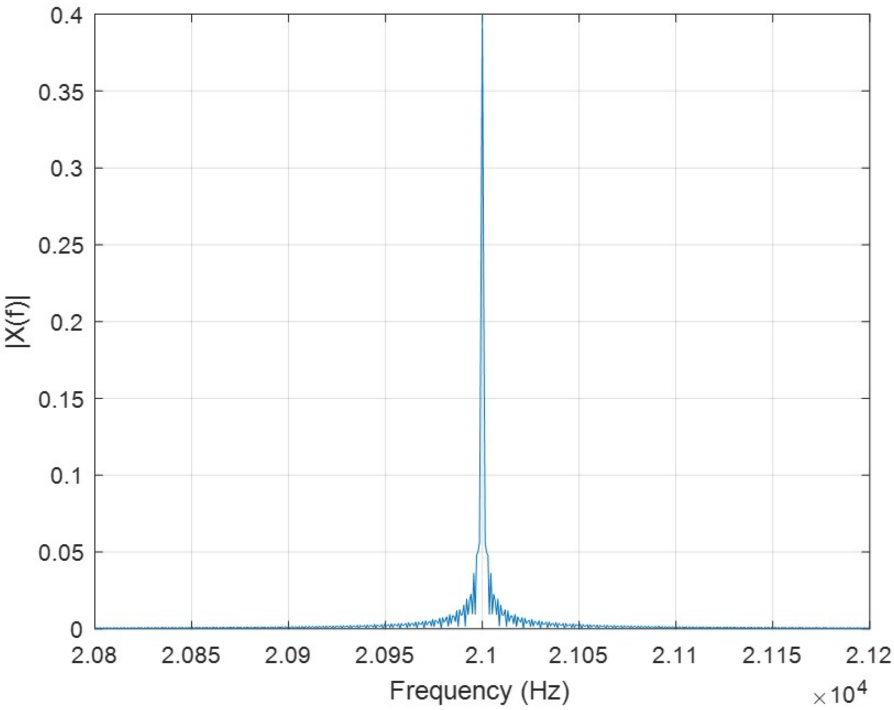


Figure 4.4: Frequency spectrum of the transmitted pulse around the central frequency f_c.

and indicate whether the the room is occupied or not. This unit also implements the self-calibration method, as described in Section 4.6, 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:

$$x[n] = \sin 2\pi n(f_c/f_s) \quad for \;\; n = 0, 1, \ldots, T_{signal} \times f_s \tag{4.2}$$

where f_s and T_{signal} are the sampling frequency and the signal duration, respectively. The frequency spectrum of the transmitted signal can be obtained from the magnitude of the Discrete Fourier Transform (DFT). Figure 4.4 shows the frequency spectrum of the transmitted pulse for $f_c = 21$kHz.

4.5 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:

$$|Y[k]| = |\mathscr{F}\{y[n]\}|_k = |\sum_{n=0}^{N-1} y[n]e^{-j\frac{2\pi}{N}nk}| \qquad for\ k = 0, 1, \ldots, N-1 \tag{4.3}$$

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, as 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 4.5 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:

$$\begin{aligned} motion\ score\ &= \sum_{k\in I} |\ |Y[k]| - |Y_{still}[k]|\ | \\ where\ I &= [f_c - \Delta_{f(max)}, f_c) \cup (f_c, f_c + \Delta_{f(max)}] \end{aligned} \tag{4.4}$$

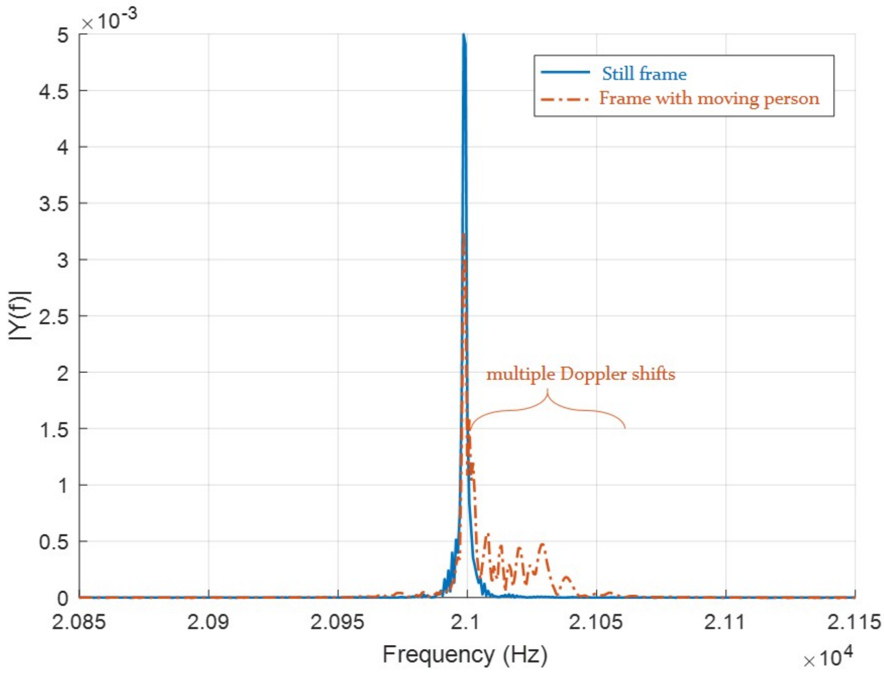


Figure 4.5: Difference in frequency spectrum between a still frame (blue) and a frame with a moving person (red).

I is the frequency interval of interest around the center frequency f_c. 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}:

$$\Delta_{f(max)} = \frac{2v_{max}}{c} f_c \tag{4.5}$$

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 5.1 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 positive 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:

$$y[n] = \sum_{m=0}^{M-1} \rho_m e^{j\phi_m} x[n - \tau_m] + v[n] \tag{4.6}$$

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.

4.5.1 Direction of Movements

It would be useful to detect not only the presence of a person inside a room, but also his direction of movement. By knowing whether the person is entering or leaving the room, controlling of smart systems would become more convenient. The information would also help to learn about the person's habits. UltraSense can identify the direction of movements, given that it knows the position in which it is installed inside a room.

According to Doppler theory, if the user is moving towards the transmitter he will cause a positive shift in the signal frequency, which will show up to the right of the central frequency f_c in the frequency spectrum. Otherwise, if the user is moving away he will cause a negative frequency shift, showing up to the left of f_c. The *positive frequency shift (PFS)* parameter detects the Doppler frequency shifts to the right of f_c in the frequency spectrum:

$$\begin{aligned} PFS &= \sum_{k \in I_{right}} |Y[k] - Y_{still}[k]| \\ where\ I_{right} &= (f_c, f_c + \Delta_{f(max)}] \end{aligned} \tag{4.7}$$

Similarly, the *negative frequency shift (NFS)* detects the Doppler frequency shifts to the left of f_c in the frequency spectrum:

$$\begin{aligned} NFS &= \sum_{k \in I_{left}} |Y[k] - Y_{still}[k]| \\ where\ I_{left} &= [f_c - \Delta_{f(max)}, f_c) \end{aligned} \tag{4.8}$$

Note that the previous two scores sum up together to the motion score:

$$motion\ score = NFS + PFS$$

When the system detects a motion inside the room, it uses Algorithm 1 to determine the direction of the movement.

4.5.2 Adjacent Rooms

Although the acoustic waves are generally confined to the room in which they are emitted, a part of these waves may still leak outside of the room in some cases (open doors, etc.). This leakage would cause an interference between signals of adjacent rooms, especially at boundary points, only if they share the same frequency. Signals interference might lead to erroneous occupancy detection results.

Algorithm 1 Detection of movement direction

if ($motion\ score > threshold$) **then**
    if ($NFS \gg PFS$) **then**
        Person is moving away from the transmitter
    else if ($NFS \ll PFS$) **then**
        Person is moving toward the transmitter
    else
        Movement detected, no specific direction
    end if
else
    No movement detected
end if

To solve this problem, distinct central frequencies need to be assigned to adjacent rooms. To guarantee no interference between the signals, the difference between the central frequencies of adjacent rooms should be at least $2 \times \Delta_{f(max)}$.

4.6 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.

4.6.1 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 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 mean value, to average out the effect of noise, assumed to be additive

Gaussian. And the threshold value is 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 repeat this process every time he installs a new module in a given room. Therefore, and in order to ensure user comfort and seamless calibration, we propose a self-calibration method for our system.

4.6.2 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: $\{|Y_0[k]|\}, \{|Y_1[k]|\}, \ldots, \{|Y_{N-1}[k]|\}$.

4.6.2.1 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 5.1), we are sure to have picked the lowest frequency components, which correspond to the still spectrum

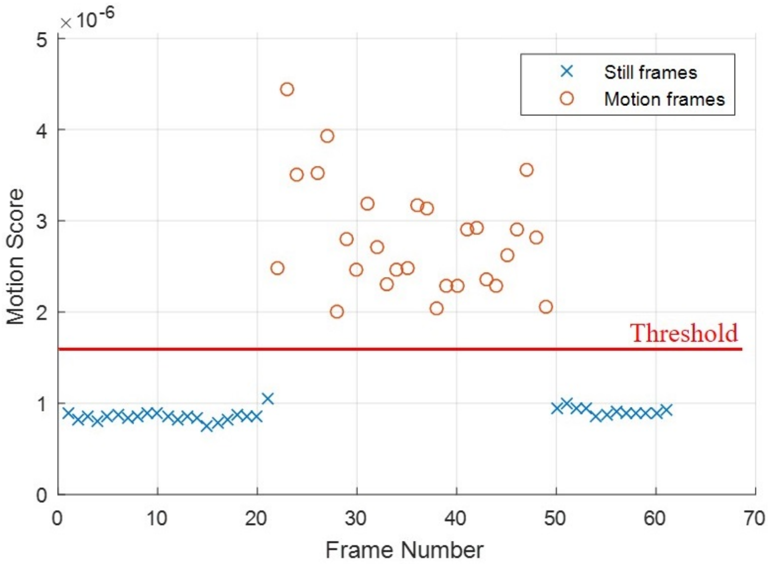


Figure 4.6: Frames clustering into *still* and *motion* frames, based on their corresponding motion scores.

$\{|Y_{still}[k]|\}$:

$$|Y_{still}[k]| = \min(|Y_0[k]|, |Y_1[k]|, \ldots, |Y_{N-1}[k]|) \quad \forall k \in I \tag{4.9}$$

4.6.2.2 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 5.1) 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.

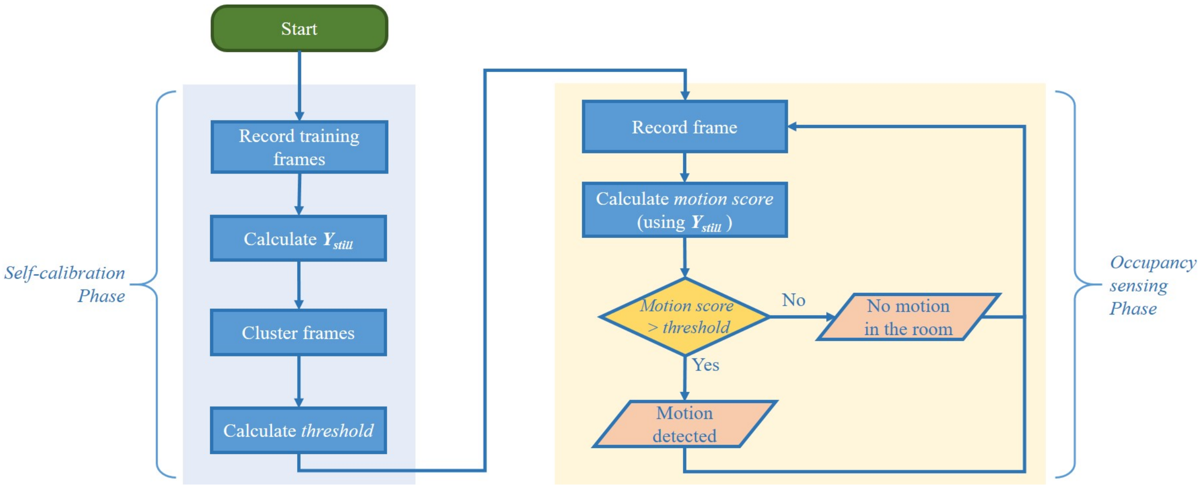


Figure 4.7: Diagram showing the self-calibration process and the occupancy sensing algorithm.

Figure 4.6 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 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 4.7.

4.6.2.3 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 5.1) is retained, thus the number of samples needed for each frame is:

$$n_{samples/frame} = 2\Delta_{f(max)} \times T_{frame} \tag{4.10}$$

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

$$Required\ memory = N \times n_{bytes/sample} \times 2\Delta_{f(max)} \times T_{frame} \tag{4.11}$$

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 $23.44kB$.

4.7 Experimental Evaluation

In order to test its functionality, we have implemented a prototype of the proposed system. The prototype, shown in Figure 4.8, comprises a low power commodity speaker, a commodity microphone, both connected to a Raspberry Pi board [91]. This board acts as the control/processing unit, and implements the calibration and occupancy detection algorithms described in the previous section. 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 purpose 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.

Figure 4.8: The implemented prototype comprises a commodity speaker and a microphone connected to a Raspberry Pi board.

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 4.6.1. Then, it runs the self-calibration method as described in Section 4.6.2, using 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 $(6 \times 3.9m)$ with clear LOS and NLOS (prototype placed behind a furniture), respectively. While the other two correspond to a large room $(6 \times 7.8m)$, 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 4.9 shows a portion of the testing set, as an

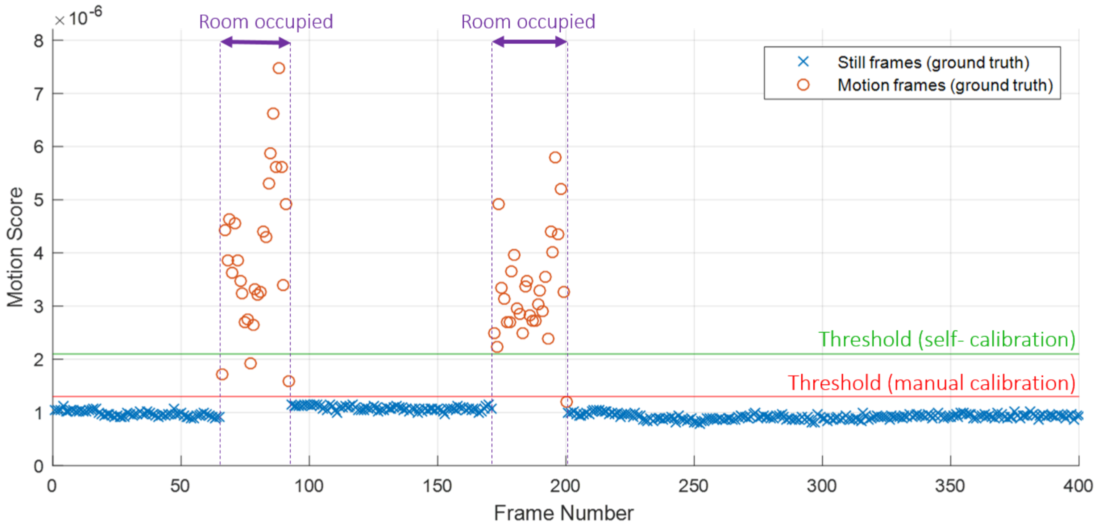


Figure 4.9: Comparison of motion detection using results obtained from manual and self-calibration, for a portion of the test set.

Table 4.1: 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%

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 4.1.

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 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.

4.8 Performance Comparison

In order to compare the performance of UltraSense, we consider the occupancy sensing system AURES, by Shih *et al.* [92]. AURES uses also a 20kHz ultrasonic signal to detect motions using Doppler effect. In the evaluation of their system, the authors differentiate between small rooms ($< 10m^2$), medium ($10 - 100m^2$), and large ($> 100m^2$). They report an accuracy of 85% with 11% false positives for a small room, 82% with 27% false positives for medium, and 75% with 29% for a large one. Comparing to our system UltraSense, it is able to achieve a much better accuracy with the self-calibration method, resulting in an accuracy of 87-97% with a much lower false positive rate (0.8-1.3%), in the tested environments.

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. For this purpose, we implemented these sensors on an Arduino board, as shown in Figure 4.10, to verify their mode of operation. For the PIR, we used a model with a wide angle motion detection (model Parallax 28032 [93]), and for the X-band motion detector we used the following model (Parallax 32213 [94]). Table 4.2 shows an overview of the

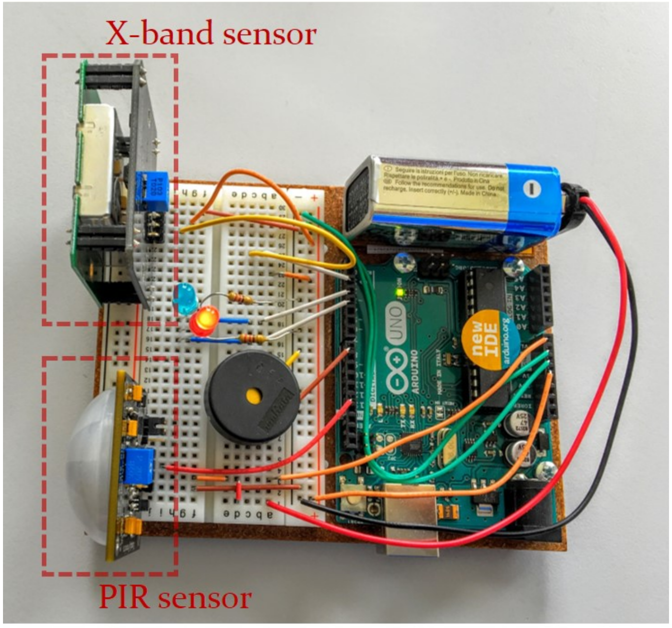


Figure 4.10: Circuit used to test the PIR and the X-band sensors.

Table 4.2: 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

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.

4.9 Summary

In this chapter, we have presented UltraSense, an ultrasound-based motion 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. The presented system is limited to detect motions inside the room and uses this information to infer the presence of persons. However, it does not detect at this stage the presence of a person standing still without moving. This issue is addressed in Chapter 6, and the system is enhanced to detect still persons by exploiting the room acoustic response under different conditions.

5 Power Hopping: Optimizing the Consumption of Motion Sensing

5.1 Chapter Abstract [1]

In the previous chapter, we have shown how ultrasonic motion sensors can be used as a mean to obtain occupancy information of indoor spaces. Although these sensors provide a high accuracy as compared to other sensors, like Passive Infrared (PIR), they require a higher power consumption in general. In this chapter, we propose an adaptive power switching technique, which we call *power hopping*. This technique allows ultrasound motion sensors to optimize their transmitter power level, in order to best fit their surrounding environment. The objective is to reduce the overall energy consumption of these sensors. We have tested our method using a sensor prototype, and the results show that, depending on the sensor's environment, a possible saving in the transmitter power can be achieved, which reached up to 78% in our experiments. We also derive an upper bound limit of the method's convergence time, and we propose an automatic sensing method to detect potential changes in the sensor's environment.

[1] Shorter versions of this chapter were published in: A. Hammoud, G. G. Anagnostopoulos, A. I. Kyritsis, M. Deriaz and D. Konstantas, "Power hopping: An automatic power optimization method for ultrasonic motion sensors," 2017 IEEE Ubiquitous Intelligence and Computing, (UIC), San Francisco, CA, 2017, pp. 1-7. and in: A. Hammoud, M. Deriaz and D. Konstantas, "Adaptive power switching technique for ultrasonic motion sensors," Journal of Ambient Intelligence and Humanized Computing, jun 2018.

5.2 Introduction and Related Work

Motion sensing is one way to infer the presence of people in indoor spaces. While several technologies have been developed for motion sensing, PIR and ultrasonic motion sensors remain the most prevalent in this respect [43].

PIR sensors are widely used to detect human motions, by responding to a change in the temperature pattern across the field of view of the sensor. A PIR sensor is considered passive as it does not emit any energy itself, but rather relies on the pattern of the received infrared radiation in the environment [44]. Different works have suggested algorithms to enhance the performance of PIR sensors and the processing of their output [47–49, 51]. PIR sensors are attractive because of their low power consumption. However, the main drawbacks of PIR sensors are their limited accuracy (decreases with increasing distance due to the use of Fresnel lens), 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.

Similarly, ultrasonic sensors can be used in occupancy sensing. Ultrasonic ranging sensors are one category of them, they are used to to detect objects in the field of view, based on the time-of-flight (ToF) of the ultrasonic signal. As stated previously, some works [95–97] use this technique to infer the occupancy at a specific location. On the other hand, ultrasonic motion sensors which we address in our work, use active ultrasonic signals to sense human motions inside an area, based on the Doppler effect principle. These sensors are helpful to obtain fine information about the room occupancy, the direction of movements and speed of occupants.

Ultrasonic motion sensors are promising as they are more sensitive and accurate than PIR ones [43]. Moreover, they are capable of sensing moving objects in non line-of-sight (NLOS), since the ultrasonic signals can propagate around objects, unlike infrared radiations. Despite these advantages, ultrasound motion sensors are sill not very popular, as it is the case with PIR ones. The fact that they are active, as compared to passive, makes their power consumption higher than PIR, and thus limits their potential applications. Example applications of these sensors can be found in [88], [90], and [98]. Another reason for the limited use of ultrasounds, is the fact that some pets can still hear them, even if not audible to humans [99]. However, reducing the transmitted signal power will also reduce the possibility of disturbing effects on pets.

While many works have discussed the use of ultrasonic sensors in occupancy sensing, the issue of power consumption has not attracted sufficient interest. In their work, Mishra *et al.* [100] try to reduce the *processing* power of ultrasound raging sensors used by robots to perceive the occupancy grid. They do so on the logic circuitry level, and show that the power consumption can be reduced by redesigning the processing logic circuit. However, and to the best of our knowledge, there is no research work in the literature that focuses on reducing the *transmitter* power consumption of ultrasonic sensors, as we suggest in our work.

In this chapter, we state that the required power for ultrasonic motion sensors is not fixed, but rather it varies as a function of the sensor's environment. We introduce the *power hopping* method as an automatic process to optimize the transmitter power level to best fit this environment. The method aims to reduce the power consumption of the sensor while preserving the performance. After testing the method using a sensor prototype, we validated that a possible saving in the transmitter power can be achieved, depending on the sensor's environment. In our experiments, the power saving reached up to 78% in transmitter power.

The rest of this chapter is organized as follows. First, Section 5.3 recalls some necessary details about the operation of ultrasound motion sensors. Section 5.4 explains the concept and algorithm of the suggested power hopping method. In Section 5.5 we derive an upper limit for the convergence time, and in Section 5.6 we present our technique to automatically detect changes in the sensor's environment.

The experimental evaluation of our method is presented in Section 5.7. Finally, Section 5.9 concludes the chapter.

5.3 Preliminaries

Ultrasound-based motion sensors use active ultrasonic signals to detect movements of people inside a certain area, based on the Doppler effect principle. They periodically transmit an ultrasonic signal and observe the corresponding reflected one. Frequency shifts in the received signal indicates the detection of movements, whereas the signal frequency remains intact when no movements occur.

Assuming that the transmitted signal is a sine pulse of frequency f_c and duration T, its sampled version can be represented by a discrete time sequence $x[n]$ of length $\lfloor T/T_s \rfloor$, where T_s is the sampling frequency. Let a *frame* represent one transmission/reception of the ultrasonic signal. The transmitted signal propagates through the environment, and reflects on obstacles and objects. Static objects (walls, furniture, etc) do not alter the signal frequency, while moving ones (people walking, etc) will cause some shifts in the signal frequency.

The sensing unit records the received signal $y[n]$ for a certain frame, and computes the magnitude $\{|Y[k]|\}$ of its Discrete Fourier Transform (DFT), which represents its frequency spectrum. To detect movements, the frequency spectrum of the current frame is compared against a reference still frame. The still frequency spectrum $\boldsymbol{Y_{still}}$ corresponds to the case with no moving objects, and should be known to the system. The difference between the two spectra reflects the frequency shifts in the signal, and is computed by the system using the following quantity, which we call the *motion score*:

$$motion\ score = \sum_{k \in I} \left| \, |Y[k]| - |Y_{still}[k]| \, \right| \tag{5.1}$$

where I is the ultrasound frequency band to consider around the signal frequency f_c. The result of Equation 5.1 is compared with a *threshold* value. If it exceeds the threshold, it can be deduced that a movement is detected, otherwise if it is smaller than the threshold, the frequency differences can be considered to be due to noise and thus no movements are reported to be detected. We define the motion intensity as the ratio of the motion score to the threshold value:

$$motion\ intensity = \frac{motion\ score}{threshold} \tag{5.2}$$

To sum-up, the values of ($\boldsymbol{Y_{still}}$, *threshold*) represent the parameters that are needed for motion detection.

5.4 Power Hopping Method

The total power consumption of an ultrasound motion sensor is mainly divided into signal transmission/reception and signal processing:

$$P_{total} = P_{transmitter} + P_{receiver} + P_{processing} \tag{5.3}$$

While the power required for the receiver and signal processing is independent from the sensor environment, the transmission power can be optimized to best fit a certain environment and cut unnecessary power consumption, thus reducing the overall power consumption of the sensing unit. The objective of the power hopping technique is to find the optimal level of transmitter power that the sensor can use, without jeopardizing the performance.

5.4.1 The Best Power for Each Setting

The required transmitter power varies from one environment to another, depending on variables like the room dimensions, presence of obstacles, and also hardware

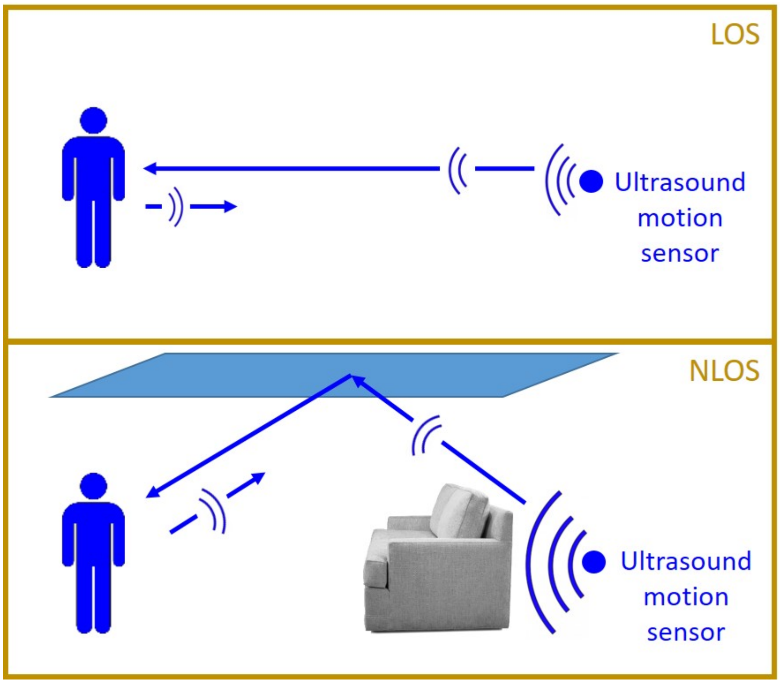


Figure 5.1: A different transmitter power is required in each case.

characteristics (receiver's sensitivity, etc.). Figure 5.1 shows how the installation environment would affect the required transmitter power. For example, if the LOS of the system is not blocked, the ultrasonic signal propagates easily and may need a low transmitter power. Whereas if the LOS is obstructed, as when the system is placed behind an obstacle or furniture, a stronger signal is needed to propagate around such obstacles.

Let $\boldsymbol{P_{max}}$ and $\boldsymbol{P_{min}}$ be respectively the maximum and minimum power levels of the sensor. $\boldsymbol{P_{max}}$ allows the sensor to work in all conditions, or in other words $\boldsymbol{P_{max}}$ yields the best achievable sensor performance. However, according to the sensor's environment, the system may still achieve the same performance with a lower power level. Power hopping allows the system to adapt to the optimal transmitter power $P_{optimal}$, which is the lowest possible transmitter power that yields the same performance. The value of $P_{optimal}$ should lie between $\boldsymbol{P_{max}}$ and

$\boldsymbol{P_{min}}$:

$$\boldsymbol{P_{min}} \leq P_{optimal} \leq \boldsymbol{P_{max}} \tag{5.4}$$

The power hopping method is supposed to take place for the first time during the initialization phase, when the sensor is installed in a new environment. Once the optimal power $P_{optimal}$ is found, the system switches to this new transmitter power level. Subsequently, the system scans the environment for any possible changes, and runs the power hopping process to reflect these changes as needed.

5.4.2 Relation Between Transmitter Power and Frequency Spectrum

Before introducing the algorithm of power hopping, it is necessary to state the relation between the transmitter power and the frequency spectrum of the received signal.

Statement. *Let the vector $\boldsymbol{Y_1}$ be the DFT of the received signal $y_1[n]$ that corresponds to a transmitted signal $x_1[n]$, and assuming that:*

- *The sensor's environment has a linear response*
- *The transmitter and receiver do not operate in their saturation region*
- *The effect of the noise on the received signal is negligible*

Then, if the amplitude of the transmitted signal is scaled by a constant α such that $x_2[n] = \alpha x_1[n]$, the magnitude $|\boldsymbol{Y_2}|$ of the DFT of the corresponding received signal $y_2[n]$ is such that

$$|Y_2[k]| = \alpha |Y_1[k]| \qquad \forall k \in I$$

Proof. Because the sensor's environment can be modeled by a linear system, when the transmitted signal is scaled by some constant α, the received signal will be also scaled by the same factor. The Fourier transform is also linear, so the scaling will also scale its result by the same factor, and therefore the magnitude of the Fourier transform, which represents the frequency spectrum of the received signal, will be scaled by α. □

Corollary. *Assume that we have the still frequency spectrum $|\boldsymbol{Y_{still}}|$ that corresponds to a certain transmitter power P. Since the power of a transmitted signal $x[n]$ of length N is*

$$P = \frac{1}{N}\sum_{n=0}^{N-1}|x[n]|^2, \tag{5.5}$$

if the amplitude of the transmitted signal $x[n]$ is scaled by α, then its power will be scaled by $\beta = \alpha^2$, and thus the new corresponding still frequency spectrum $|\boldsymbol{Y_{still(new)}}|$ will be equal to $\{\alpha \times |\boldsymbol{Y_{still}}|\}$ (or $\{\sqrt{\beta} \times |\boldsymbol{Y_{still}}|\}$).

Following a similar reasoning, the new threshold value to be used for comparison needs also to be scaled by the same constant α.

5.4.3 Power Hopping Algorithm

Initially, the transmitter power that is used by the system is $\boldsymbol{P_{max}}$. The parameters of the system ($|\boldsymbol{Y_{still}}|$, *threshold*) that are initially used correspond to $\boldsymbol{P_{max}}$. The system then tries to switch to a lower transmitter power $P_{candidate}$.

P_{valid} is the transmitter power level for which the sensor works well, and is initialized to $\boldsymbol{P_{max}}$, while $P_{invalid}$ is the transmitter power level which is too weak to detect motions and is initialized to $\boldsymbol{P_{min}}$.

When a motion is detected inside the room, the system hops between P_{valid} and $P_{candidate}$ back and forth several times. For $P_{candidate}$ to become valid, it should detect the motions that P_{valid} can detect with the same intensity every time, otherwise it is considered invalid. The number of times the system hops between the two power levels is a design choice parameter, which we call it n_{hops}. Setting the value of this parameter is a trade-off: on one hand, the higher n_{hops} is, the more robust the switching between the two power levels is, but also the convergence time of the power hopping method is longer. On the other hand if n_{hops} is low, the method converges faster, but the switching is less robust. In our design, we choose n_{hops} to be 3, which we empirically found to be a good middle choice to keep the switching robust while keeping the convergence time short enough.

When the system hops between P_{valid} and $P_{candidate}$, it calculates every time the motion score:

$$\begin{aligned} motion\ score_{(valid)} &= \textstyle\sum_{k\in I} ||Y_{valid}[k]| - |Y_{still}[k]|| \\ motion\ score_{(candidate)} &= \textstyle\sum_{k\in I} ||Y_{candidate}[k]| \\ &\quad - \sqrt{P_{candidate}/P_{valid}} \times |Y_{still}[k]|| \end{aligned} \tag{5.6}$$

Note that in Equation 5.6, the new still frequency spectrum is calculated using the reasoning of Corollary 5.4.2 (hence the square root in the equation).

$P_{candidate}$ is then considered valid, if the following holds for each time:

$$\begin{cases} motion\ score_{(valid)} > threshold \\ \quad and \\ motion\ score_{(candidate)} > \sqrt{P_{candidate}/P_{valid}} \times threshold \\ \quad and \\ \frac{motion\ score_{(valid)}}{threshold} \approx \frac{motion\ score_{(candidate)}}{\sqrt{P_{candidate}/P_{valid}} \times threshold} \end{cases} \tag{5.7}$$

The new threshold value is calculated as discussed in Corollary 5.4.2 as well. The first condition in Equation 5.7 indicates that a motion is being detected with P_{valid}, the second condition means that the motion can also be detected with $P_{candidate}$. The last condition requires that $P_{candidate}$ detects the motion with the same intensity compared to P_{valid}, ensuring that the switch of power levels is robust. The approximate equality, instead of full equality, is used to account for possible noise in the signals.

When $P_{candidate}$ is found to be valid, the system switches to this new power level and updates the parameters ($|\boldsymbol{Y_{still}}|$, *threshold*), otherwise it picks another candidate power level, as the middle value between P_{valid} and $P_{invalid}$, similar to a binary search. We assume that during the short time that this iteration takes, it is valid to consider that a person's movement is continuous.

The system continues the power hopping process, until the valid power P_{valid} does not change more than a certain amount ϵ. At this time, the optimal power $P_{optimal}$ is assumed to be found, and the system switches to this new transmitter power level. Algorithm 2 presents the power hopping method in pseudo-code.

Algorithm 2 Power hopping algorithm

procedure POWER HOPPING
initialization:
  $P_{valid} \leftarrow \boldsymbol{P_{max}}$
  $P_{invalid} \leftarrow \boldsymbol{P_{min}}$
  $P_{candidate} \leftarrow \boldsymbol{P_{min}}$
iteration:
  while ($P_{valid} - P_{candidate} > \epsilon$) and (*motion detected*) **do**
    hop between P_{valid} and $P_{candidate}$
    if $P_{candidate}$ *is valid* **then**
      $Y_{still}[k] \leftarrow \sqrt{P_{candidate}/P_{valid}} \times Y_{still}[k] \ \forall k \in I$
      $threshold \leftarrow \sqrt{P_{candidate}/P_{valid}} \times threshold$
      $P_{valid} \leftarrow P_{candidate}$
    else
      $P_{invalid} \leftarrow P_{candidate}$
    end if
    $P_{candidate} \leftarrow (P_{valid} + P_{invalid})/2$
  end while
result:
  $P_{optimal} \leftarrow P_{valid}$
end procedure

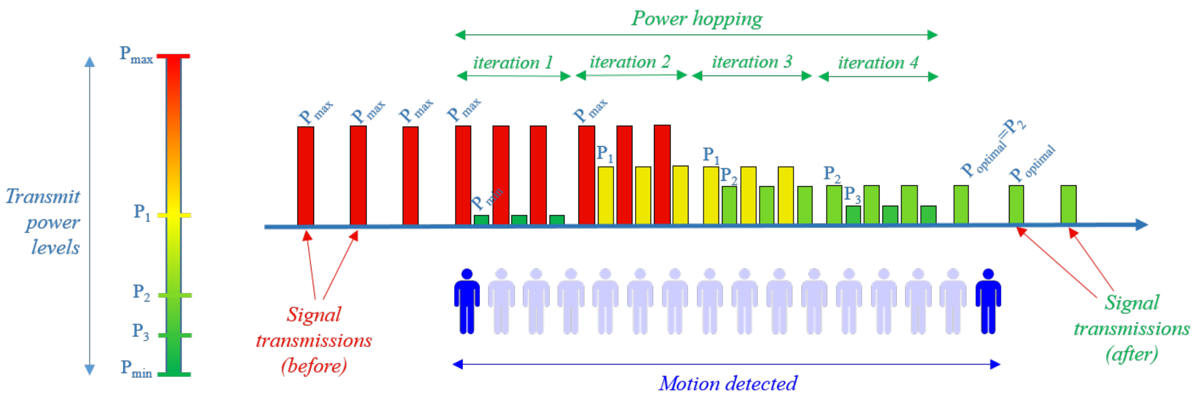


Figure 5.2: Power hopping example: adapting to the optimal transmitter power level.

5.4.4 Power Hopping Example

In this section, we illustrate an example case showing how the power hopping method works. We consider the scenario shown in Figure 5.2. First, the system is using the maximum power P_{max} to detect persons'movements. Once it detects a motion, it triggers the power hopping process. For the sake of this example, we assume that the power hopping converges in 4 iterations in this particular scenario:

- Iteration 1: P_{max} is a valid power level. P_{min} is the candidate power level. The system hops between P_{max} and P_{min}. P_{min} fails to detect motions, so the candidate power is updated to $P_1 = {}^{(P_{max}+P_{min})}/2$.
- Iteration 2: power hopping between P_{max} and P_1. P_1 succeeds to detect motions, so it becomes the valid power level. The new candidate power is now $P_2 = {}^{(P_1+P_{min})}/2$.
- Iteration 3: power hopping between P_1 and P_2. P_2 succeeds to detect motions, so the updates take place similar to Iteration 2.
- Iteration 4: power hopping between P_2 and P_3. P_3 fails to detect motions. In this particular example, we assume that the new candidate power is such that $P_2 - P_{candidate} < \epsilon$, and the power hopping process terminates at this point.

Power hopping converges to P_2, which is considered to be the optimal power level. The system switches to this power level, and from this moment on uses it to detect motions.

5.5 Convergence Time

The time required for the power hopping method to converge, depends on several parameters. In this section, we derive an upper bound of this time.

Let $n_{iterations}$ be the number of iterations needed for the system to converge. The method runs as long as the following condition holds:

$$\frac{P_{max} - P_{min}}{2^{n_{iterations}-1}} > \epsilon \tag{5.8}$$

Solving for $n_{iterations}$ yields:

$$n_{iterations} < 1 + \log_2\left(\frac{P_{max} - P_{min}}{\epsilon}\right) \tag{5.9}$$

which means that the maximum number of iterations for the method to converge is:

$$n_{iterations} = 1 + \left\lfloor \log_2\left(\frac{P_{max} - P_{min}}{\epsilon}\right)\right\rfloor \tag{5.10}$$

The total time of the process depends on the time required for each iteration. Assuming that the processing time after each transmission is negligible, the time it takes for each iteration $t_{iteration}$ depends on the number of hops n_{hops} from P_{valid} to $P_{candidate}$ and the time of each transmission $t_{transmission}$:

$$t_{iteration} = 2 \times n_{hops} \times t_{transmission} \tag{5.11}$$

The maximum required time for the power hopping process is:

$$t_{max} = t_{iteration} \times n_{iterations} \tag{5.12}$$

Yielding finally:

$$t_{max} = 2 \times n_{hops} \times t_{transmission} \times (1 + \lfloor \log_2(\frac{P_{max} - P_{min}}{\epsilon}) \rfloor) \tag{5.13}$$

In our design, we choose n_{hops} to be 3, as a middle choice to make the switching decision robust while keeping the time required short enough. For a transmitted signal duration of $10ms$, and a desired resolution of $\epsilon = {}^{(P_{max}-P_{min})}/_{128}$, the maximum convergence time would be $t_{max} = 0.48sec$

5.6 Automatic Detection of Environment Changes

5.6.1 Objective

The proposed power hopping method finds the optimal transmit power for a given environment, as previously described. However, as indoor environments are likely to be changed with time (motion sensor moved to a new place, furniture moved around, obstacle abundance changed, etc.), this optimal transmit power might become invalid, and needs to be recalculated for every new setting. Therefore, we have designed an automatic technique whose objective is to sense whether the surrounding environment has changed, and to re-trigger the power hopping process. As shown in the flow chart of Figure 5.3, the motion sensor checks periodically for changes in the environment, and runs the power hopping process when some changes are detected.

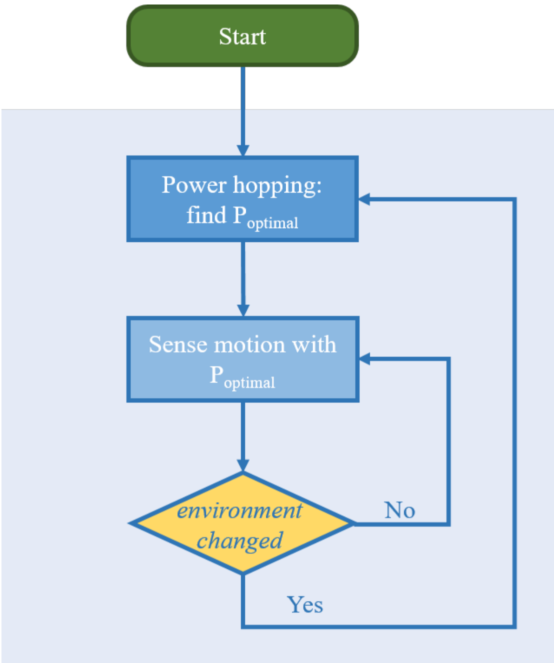


Figure 5.3: Flow chart showing how the power hopping is triggered when the environment is detected to be changed.

5.6.2 Technique

Detecting changes in the indoor environment is based on emitting an ultrasonic signal and observing the corresponding reflected one. Our technique is based on the concept that each environment is characterized by a specific response to the emitted ultrasonic signal. Changes in the layout or obstacles will cause some variations to the environment's response which will be reflected in the received ultrasonic signal. The aim of our technique is to spot any variations in the environment's response.

The sensor then processes the received signal to get the *reflection pattern* of the environment. We call a *reflection pattern*, the result of the environment's response to the emitted ultrasonic signal, which depends on several parameters, like the environment's dimensions, boundaries, the position of obstacles, furniture, etc. Therefore, any changes in this environment will be observed in the reflection pattern.

When the sensor switches to a new optimal transmit power level $P_{optimal}$, it records the corresponding reflection pattern of the environment. Then, it checks periodically if the reflection pattern has changed. Once the acquired reflection pattern of the environment does not match the recorded one anymore, this indicates that the environment has changed and the power hopping technique is re-triggered, to compute the new optimal power level.

5.6.3 Obtaining The Reflection Pattern

To obtain the reflection pattern of the environment, the sensor emits a short-time ultrasound signal. We have investigated different signal types, and our tests showed that a linear frequency 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 method is a chirp signal, with $f_0 = 20kHz$ and $f_1 = 21kHz$ as lower and upper frequency limits respectively. Its discrete-time representation is:

$$x[n] = \sin 2\pi(\frac{f_0}{f_s})n + \frac{q}{2}(\frac{n}{f_s})^2 \text{ for } 0 \leq n \leq \lfloor f_s \times T_{chirp} \rfloor \tag{5.14}$$

where f_s is the sampling rate, T_{chirp} is the chirp duration, $q = (f_1 - f_0)/2$.

As the signal frequency range falls in the supported frequency range, the same hardware previously used can still be leveraged for emitting the chirp signal and receiving the reflected one.

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:

$$h[n] = \sum_{m=0}^{M-1} a_m e^{j\phi_m} \delta(n - \tau_m) \tag{5.15}$$

where a_m, ϕ_m, and τ_m represent the signal attenuation, phase difference, and time delay of the m^{th} multipath signal respectively.

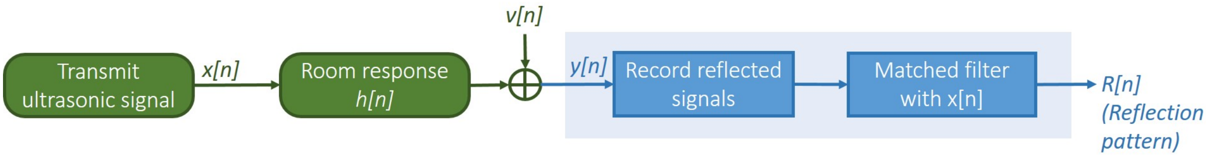


Figure 5.4: Obtaining the reflection pattern.

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 $v[n]$ assumed to be white Gaussian:

$$y[n] = x[n] * h[n] + v[n] \tag{5.16}$$

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.). The reflection pattern $R[n]$ is obtained by applying a matched filter to the received signal $y[n]$, as depicted in Figure 5.4.

5.6.4 Comparing Reflection Patterns

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 current optimal power level $P_{optimal}$. A new acquired reflection pattern $R[n]$ is compared to the reference $R_{ref}[n]$ in order to infer whether the indoor environment has changed. 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:

$$similarity\ index = max|\textit{cross-correlation}(\boldsymbol{R_{ref}}, \boldsymbol{R})| \tag{5.17}$$

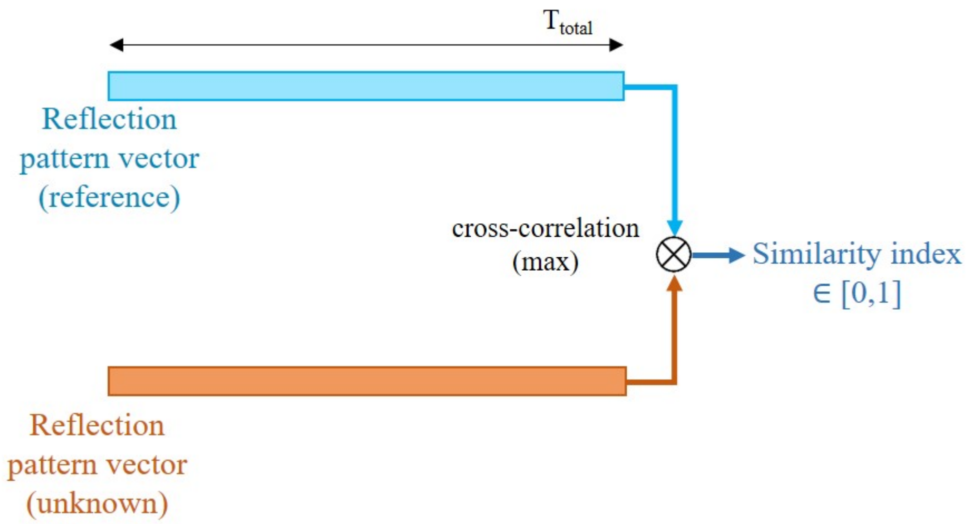


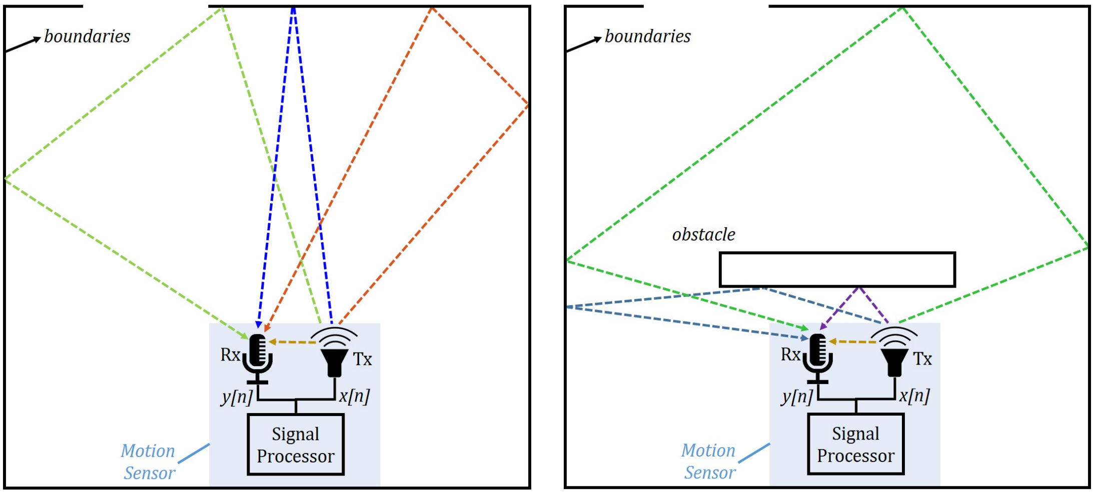
Figure 5.5: Comparing two reflection patterns.

Figure 5.5 shows how two reflection patterns are compared. 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 did not change. On the other hand, a low similarity index indicates the compared reflection patterns are uncorrelated and therefore the environment response has changed. A threshold value is used to differentiate the similarity indices, which we empirically set to (0.9).

In Figure 5.6, we show an indicative example of the signal propagation in the case where the environment changes. This example aims to show only the concept of the difference in the environment's response, rather than the actual exact propagation obeying physics laws.

5.6.5 Algorithm

Algorithm 3 describes in pseudo-code the technique of detecting the variations in the sensor's environment.



(a) Motion sensor in LOS **(b)** Motion sensor behind obstacle

Figure 5.6: Indicative example showing the difference of the environment response, when there is a change in its layout.

Algorithm 3 Detecting environment changes

while (*sensor is ON*) **do**
  power hopping: find $P_{optimal}$
  compute $R_{ref}[n]$ ▷ reference reflection pattern
  $environment\_changed \leftarrow false$
  while (! $environment\_changed$) **do**
    compute $R[n]$ ▷ current reflection pattern
    calculate similarity_index (R_{ref}, R)
    if ($similarity\_index < 0.9$) **then**
      $environment\_changed = true$
    end if
  end while
end while

5.7 Experimental Evaluation

5.7.1 Prototype

In order to test the performance of the suggested power hopping method, we use the prototype of the ultrasound motion sensor, previously implmented. The prototype, described in the previous chapter, is composed of a transmitter (a commodity speaker) and a receiver (a commodity microphone) both connected to a Raspberry Pi board [91], which acts as the control/processing unit, and implements the described power hopping method. The transmitted signal frequency used is 21kHz, and the frequency band considered in the processing of the received signal is 20kHz-22kHz.

5.7.2 Testing Methodology

The prototype of the sensor is fixed inside a certain area. For a chosen maximum transmitter power P_{max}, the detection parameters ($|\boldsymbol{Y_{still}}|$, *threshold*) are calibrated as described in Chapter 5. The sensor waits to detect movements before triggering the power hopping process. A person walks to the designated area, moves for few seconds and then leaves the area. During this time, the sensor runs the power hopping method, and switches to the optimal power level.

Aiming to cover different environments, the previous testing process is repeated for 4 different cases, as follows:

- Case 1: The area is a large room with dimensions $6 \times 7.8m$, the sensing unit is placed such that the LOS is not obstructed.
- Case 2: Same area of case 1, but the sensing unit is placed behind an obstacle blocking the LOS.

Table 5.1: Power saving as a result of the power hopping method

Case	Original Transmit Power	New Transmit Power	Power Saving
#1: large room, LOS	P_{max}	$0.31P_{max}$	69%
#2: large room, NLOS	P_{max}	$0.96P_{max}$	4%
#3: small room, LOS	P_{max}	$0.22P_{max}$	78%
#4: small room, NLOS	P_{max}	$0.76P_{max}$	24%

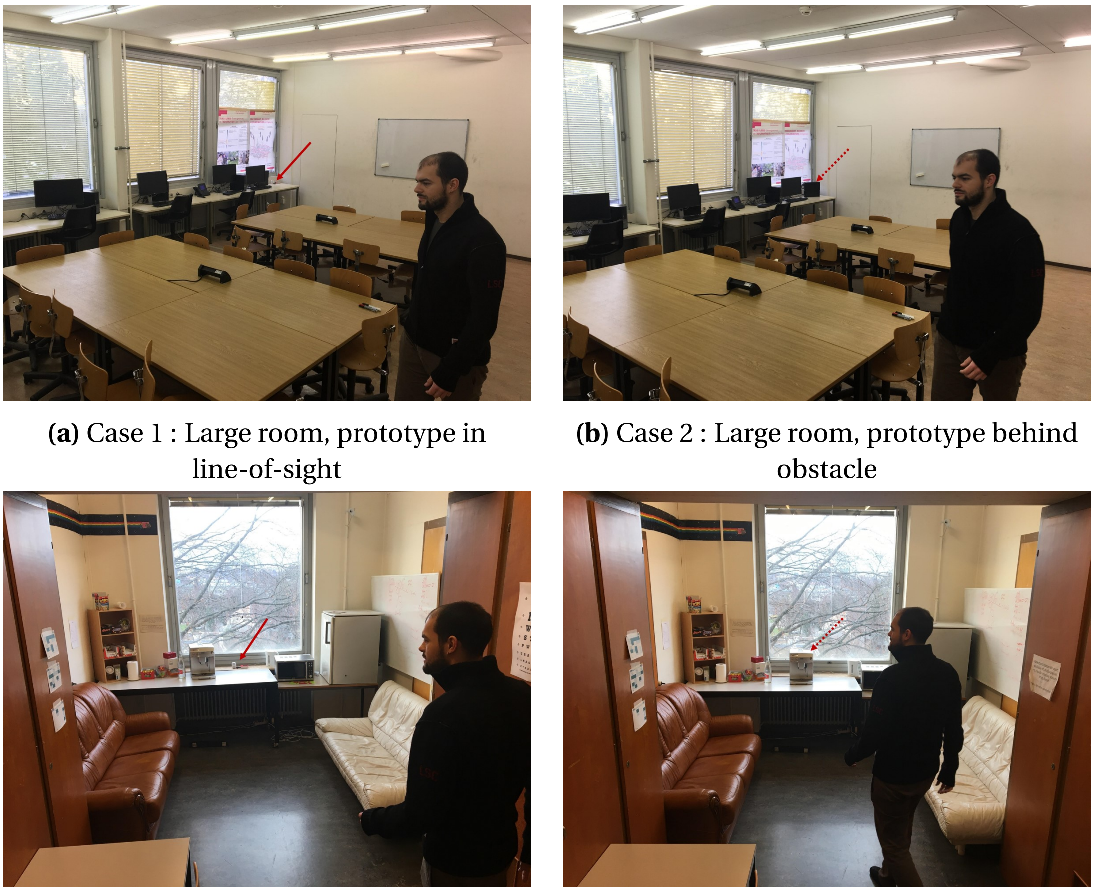
- Case 3: The area is a small room with dimensions $6 \times 3.9m$, LOS not obstructed.
- Case 4: Same area of case 3, with the sensing unit placed behind an obstacle blocking the LOS.

Figure 5.7 illustrates the different test cases for which the power hopping method was tested. In each case, we note the obtained optimal power level $P_{optimal}$. Once the power hopping process is over, and as a double check, we verified that the new transmitter power is capable of detecting the motions in the room as the previous power P_{max}.

5.7.3 Results

The results summarized in Table 5.1 show the optimal level of transmitter power $P_{optimal}$ obtained through the power hopping process, and also the power saving in each case.

The power hopping method aims to find the optimal transmitter power, and to cut unnecessary transmitter power amount. In general, we see that an important power saving in the transmitter power can be achieved (up to 78% as in case 3). The obtained results show that the required transmitter power varies in function of the specific environment (room size, obstacles, etc.). A big room, compared to a small one, requires more signal power to cover the whole area and detect movements inside it. This explains why, under the same settings, the system



(a) Case 1 : Large room, prototype in line-of-sight

(b) Case 2 : Large room, prototype behind obstacle

(c) Case 3 : Small room, prototype in line-of-sight

(d) Case 4 : Small room, prototype behind obstacle

Figure 5.7: Illustration of the different test cases

placed in a small room (case 3) requires less power than the case of a big room (case 1), yielding more saving in the transmitter power (78% vs 69%). On the other hand, when the sensor is placed behind an obstacle, a higher transmitter power is needed to propagate around the obstacle and detect movements behind it, as compared to a case with a direct LOS. This is the reason why we notice more power savings in cases 1 (69%) and 3 (78%), compared to cases 2 (4%) and 4 (24%) respectively. Case 2 represents an extreme environment in terms of size and obstacles, this is why a very little saving in the transmitter power is achieved (4%). This shows that the full maximum power level P_{max} might still be needed in such environments.

It is worth noting that although the obtained results show that it is possible to achieve a saving in the transmitter power in some environments, the actual amount of power saving remain specific for the settings of each environment, and the values we obtained are only indicative in this regard.

5.7.4 Testing Environment Changes

In order to test our proposed technique for detecting the changes in the sensor's environment, we proceed as follows: For each of the scenarios tested above, when the power hopping process has converged and the $P_{optimal}$ is found, the corresponding reflection pattern is obtained by the sensor when the room is vacant. We compare all the collected reflection patterns corresponding to the different environments:

1. $R_1[n]$: reflection pattern of Room A, sensor in LOS.
2. $R_2[n]$: reflection pattern of Room A, sensor in NLOS.
3. $R_3[n]$: reflection pattern of Room B, sensor in LOS.
4. $R_4[n]$: reflection pattern of Room B, sensor in NLOS.

Table 5.2: Similarity indices of different reflection patterns

Reflection patterns	$R_1[n]$	$R_2[n]$	$R_3[n]$	$R_4[n]$
$R_1[n]$	1	0.41	0.26	0.35
$R_2[n]$		1	0.43	0.44
$R_3[n]$			1	0.62
$R_4[n]$				1

The aim of having multiple cases is to check how well can the changes in the environment be detected using the reflection patterns. In the first case, we have a large room where the sensor is placed in the corner with a direct LOS. In the second case, the layout of the room is kept unchanged except that an obstacle is placed in front of the sensor, blocking the LOS. Since in this case, the sensor is supposed to detect that a change occurred and to recompute the optimal transmit power $P_{optimal}$, it is essential to check that this change is detectable by comparing the reflection patterns of the two Cases 1 and 2. The same reasoning is used when comparing Cases 3 and 4, but this time in a small room with the sensor placed in LOS and NLOS respectively.

On the other hand, comparing the reflection pattern of Case 1 or 2 with that of 3 or 4, shows whether placing the sensor in a completely new environment is detectable by our method. This can show that when the sensor is re-installed or moved to in a new place, it is able to detect this change and trigger the power hopping process accordingly, to recompute $P_{optimal}$.

Results

The similarity index between each two reflection patterns is calculated as described in Section 5.6, to test if the proposed technique is capable of detecting the changes in the sensor's environment. In Table 5.2, we present the values of the similarity indices between the different reflection patterns. The results show that the change in the environment, whether it is placing in a new environment

(1 compared to 3 or 4 for instance), or variations within the same environment (1 compared to 2, or 3 compared to 4), is possible to detect using the value of the similarity index of reflection patterns. All the similarity indices fall below the threshold of 0.9 for reflection patterns of changed environment. This proves that the proposed technique is capable of sensing any changes in the sensor's environment, and triggering the power hopping when it is the case.

5.8 Limitations of the Proposed Method

We present in this section the possible limitations that could reduce the efficiency of our proposed method:

- The method detects major changes in the environment, and triggers the power hopping process when it is the case, in order to recalculate the new optimal power level. The new power level is then used for motion detection, until the environment changes again. However, if a given environment is continuously changing, then the optimal power level will be continuously recalculated and updated, thus reducing the general efficiency of the power hopping process in achieving power saving.

- As we saw previously in the obtained results, the cut in power consumption is higher with limited-size environments, and with low obstacle abundance. However, if the ultrasonic sensor is used to cover a very large area, or if the density of obstacles is relatively high, then the power reduction achieved by the power hopping method would not be significant.

5.9 Summary

In this chapter, we have presented the *power hopping* method, a power optimization technique for ultrasound motion sensors. The method aims to reduce the overall power consumption of these sensors, by cutting unnecessary transmitter power used. The results show that a possible saving in the transmitter power can be achieved, which can be significant or minor depending on the environment. The power hopping method can be very useful especially when the energy source is limited, like when the sensor is battery-powered, so that the battery life is extended. We have also derived an upper bound limit of the method's convergence time. Additionally, we have designed a technique to automatically detect potential changes in the sensor's environment. This technique complements the power hopping process by making sure the obtained optimal power level is valid for the unchanged environment, and automatically triggering the process when changes are detected.

6 Still Presence Sensing Using Supervised Learning

6.1 Chapter Abstract [1]

In Chapter 4, we showed how motion sensing could be used for occupancy detection. However, the previously presented system is not able to detect still persons. In this chapter, we address the problem of still persons detection. Accordingly, 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.

[1] A shorter version of this chapter was published in: A. Hammoud, M. Deriaz and D. Konstantas, "Enhanced still presence sensing with supervised learning over segmented ultrasonic reflections," 2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN), Sapporo, 2017, pp. 1-8.

6.2 Introduction and Related Work

In the previous chapters 4 and 5, we addressed the motion sensing using ultrasound. Motion sensing is one means to infer the occupancy of indoor environments. However, in many cases the occupants may not be moving, they may be still (sitting, standing, etc.) and hence the occupancy sensing system should be able to account for these cases. In this chapter, we handle the problem of still persons detection using ultrasounds.

The use of ultrasound to sense the presence of occupants has been the subject of many research works. Some of these works suggested the use of ultrasonic ranging sensors, which 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 [95], 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. Ranging sensors can also be used to infer the presence at a particular location in the room. In [97], ultrasonic ranging sensors are fixed on the computer screen to sense the presence of a worker at his desk. The authors train a stochastic recognition model based on Kernel Density Estimation (KDE) for this purpose, and show a high accuracy in sensing the presence of the user. Similarly, Jaramillo *et al.* [96] follow a similar approach using ranging sensors, but use a hidden Markov model with Log Likelihood Ratio (LLR), in order to determine the presence of a user. 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. Another work [101] considers sound-based sensors in addition to other environmental sensors like CO_2, light, current, and PIR. In order to detect the presence of a worker at his desk, the authors apply supervised learning to train a decision tree model using collected occupancy data.

Caicedo *et al.* [98] present a sensor with one ultrasonic transmitter and an array of ultrasonic receivers, in order to sense the presence and determine the location of a moving person inside a room. In their designed system, they consider the case of multipath propagation with one signal reflection. They also base the signal processing on the assumption that the LOS signal is one of the multipath components, and that the occupant is in line-of-sight. The system shows a high accuracy in locating one occupant, but the authors do not mention the expected result in case of multiple occupants present in the room. Bordoy *et al.* [102] 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.

In our 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. 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 most comparable work to ours is the one recently published by Zou *et al.* [103], which uses modified COTS WiFi routers to observe changes in the channel state information (CSI). Aside from using electromagnetic signals (WiFi) in comparison to mechanical signals (ultrasound), the main differentiation from our work is that they observe the change in the CSI over frequency subcarriers by using OFDM packets. Whereas in our work, we observe the changes over the segments of the channel response in time domain. While it is hard to argue which approach is more accurate as this depends on the specific environment in which the sensor is placed, it is clear that relying on the channel diversity yields a better performance, which both methods consider. Their approach follows more or less the same methodology: First a transmitter sends a packet, a receiver receives the reflected/scattered signals (in their case the receiver is placed opposite to the transmitter assuming LOS, while in our case they are co-placed), variations in CSI between adjacent recordings indicate the presence of a person, supervised learning is used to train the model for presence sensing (random forest in their case). One limitation of using WiFi is that it is not tailored to room-level occupancy. In the mentioned system, the authors consider that the person is passing through the LOS region. If this would be changed, i.e if the transmitter and receiver are not placed in direct LOS with respect to each other, or if both are placed next to each other (behind an obstacle for instance), then due to the nature of WiFi signals propagation, a person who is passing in the corresponding room or a person in an adjacent room will both cause some variations in the CSI. These variations will be hard to map to the corresponding environment. Therefore, any person present within a certain range of the WiFi routers, will trigger the occupancy presence, regardless of whether he is in the same room, or behind walls in other adjacent rooms (or even outside near the window, or in the upper or lower floor). In order to have a better overview, we compare both works in Table 6.1.

The main contribution of our work, 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

Table 6.1: Comparison between our work and [103]

	Work of Zou *et al.* [103]	**Our work**
Underlying Technology	WiFi	Ultrasound
Wave Type	Electromagnetic	Mechanical
Tx/Rx position	Opposite to each other	Co-located
Channel State Information	Frequency domain (OFDM subcarriers)	Time domain (segemented reflection patterns)
Classification Method	Supervised learning	Supervised learning
Selected Classifier	Random forest	Linear SVM
Requires LOS	Yes	No
Tailored to room-level	No	Yes

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.

The rest of this chapter is organized as follows. First, Section 6.3 explains in detail our proposed method for presence sensing and discusses the reasoning behind it. In Section 6.4 we present the experimental evaluation of the method and we comment on the obtained results. Finally, Section 6.5 concludes the chapter.

6.3 Proposed Presence Sensing Method

6.3.1 Concept

Detecting the presence of a still 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, similar to the reasoning already presented in 5.6. 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 ultrasonic signal $x[n]$ is a short-time linear frequency chirp.

6.3.2 Reflection Pattern

As we stated in the previous chapter, each indoor environment is characterized by a given response, which depends on parameters like the environment's dimensions, boundaries, obstacles, furniture, etc. $h[n]$ denotes the environment's impulse response which defines the multipath propagation of the emitted signal's reflections:

$$h[n] = \sum_{m=0}^{M-1} a_m e^{j\phi_m} \delta(n - \tau_m) \tag{6.1}$$

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 $\boldsymbol{m} = \mathbf{0}$ is the direct propagation of the emitted signal, between the transmitter and receiver.

The reflection pattern which characterizes a given environment can be obtained by the same procedure depicted in Figure 5.4.

6.3.3 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.

In this chapter, we call $R_{ref}[n]$ the reference reflection pattern that 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 done through the *similarity index*:

$$similarity\ index = max|\textit{cross-correlation}(\boldsymbol{R_{ref}}, \boldsymbol{R})| \tag{6.2}$$

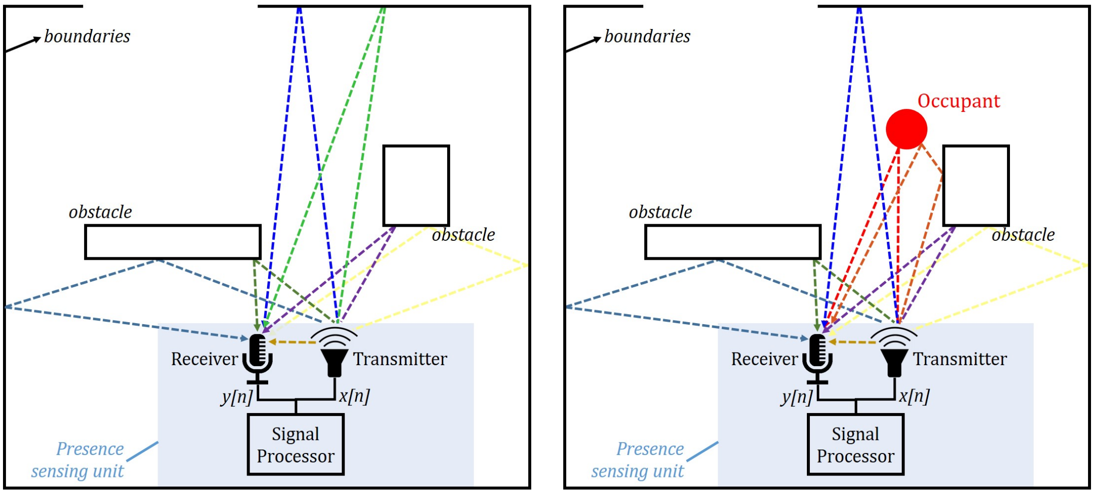
A high similarity index (close to 1) shows high similarity of the compared reflection patterns meaning that the environment is vacant. On the other hand, a low similarity index indicates some variations in the environment response, and therefore the environment has been occupied.

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:

$$R_{ref}[n] = \frac{1}{L}\sum_{k=1}^{L} R_{ref,k}[n] \tag{6.3}$$

6.3.4 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 6.1, we show an indicative example of the signal propagation in the case where the environment is vacant, and when it is occupied.



(a) Vacant environment **(b)** Occupied environment

Figure 6.1: Indicative example showing the difference of the emitted signal's multipath propagation, in the cases of (a) vacant and (b) occupied environments.

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:

$$\tau_0 < \tau_1 < ... < \tau_M \tag{6.4}$$

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

$$a_0 > a_1 > ... > a_M \tag{6.5}$$

6.3.5 Segmented Reflection Patterns

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

$$\begin{aligned} h_{ref}[n] &= \sum_{m=0}^{M-1} a_m e^{j\phi_m} \delta(n-\tau_m) \\ &= a_0 e^{j\phi_0}\delta(n-\tau_0) + a_1 e^{j\phi_1}\delta(n-\tau_1) + \ldots \\ &\quad + a_M e^{j\phi_{M-1}}\delta(n-\tau_{M-1}) \end{aligned} \tag{6.6}$$

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

$$\begin{aligned} h_{occupied}[n] &= \sum_{m=0}^{M'-1} a'_m e^{j\phi'_m} \delta(n-\tau'_m) \\ &= a'_0 e^{j\phi'_0}\delta(n-\tau'_0) + \ldots + a'_{M'} e^{j\phi'_{M'-1}}\delta(n-\tau'_{M'-1}) \end{aligned} \tag{6.7}$$

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

$$\begin{aligned} h_{occupied}[n] &= \sum_{m=0}^{M'-1} a'_m e^{j\phi'_m} \delta(n-\tau'_m) \\ &= a_0 e^{j\phi_0}\delta(n-\tau_0) + \ldots + a_{p-1} e^{j\phi_{p-1}}\delta(n-\tau_{p-1}) \\ &\quad + a'_p e^{j\phi'_p}\delta(n-\tau'_p) + \ldots + a'_{M'-1} e^{j\phi'_{M'-1}}\delta(n-\tau'_{M'-1}) \end{aligned} \tag{6.8}$$

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

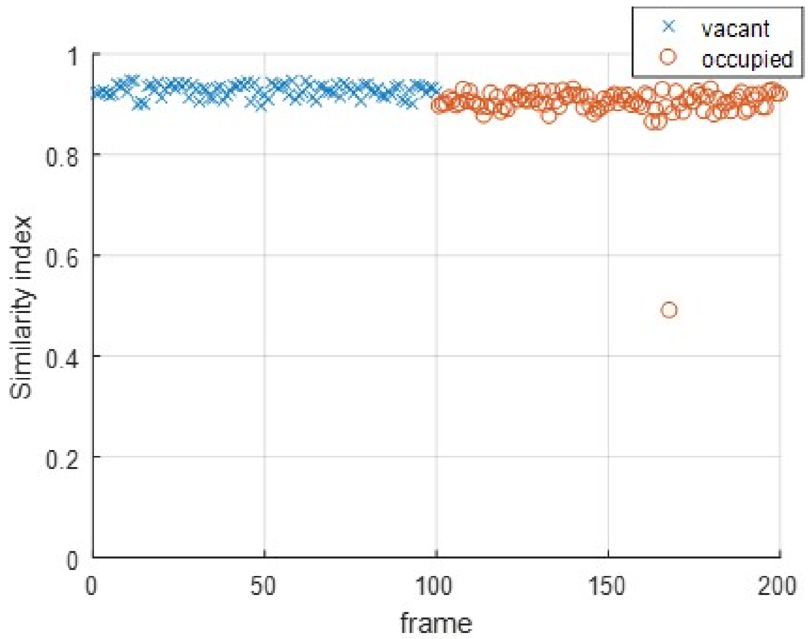


Figure 6.2: Similarity indices of frames corresponding respectively to vacant and occupied environment.

and obstacles might mask the presence of the occupant, especially when she 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 6.2). Hence, relying on the single similarity index evaluated over the whole reflection pattern, may not be decisive to detect the presence of person, especially when the SNR is not high enough.

To illustrate the problem, we show in Figure 6.2 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 6.2, 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 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:

$$similarity\ index\ [i] = max|\textit{cross-correlation}(\boldsymbol{R_{ref,i}}\ , \boldsymbol{R_i})| \tag{6.9}$$

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

$$\boldsymbol{R_i} = \boldsymbol{R}\{k, k+1, \ldots, N\} \tag{6.10}$$

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

Figure 6.3 illustrates the evaluation of the similarity indices over segmented reflection patterns. In our design we use a 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 6.4 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.

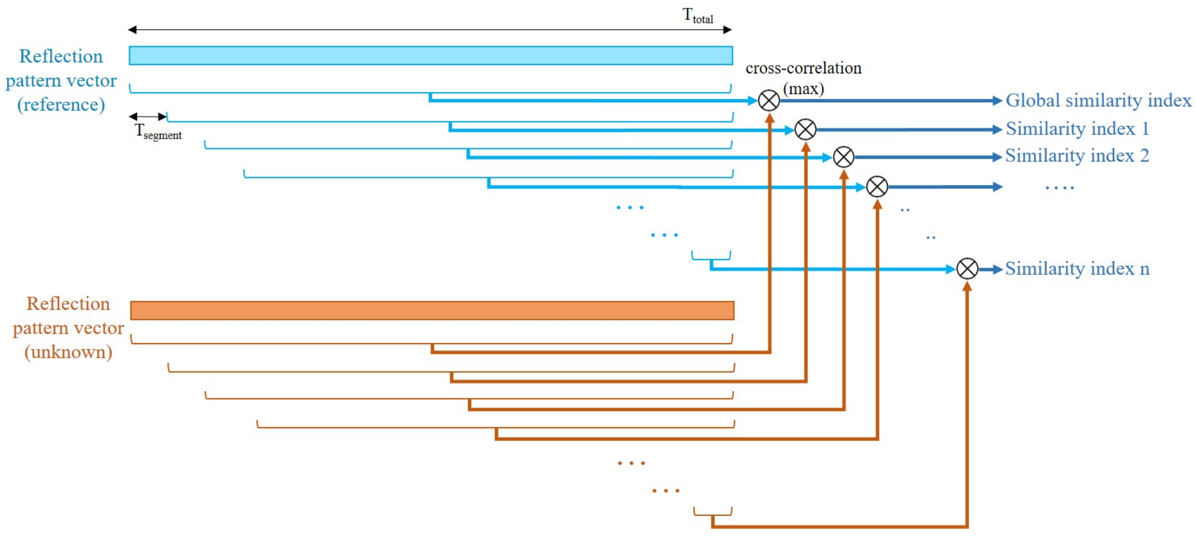


Figure 6.3: Similarity indices evaluated over segmented reflection patterns.

Figure 6.4: Segmenting the reflection pattern is equivalent to dividing the environment into segmented spaces (iteratively discarding the first i segments).

6.3.6 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 6.2, and the rest of similarity indices as in Equation 6.9. The feature vector is then formed as follows:

$$\boldsymbol{V_{features}} = \begin{bmatrix} global\ similarity\ index \\ similarity\ index\ [1] \\ similarity\ index\ [2] \\ \vdots \\ similarity\ index\ [N_{segments}] \end{bmatrix} \tag{6.11}$$

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.

6.4 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.

6.4.1 Set-up

For our tests, we used an ultrasonic prototype using commercial speaker and microphone, similarly to the previous chapter. 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.

6.4.2 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 (~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 6.5 shows the distribution of the frames forming the dataset.

The described procedure is repeated for the following environments:

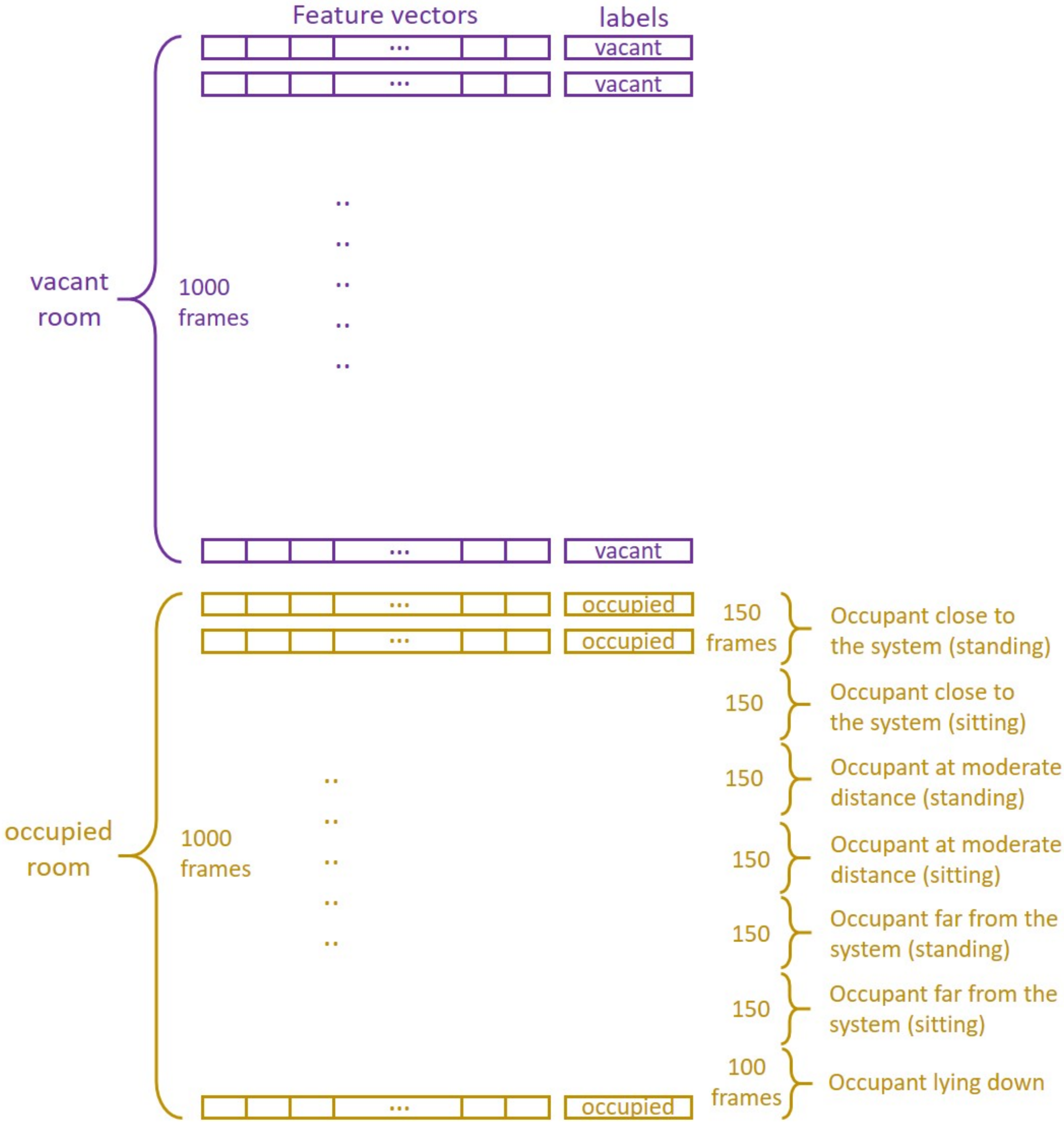


Figure 6.5: Dataset's frames distribution.

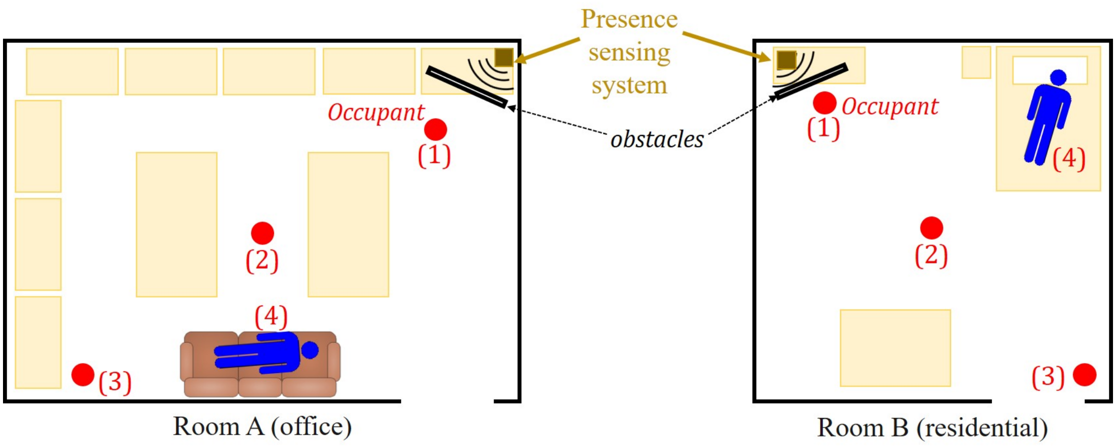


Figure 6.6: Tests' scenarios showing the occupant's position for the *occupied* frames: (1) close to the transmitter (standing/sitting), (2) at moderate distance (standing/sitting), (3) far from the system (standing/sitting), and (4) lying down. Obstacles are placed to simulate the NLOS case, and removed for LOS case

- 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 6.6, 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 levels, 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.

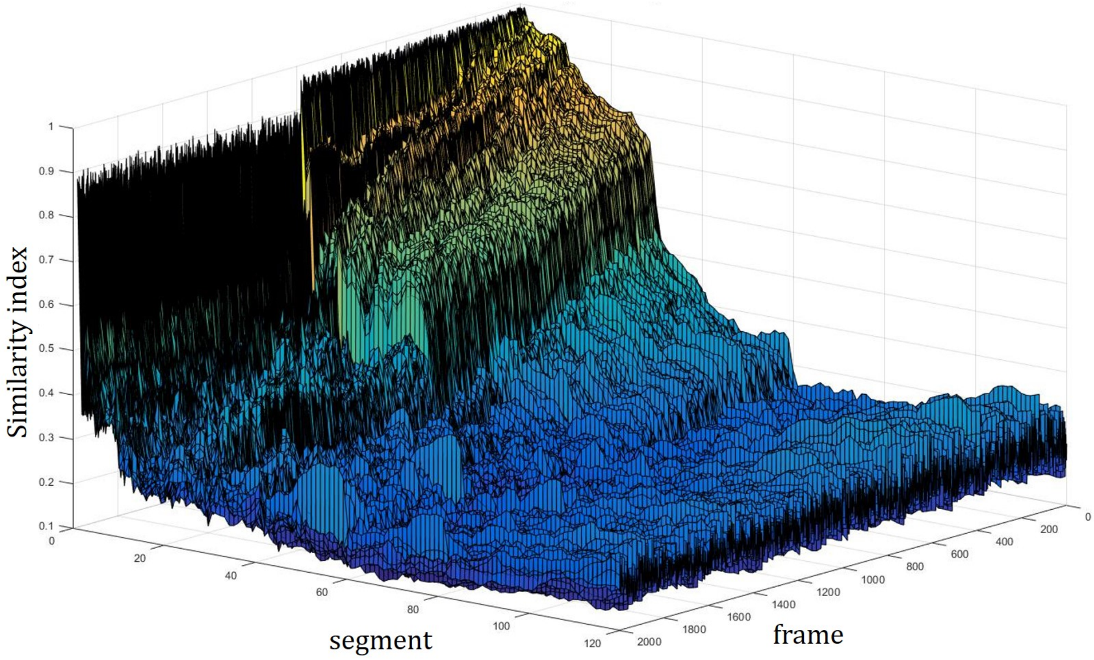


Figure 6.7: Similarity indices over segmented reflection patterns for vacant (frames 1-1000) and occupied environment (frames 1001-2000), case of high SNR, Room A, LOS.

In Figure 6.7, we consider one of the test cases, and we visualize the evaluated similarity indices over segmented reflection patterns, which form the feature vectors.

6.4.3 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 6.2 shows the

Table 6.2: 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 6.3: 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%

performance of each of the models in the case of low SNR, and Table 6.3 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 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.

6.4.4 Performance comparison

We compare the results of our proposed system to the work of Zou *et al.* [103]. In their work, they used two routers placed at 5 meters from each other. While the maximum range is not stated in the work, if we assume that this will also be equal to the routers' distance (5 meters), we can estimate the area with a room whose surface is $25m^2$. They report an accuracy of 95.52% with a false positive rate of 8%. Whereas in our system, and with a low SNR, we have reached an accuracy of 98.4% with 1.3% false positive rate, in the small room ($18.7m^2$) using SVM, and 94.4% with 4.9% false positive rate, in the large room ($45m^2$). These results show that the achieved accuracy is better than the mentioned work which uses two routers for sensing, compared to a single one in our case. In the case of high SNR, the perfect achieved results in our system clearly outperform the mentioned system [103].

6.4.5 Remarks

During the performed 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 and studied in Chapter 4, 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.

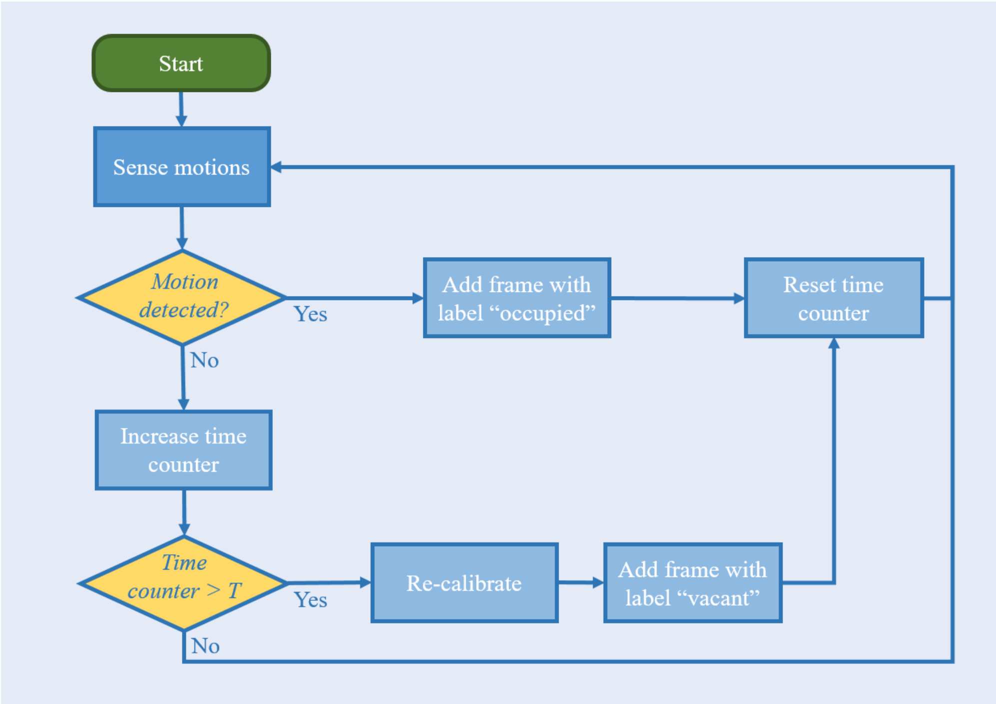


Figure 6.8: Flow chart of the fusion of motion and still presence detection in one system.

6.4.6 Motion and still presence sensing fusion

In Chapter 4, we have presented UltraSense, a system to detect motions, whereas in this chapter we describe how still persons can be detected. However, these two systems can complement each other, since the occupants may typically move sometimes, and remain still for some other time. Motion detection can be used to label the frames for training the still presence sensing method, marking frames as vacant when no movement is detected for a given time duration, and as occupied when movements are 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. A typical chosen time duration T for re-calibration would be in the order of hours (12 or 24 hours). This will also take into account the adaption to small changes in the environment (like moving furniture for example). In Figure 6.8, we show the flow chart of the possible fusion of motion and still presence detection in one system. In this case, an online learning model would be more suitable for use than a batch learning model.

6.5 Summary

In this chapter, 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.

7 Conclusions

The goal of this thesis was to come up with new methods and algorithms that build on the advantages of ultrasonic signals, to sense the occupancy of indoor spaces. Throughout our work, we addressed device-based and device-free approaches. We focused on designing methods that are compatible with existing and commercial hardware available to the public, and we developed algorithms that take into consideration the robustness to noise and changing conditions, the power consumption of the system, the computational complexity and memory constraints. To validate our propositions, we implemented systems using commodity hardware and components, and we assess their performance in practice. In particular, the thesis brings the following contributions:

Device-based room-level occupancy sensing: Our solution for a device-based occupancy sensing offers a convenient solution for smartphones to determine their room location, by leveraging commodity sound speakers as ultrasonic beacons. Since the system consists of placing one speaker per room, its deployment will have a low cost when implemented in a residential house. The system has a low complexity on the receiver side, since no synchronization is needed between the transmitter and the receiver, and decoding the packets and detecting collisions require a limited number of computations.

Since our presented solution uses commodity speakers, it allows to augment many environments seamlessly with occupancy sensing systems. Virtually any place that is traditionally equipped with sound speakers to broadcast voice messages or playing music, can implement our localization system. This can offer a handy solution for environments like airports, shopping malls, hospitals, museums, and can be used not only for energy management, but also for collecting statistics to assess users' experience, or in the case of emergencies.

Self-calibrating motion detection: We have presented a self-calibration method for a Doppler-based motion detection system, that is used to infer the presence of persons in a given place. The method allows for an easy deployment of the motion sensors, without worrying about the specific characteristics of the environment, and suppresses the need for a manual calibration by a technical person. We also demonstrated how the system can be built out of commodity hardware, and offers a high detection accuracy even in non line-of-sight scenarios.

The system can be implemented in a sensing module, and placed in the target environment to detect persons' movements and infer the occupancy. Moreover, the compatibility with commercial hardware offers the advantage of seamless integration with different types of existing devices and systems. In the introduction, we described how this method can turn devices like smartphones and PC's into smarter ones. In addition, the same environments that are equipped with sound speakers, can be equipped only with small microphones to create a device-free occupancy sensing system across an entire building (like airports, museums, malls, etc.).

We have shown how the direction of movements can be determined from the reflected ultrasonic signals. However, this information will only be useful in case we know the position of the sensor inside the room, so that we would be able to know whether the user is entering or exiting the room. Moreover, in case multiple users are moving in opposite directions, our system will not be able to differentiate the direction of movement of each of them, which requires a more enhanced and refined algorithm.

Power hopping for automatic transmit power switching: While ultrasonic motion sensors are more accurate than PIR and can operate beyond line-of-sight, they still lag behind PIR when it comes to the power consumption. Our method called power hopping finds the optimal power usage for an ultrasonic sensor according to its environment, and cuts unnecessary transmit power. This reduces the gap between the power consumption of the two sensor types, and allows more potential for ultrasonic motion sensing to be employed in real world deployments. A lower power consumption means an extended operational time for the motion sensor, especially when the energy source is limited, like the case of battery-powered.

Still motion detection: To complete the motion detection part, we introduced our technique for detecting persons when they are still and not moving (sitting, sleeping, etc.). By segmenting the reflection patterns, we can detect the minute variations in the environment response, making sure that the persons are not masked by the structures and furniture, even in poor signal conditions (low signal-to-noise ratio).

The method's use can be extended beyond occupancy sensing. In fact, by applying the same technique over smaller segments of the reflection patterns, one can detect variations even to the millimeter accuracy level. An application of such precision would be to monitor the status of specific objects, like expensive jewelry in a shop's vitrine, or artifacts exhibited in a museum (Figure 7.1). The same technique can be used with a different accuracy, to estimate the inventory in a warehouse. By comparing the reflection pattern between the beginning and the end of the day, one may be able to get a quick estimate of the difference in inventory, given a suitable learning algorithm (Figure 7.2). This can be handy especially when the inventory is homogeneous (same type, box size).

Figure 7.1: An ultrasonic sensor can be placed inside a vitrine to periodically check if an item is missing, using our described technique with segmented reflections patterns

Source:
https://image.shutterstock.com/image-photo/dubai-united-arab-emirates-uae-450w-256930495.jpg - https://upload.wikimedia.org/wikipedia/commons/4/48/Yosemite_Museum_Artifacts.jpg

Figure 7.2: An ultrasonic sensor may be used to get a rough estimate of the difference in inventory's quantity

Source:
https://whyallaselfstorage.com.au/wp-content/uploads/2017/03/long-term-storage-845x321.jpg

It is worth to note that the objective of the prototypes we have developed and presented, was to examine the performance and capabilities of the proposed methods and algorithms, rather than creating a final product. However, once the design has been validated, transforming the prototype into a more compact model should be straightforward, provided the availability of the right hardware components.

7.1 Looking Forward

We aim through our work to open the doors for application of ultrasounds in occupancy sensing, and to shed lights on the advantages offered by this technology, compared to other traditional solutions. Nonetheless, we envision new directions of research that can be interesting to explore, to further enhance occupancy sensing or use similar methods and algorithms to employ ultrasonic signals in different applications:

Room-level localization with smartphones: We have suggested in our method a way to assign different emission periods for ultrasonic beacons, in order to reduce the probability of packet collisions. This requires an attention at the moment of installation, to make sure the emission periods are correctly distributed for adjacent rooms. However, another possibility is to have the ultrasonic beacons use random emission periods. In this case, an ultrasonic beacon would continuously pick a different emission period from a certain predefined interval. This also requires adjusting the listening and decoding algorithm at the receiver to take varying emission periods into consideration. A research direction would be to evaluate the performance of such method, in terms of packet collision occurrence for a given number of adjacent transmitters, in addition to the decoding complexity at the receiver.

Occupancy count: We have focused on determining the binary occupancy, i.e. to know whether the indoor space is occupied or not. This is useful for a certain set of applications, like lighting control, heating and cooling systems, etc. Additionally, the information about the exact occupancy count can open the door for new types of applications. Exploring techniques to infer the exact number of occupants can be an interesting research direction. To make the link with our work, we can think of examining the value of the motion score when sensing movements, which is supposed to increase with a higher number of occupants. As for still occupancy sensing, the characteristics of the reflection patterns can hold information about the number of occupants, like to observe how the signals dissipate differently with different number of occupants.

Activity recognition: Reflection patterns of the ultrasonic signals hold information about the objects in the environment. The persons who are present reflect the signals differently when having different postures. By processing these signals and inferring the activity of the occupants (standing, sitting, sleeping, exercising, etc.), 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.

In addition to processing the reflection patterns in time domain like in our described method, frequency diversity can be explored for this purpose. Accordingly, we may think of using OFDM (orthogonal frequency division multiplexing) packets to gain more information about the channel state.

Distinguish the type of motions: Although we can detect the movements in a given space, we are not yet able to distinguish the type of these movements, whether they belong to humans or pets. By examining how different bodies respond to the emitted signals, we may be able to identify the type of moving objects.

Non invasive monitoring: Ultrasounds can offer the possibility of non invasive monitoring of vital signs. For example, by combining results from the motion detection and changing reflection patterns, one may infer the breath rate of a person, without requiring any physical contact with them.

Finally, we truly believe that using ultrasonic signals and efficiently processing them can extend the senses of smart systems and devices, and that the advances in internet-of-things and ubiquitous computing represent the fertile ground for this technology to flourish and become more and more of use.

Bibliography

[1] N. E. Klepeis, W. C. Nelson, W. R. Ott, J. P. Robinson, A. M. Tsang, P. Switzer, J. V. Behar, S. C. Hern, and W. H. Engelmann, "The national human activity pattern survey (NHAPS): a resource for assessing exposure to environmental pollutants," *Journal of Exposure Science & Environmental Epidemiology*, vol. 11, no. 3, pp. 231–252, jul 2001. [Online]. Available: https://doi.org/10.1038/sj.jea.7500165

[2] V. L. Erickson and A. E. Cerpa, "Occupancy based demand response hvac control strategy," in *Proceedings of the 2Nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Building*, ser. BuildSys '10. ACM, 2010, pp. 7–12. [Online]. Available: http://doi.acm.org/10.1145/1878431.1878434

[3] V. L. Erickson, M. . Carreira-Perpiñán, and A. E. Cerpa, "Observe: Occupancy-based system for efficient reduction of hvac energy," in *Proceedings of the 10th ACM/IEEE International Conference on Information Processing in Sensor Networks*, April 2011, pp. 258–269.

[4] M. Schroeder, T. D. Rossing, F. Dunn, W. M. Hartmann, D. M. Campbell, and N. H. Fletcher, *Springer Handbook of Acoustics*, 1st ed. Springer Publishing Company, Incorporated, 2007.

[5] R. Fay, *Hearing in Vertebrates: A Psychophysics Databook.* Hill-Fay Associates, 1988. [Online]. Available: https://books.google.ch/books?id=DoJwQgAACAAJ

[6] J. Xiao, Z. Zhou, Y. Yi, and L. M. Ni, “A survey on wireless indoor localization from the device perspective,” *ACM Comput. Surv.*, vol. 49, no. 2, pp. 25:1–25:31, Jun. 2016. [Online]. Available: http://doi.acm.org/10.1145/2933232

[7] N. J. N. S. Nick Stogdale, Steve Hollock, “Array-based infra-red detection: an enabling technology for people counting, sensing, tracking, and intelligent detection,” vol. 5071, 2003, pp. 5071 – 5071 – 11. [Online]. Available: https://doi.org/10.1117/12.486911

[8] J. Schiff and K. Goldberg, “Automated intruder tracking using particle filtering and a network of binary motion sensors,” in *2006 IEEE International Conference on Automation Science and Engineering*, Oct 2006, pp. 580–587.

[9] F. Adib, Z. Kabelac, D. Katabi, and R. C. Miller, “3d tracking via body radio reflections,” in *Proceedings of the 11th USENIX Conference on Networked Systems Design and Implementation*, ser. NSDI’14. USENIX Association, 2014, pp. 317–329. [Online]. Available: http://dl.acm.org/citation.cfm?id=2616448.2616478

[10] L. M. Candanedo and V. Feldheim, “Accurate occupancy detection of an office room from light, temperature, humidity and co2 measurements using statistical learning models,” *Energy and Buildings*, vol. 112, pp. 28 – 39, 2016. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0378778815304357

[11] F. Adib, H. Mao, Z. Kabelac, D. Katabi, and R. C. Miller, “Smart homes that monitor breathing and heart rate,” in *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, ser. CHI ’15. ACM, 2015, pp. 837–846. [Online]. Available: http://doi.acm.org/10.1145/2702123.2702200

[12] Yang, Gonzalez-Banos, and Guibas, "Counting people in crowds with a real-time network of simple image sensors," in *Proceedings Ninth IEEE International Conference on Computer Vision*, Oct 2003, pp. 122–129 vol.1.

[13] A. O. Ercan, A. E. Gamal, and L. J. Guibas, "Object tracking in the presence of occlusions via a camera network," in *2007 6th International Symposium on Information Processing in Sensor Networks*, April 2007, pp. 509–518.

[14] R. Melfi, B. Rosenblum, B. Nordman, and K. Christensen, "Measuring building occupancy using existing network infrastructure," in *2011 International Green Computing Conference and Workshops*, July 2011, pp. 1–8.

[15] S. Palipana, B. Pietropaoli, and D. Pesch, "Recent advances in rf-based passive device-free localisation for indoor applications," *Ad Hoc Networks*, vol. 64, pp. 80 – 98, 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1570870517301257

[16] A. Hammoud, M. Deriaz, and D. Konstantas, "Robust ultrasound-based room-level localization system using cots components," in *2016 Fourth International Conference on Ubiquitous Positioning, Indoor Navigation and Location Based Services (UPINLBS)*, Nov 2016, pp. 11–19.

[17] ——, "Ultrasense: A self-calibrating ultrasound-based room occupancy sensing system," *Procedia Computer Science*, vol. 109C, pp. 75–83, 2017, 8th International Conference on Ambient Systems, Networks and Technologies, ANT 2017, May 2017.

[18] A. Hammoud, G. G. Anagnostopoulos, A. I. Kyritsis, M. Deriaz, and D. Konstantas, "Power hopping: An automatic power optimization method for ultrasonic motion sensors," in *2017 IEEE SmartWorld, Ubiquitous Intelligence Computing, Advanced Trusted Computed, Scalable Computing Communications, Cloud Big Data Computing, Internet of People and Smart*

City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI), Aug 2017, pp. 1–7.

[19] A. Hammoud, M. Deriaz, and D. Konstantas, "Adaptive power switching technique for ultrasonic motion sensors," *Journal of Ambient Intelligence and Humanized Computing*, jun 2018. [Online]. Available: https://doi.org/10.1007/s12652-018-0888-y

[20] A. Hammoud, A. I. Kyritsis, M. Deriaz, and D. Konstantas, "Enhanced still presence sensing with supervised learning over segmented ultrasonic reflections," in *2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Sept 2017, pp. 1–8.

[21] "GPS: The Global Positioning System," https://www.gps.gov/, [Online].

[22] "GLONASS: Global Navigation Satellite System," https://www.glonass-iac.ru/en/, [Online].

[23] S. Adler, S. Schmitt, K. Wolter, and M. Kyas, "A survey of experimental evaluation in indoor localization research," in *Indoor Positioning and Indoor Navigation (IPIN), 2015 International Conference on*, Oct 2015, pp. 1–10.

[24] L. Mainetti, L. Patrono, and I. Sergi, "A survey on indoor positioning systems," in *Software, Telecommunications and Computer Networks (SoftCOM), 2014 22nd International Conference on*, Sept 2014, pp. 111–120.

[25] D. Dardari, P. Closas, and P. Djuric, "Indoor tracking: Theory, methods, and technologies," *Vehicular Technology, IEEE Transactions on*, vol. 64, no. 4, pp. 1263–1278, April 2015.

[26] G. Anagnostopoulos, "Addressing crucial issues of indoor positioning systems," 2017. [Online]. Available: https://archive-ouverte.unige.ch/unige:101628

[27] B. Balaji, J. Xu, A. Nwokafor, R. Gupta, and Y. Agarwal, "Sentinel: Occupancy based hvac actuation using existing wifi infrastructure within commercial buildings," in *Proceedings of the 11th ACM Conference on Embedded Networked Sensor Systems*, ser. SenSys '13. ACM, 2013, pp. 17:1–17:14. [Online]. Available: http://doi.acm.org/10.1145/2517351.2517370

[28] C. Wu, Z. Yang, Y. Liu, and W. Xi, "Will: Wireless indoor localization without site survey," *IEEE Transactions on Parallel and Distributed Systems*, vol. 24, no. 4, pp. 839–848, April 2013.

[29] H. Zou, Y. Zhou, H. Jiang, S.-C. Chien, L. Xie, and C. J. Spanos, "Winlight: A wifi-based occupancy-driven lighting control system for smart building," *Energy and Buildings*, vol. 158, pp. 924 – 938, 2018. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0378778817313907

[30] H. Liu, J. Yang, S. Sidhom, Y. Wang, Y. Chen, and F. Ye, "Accurate wifi based localization for smartphones using peer assistance," *Mobile Computing, IEEE Transactions on*, vol. 13, no. 10, pp. 2199–2214, Oct 2014.

[31] A. Bekkelien, M. Deriaz, and S. Marchand-Maillet, "Bluetooth indoor positioning," *Master's thesis, University of Geneva*, 2012.

[32] "iBeacon Technology and Estimote's Bluetooth Beacons," https://www.nanalyze.com/2016/01/ibeacon-technology-and-estimotes-bluetooth-beacons/, [Online].

[33] A. I. Kyritsis, P. Kostopoulos, M. Deriaz, and D. Konstantas, "A ble-based probabilistic room-level localization method," in *2016 International Conference on Localization and GNSS (ICL-GNSS)*, June 2016, pp. 1–6.

[34] Z. Jianyong, L. Haiyong, C. Zili, and L. Zhaohui, "Rssi based bluetooth low energy indoor positioning," in *2014 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Oct 2014, pp. 526–533.

[35] A. Filippoupolitis, W. Oliff, and G. Loukas, "Bluetooth low energy based occupancy detection for emergency management," in *2016 15th International Conference on Ubiquitous Computing and Communications and 2016 International Symposium on Cyberspace and Security (IUCC-CSS)*, Dec 2016, pp. 31–38.

[36] A. Corna, L. Fontana, A. A. Nacci, and D. Sciuto, "Occupancy detection via ibeacon on android devices for smart building management," in *Proceedings of the 2015 Design, Automation & Test in Europe Conference & Exhibition*, ser. DATE '15. EDA Consortium, 2015, pp. 629–632. [Online]. Available: http://dl.acm.org/citation.cfm?id=2755753.2755896

[37] N. Masoudifar, A. Hammad, and M. Rezaee, "Monitoring occupancy and office equipment energy consumption using real-time location system and wireless energy meters," in *Proceedings of the Winter Simulation Conference 2014*, Dec 2014, pp. 1108–1119.

[38] R. Mautz, "Indoor positioning technologies," Ph.D. dissertation, Habilitationsschrift ETH Zürich, 2012, 2012.

[39] N. Li, G. Calis, and B. Becerik-Gerber, "Measuring and monitoring occupancy with an rfid based system for demand-driven hvac operations," *Automation in Construction*, vol. 24, pp. 89 – 99, 2012. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0926580512000283

[40] F. Manzoor, D. Linton, and M. Loughlin, "Occupancy monitoring using passive rfid technology for efficient building lighting control," in *2012 Fourth International EURASIP Workshop on RFID Technology*, Sept 2012, pp. 83–88.

[41] J. Scott, A. Bernheim Brush, J. Krumm, B. Meyers, M. Hazas, S. Hodges, and N. Villar, "Preheat: Controlling home heating using occupancy prediction," in *Proceedings of the 13th International Conference*

on Ubiquitous Computing, ser. UbiComp '11. ACM, 2011, pp. 281–290. [Online]. Available: http://doi.acm.org/10.1145/2030112.2030151

[42] "RFID technology," http://senseslab.di.uniroma1.it/rfid-systems, [Online].

[43] T. Teixeira, G. Dublon, and A. Savvides, "A survey of human-sensing: Methods for detecting presence, count, location, track, and identity," *ACM Computing Surveys*, vol. 5, no. 1, 2010.

[44] X. Guo, T. D. K., G. P. Henze, and C. E. Waters, "The performance of occupancy-based lighting control systems: A review," *Lighting Research Technology*, vol. 42, no. 4, 2010.

[45] Y. Agarwal, B. Balaji, R. Gupta, J. Lyles, M. Wei, and T. Weng, "Occupancy-driven energy management for smart building automation," in *Proceedings of the 2Nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Building*, ser. BuildSys '10. ACM, 2010, pp. 1–6. [Online]. Available: http://doi.acm.org/10.1145/1878431.1878433

[46] R. H. Dodier, G. P. Henze, D. K. Tiller, and X. Guo, "Building occupancy detection through sensor belief networks," *Energy and Buildings*, vol. 38, no. 9, pp. 1033 – 1043, 2006. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0378778806000028

[47] J. Yin, M. Fang, G. Mokhtari, and Q. Zhang, "Multi-resident location tracking in smart home through non-wearable unobtrusive sensors," in *Proceedings of the 14th International Conference on Inclusive Smart Cities and Digital Health - Volume 9677*, ser. ICOST 2016. Springer-Verlag, 2016, pp. 3–13. [Online]. Available: https://doi.org/10.1007/978-3-319-39601-9_1

[48] X. Luo, T. Liu, B. Shen, Qinqun, L. Gao, and X. Luo, "Human indoor localization based on ceiling mounted pir sensor nodes," in *2016 13th IEEE Annual Consumer Communications Networking Conference (CCNC)*, Jan 2016, pp. 868–874.

[49] J. Kuutti, P. Saarikko, and R. E. Sepponen, “Real time building zone occupancy detection and activity visualization utilizing a visitor counting sensor network,” in *2014 11th International Conference on Remote Engineering and Virtual Instrumentation (REV)*, Feb 2014, pp. 219–224.

[50] Y. P. Raykov, E. Ozer, G. Dasika, A. Boukouvalas, and M. A. Little, “Predicting room occupancy with a single passive infrared (pir) sensor through behavior extraction,” in *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, ser. UbiComp ’16. ACM, 2016, pp. 1016–1027. [Online]. Available: http://doi.acm.org/10.1145/2971648.2971746

[51] S. Narayana, R. V. Prasad, V. S. Rao, T. V. Prabhakar, S. S. Kowshik, and M. S. Iyer, “Pir sensors: Characterization and novel localization technique,” in *Proceedings of the 14th International Conference on Information Processing in Sensor Networks*, ser. IPSN ’15. ACM, 2015, pp. 142–153. [Online]. Available: http://doi.acm.org/10.1145/2737095.2742561

[52] A. R. Kaushik and B. G. Celler, “Characterization of pir detector for monitoring occupancy patterns and functional health status of elderly people living alone at home,” *Technol. Health Care*, vol. 15, no. 4, pp. 273–288, Dec. 2007. [Online]. Available: http://dl.acm.org/citation.cfm?id=1377644.1377649

[53] R. Brown, N. Ghavami, H.-U.-R. Siddiqui, M. Adjrad, M. Ghavami, and S. Dudley, “Occupancy based household energy disaggregation using ultra wideband radar and electrical signature profiles,” *Energy and Buildings*, vol. 141, pp. 134 – 141, 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0378778816317261

[54] S. Depatla, A. Muralidharan, and Y. Mostofi, “Occupancy estimation using only wifi power measurements,” *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 7, pp. 1381–1393, July 2015.

[55] F. Adib and D. Katabi, “See through walls with wifi!” *SIGCOMM Comput. Commun. Rev.*, vol. 43, no. 4, pp. 75–86, Aug. 2013. [Online]. Available: http://doi.acm.org/10.1145/2534169.2486039

[56] V. L. Erickson, S. Achleitner, and A. E. Cerpa, “Poem: Power-efficient occupancy-based energy management system,” in *Proceedings of the 12th International Conference on Information Processing in Sensor Networks*, ser. IPSN ’13. ACM, 2013, pp. 203–216. [Online]. Available: http://doi.acm.org/10.1145/2461381.2461407

[57] D. Ioannidis, S. Krinidis, A. Drosou, D. Tzovaras, and S. Likothanassis, “Occupant-aware indoor monitoring for enhanced building analysis,” in *Proceedings of the Symposium on Simulation for Architecture & Urban Design*, ser. SimAUD ’15. Society for Computer Simulation International, 2015, pp. 87–94. [Online]. Available: http://dl.acm.org/citation.cfm?id=2873021.2873034

[58] J. Zou, Q. Zhao, W. Yang, and F. Wang, “Occupancy detection in the office by analyzing surveillance videos and its application to building energy conservation,” *Energy and Buildings*, vol. 152, pp. 385 – 398, 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0378778816320394

[59] A. M. PhD, PEng, A. C. MScOT, C. L. MScOT, and J. B. MASc, “The acceptability of home monitoring technology among community-dwelling older adults and baby boomers,” *Assistive Technology*, vol. 20, no. 1, pp. 1–12, 2008, pMID: 18751575. [Online]. Available: https://doi.org/10.1080/10400435.2008.10131927

[60] W. Kleiminger, C. Beckel, T. Staake, and S. Santini, "Occupancy detection from electricity consumption data," in *Proceedings of the 5th ACM Workshop on Embedded Systems For Energy-Efficient Buildings*, ser. BuildSys'13. ACM, 2013, pp. 10:1–10:8. [Online]. Available: http://doi.acm.org/10.1145/2528282.2528295

[61] M. Jin, R. Jia, Z. Kang, I. C. Konstantakopoulos, and C. J. Spanos, "Presencesense: Zero-training algorithm for individual presence detection based on power monitoring," in *Proceedings of the 1st ACM Conference on Embedded Systems for Energy-Efficient Buildings*, ser. BuildSys '14. ACM, 2014, pp. 1–10. [Online]. Available: http://doi.acm.org/10.1145/2674061.2674073

[62] W. Kleiminger, C. Beckel, and S. Santini, "Household occupancy monitoring using electricity meters," in *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, ser. UbiComp '15. ACM, 2015, pp. 975–986. [Online]. Available: http://doi.acm.org/10.1145/2750858.2807538

[63] G. Tang, K. Wu, J. Lei, and W. Xiao, "The meter tells you are at home! non-intrusive occupancy detection via load curve data," in *2015 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, Nov 2015, pp. 897–902.

[64] D. Calì, P. Matthes, K. Huchtemann, R. Streblow, and D. Müller, "Co2 based occupancy detection algorithm: Experimental analysis and validation for office and residential buildings," *Building and Environment*, vol. 86, pp. 39 – 49, 2015. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0360132314004223

[65] C. Jiang, M. K. Masood, Y. C. Soh, and H. Li, "Indoor occupancy estimation from carbon dioxide concentration," *Energy and Buildings*, vol.

131, pp. 132 – 141, 2016. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0378778816308027

[66] Z. Yang, N. Li, B. Becerik-Gerber, and M. Orosz, "A multi-sensor based occupancy estimation model for supporting demand driven hvac operations," in *Proceedings of the 2012 Symposium on Simulation for Architecture and Urban Design*, ser. SimAUD '12. Society for Computer Simulation International, 2012, pp. 2:1–2:8. [Online]. Available: http://dl.acm.org/citation.cfm?id=2339453.2339455

[67] B. Dong and B. Andrews, "Sensor-based occupancy behavioral pattern recognition for energy and comfort management in intelligent buildings," 01 2009.

[68] N. B. Priyantha, A. Chakraborty, and H. Balakrishnan, "The cricket location-support system," in *Proceedings of the 6th Annual International Conference on Mobile Computing and Networking*, ser. MobiCom '00. ACM, 2000, pp. 32–43. [Online]. Available: http://doi.acm.org/10.1145/345910.345917

[69] "The Bat Ultrasonic Location System," http://www.cl.cam.ac.uk/research/dtg/attarchive/bat/, [Online].

[70] A. Ens, L. M. Reindl, J. Bordoy, J. Wendeberg, and C. Schindelhauer, "Unsynchronized ultrasound system for tdoa localization," in *2014 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Oct 2014, pp. 601–610.

[71] D. Hauschildt and N. Kirchhof, "Improving indoor position estimation by combining active tdoa ultrasound and passive thermal infrared localization," in *2011 8th Workshop on Positioning, Navigation and Communication*, April 2011, pp. 94–99.

[72] R. Zhang, F. Höflinger, and L. Reindl, "Tdoa-based localization using interacting multiple model estimator and ultrasonic transmitter/receiver," *IEEE Transactions on Instrumentation and Measurement*, vol. 62, no. 8, pp. 2205–2214, Aug 2013.

[73] A. Yazici, U. Yayan, and H. Yücel, "An ultrasonic based indoor positioning system," in *2011 International Symposium on Innovations in Intelligent Systems and Applications*, June 2011, pp. 585–589.

[74] H. Schweinzer and M. Syafrudin, "Losnus: An ultrasonic system enabling high accuracy and secure tdoa locating of numerous devices," in *2010 International Conference on Indoor Positioning and Indoor Navigation*, Sept 2010, pp. 1–8.

[75] R. Jia, M. Jin, Z. Chen, and C. Spanos, "Soundloc: Accurate room-level indoor localization using acoustic signatures," in *Automation Science and Engineering (CASE), 2015 IEEE International Conference on*, Aug 2015, pp. 186–193.

[76] S. P. Tarzia, P. A. Dinda, R. P. Dick, and G. Memik, "Indoor localization without infrastructure using the acoustic background spectrum," in *Proceedings of the 9th International Conference on Mobile Systems, Applications, and Services*, ser. MobiSys '11. ACM, 2011, pp. 155–168. [Online]. Available: http://doi.acm.org/10.1145/1999995.2000011

[77] B. Shahid, A. Kannan, N. Lovell, and S. Redmond, "Ultrasound user-identification for wireless sensor networks," in *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*, Aug 2010, pp. 5756–5759.

[78] S. Holm, "Hybrid ultrasound-rfid indoor positioning: Combining the best of both worlds," in *2009 IEEE International Conference on RFID*, April 2009, pp. 155–162.

[79] M. C. Perez, D. Gualda, J. M. Villadangos, J. Ureña, P. Pajuelo, E. Diaz, and E. Garcia, "Android application for indoor positioning of mobile devices using ultrasonic signals," in *2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Oct 2016, pp. 1–7.

[80] G. Borriello, A. Liu, T. Offer, C. Palistrant, and R. Sharp, "Walrus: Wireless acoustic location with room-level resolution using ultrasound," in *Proceedings of the 3rd International Conference on Mobile Systems, Applications, and Services*, ser. MobiSys '05. ACM, 2005, pp. 191–203. [Online]. Available: http://doi.acm.org/10.1145/1067170.1067191

[81] V. Filonenko, C. Cullen, and J. Carswell, "Investigating ultrasonic positioning on mobile phones," in *Indoor Positioning and Indoor Navigation (IPIN), 2010 International Conference on*, Sept 2010, pp. 1–8.

[82] C. Peng, G. Shen, Y. Zhang, Y. Li, and K. Tan, "Beepbeep: A high accuracy acoustic ranging system using cots mobile devices," in *Proceedings of the 5th International Conference on Embedded Networked Sensor Systems*, ser. SenSys '07. ACM, 2007, pp. 1–14. [Online]. Available: http://doi.acm.org/10.1145/1322263.1322265

[83] N. Giordano, *College Physics: Reasoning and Relationships.* Brooks Cole, 2009.

[84] "ITU Radio Regulations, ," Section IV. Radio Stations and Systems – Article 1.16, definition: allocation (of a frequency band).

[85] J. L. Geisheimer, W. S. Marshall, and E. Greneker, "A continuous-wave (cw) radar for gait analysis," in *Conference Record of Thirty-Fifth Asilomar Conference on Signals, Systems and Computers (Cat.No.01CH37256)*, vol. 1, Nov 2001, pp. 834–838 vol.1.

[86] Z. Zhang, P. O. Pouliquen, A. Waxman, and A. G. Andreou, "Acoustic micro-doppler radar for human gait imaging," *The Journal of the Acoustical*

Society of America, vol. 121, no. 3, pp. EL110–EL113, Mar 2007. [Online]. Available: http://dx.doi.org/10.1121/1.2437842

[87] A. Ekimov and J. M. Sabatier, "Human motion analyses using footstep ultrasound and doppler ultrasound," *The Journal of the Acoustical Society of America*, vol. 123, no. 6, pp. EL149–EL154, Jun 2008. [Online]. Available: http://dx.doi.org/10.1121/1.2908823

[88] A. Mehmood, J. M. Sabatier, M. Bradley, and A. Ekimov, "Extraction of the velocity of walking human's body segments using ultrasonic doppler," *The Journal of the Acoustical Society of America*, vol. 128, no. 5, pp. EL316–EL322, 2010.

[89] A. Mehmood, J. M. Sabatier, and T. Damarla, "Ultrasonic doppler methods to extract signatures of a walking human," *The Journal of the Acoustical Society of America*, vol. 132, no. 3, pp. EL243–EL249, Sep 2012. [Online]. Available: http://dx.doi.org/10.1121/1.4746421

[90] B. Raj, K. Kalgaonkar, C. Harrison, and P. Dietz, "Ultrasonic doppler sensing in hci," *IEEE Pervasive Computing*, vol. 11, no. 2, pp. 24–29, Feb 2012.

[91] "Raspberry Pi 3 Model B," https://www.raspberrypi.org/products/raspberry-pi-3-model-b/, [Online].

[92] O. Shih, P. Lazik, and A. Rowe, "Aures: A wide-band ultrasonic occupancy sensing platform," in *Proceedings of the 3rd ACM International Conference on Systems for Energy-Efficient Built Environments*, ser. BuildSys '16. ACM, 2016, pp. 157–166. [Online]. Available: http://doi.acm.org/10.1145/2993422.2993580

[93] "Wide Angle PIR Sensor," https://www.parallax.com/product/28032, [Online].

[94] "X-band Motion Detector," https://www.parallax.com/product/32213, [Online].

[95] G. Mokhtari, Q. Zhang, G. Nourbakhsh, S. Ball, and M. Karunanithi, "Bluesound: A new resident identification sensor - using ultrasound array and ble technology for smart home platform," *IEEE Sensors Journal*, vol. PP, no. 99, pp. 1–1, 2017.

[96] P. Jaramillo and J. P. Linnartz, "Hidden markov model for improved ultrasound-based presence detection," in *Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing (CIT/IUCC/DASC/PICOM), 2015 IEEE International Conference on*, Oct 2015, pp. 68–74.

[97] L. I. L. Gonzalez, U. Großekathöfert, and O. Amft, "Novel stochastic model for presence detection using ultrasound ranging sensors," in *2014 IEEE International Conference on Pervasive Computing and Communication Workshops (PERCOM WORKSHOPS)*, March 2014, pp. 55–60.

[98] D. Caicedo and A. Pandharipande, "Ultrasonic arrays for localized presence sensing," *IEEE Sensors Journal*, vol. 12, no. 5, pp. 849–858, May 2012.

[99] "Ultrasound in the Animal Laboratory Environment, Gladys Unger, Ph.D." https://www.laboratoryequipment.com/article/2015/03/ultrasound-animal-laboratory-environment, [Online].

[100] P. Mishra, H. N. Shankar, P. D. G., and M. Mathur, "An ultra-low power real time embedded system for map generation using ultrasound sensors," in *2009 Third UKSim European Symposium on Computer Modeling and Simulation*, Nov 2009, pp. 579–584.

[101] E. Hailemariam, R. Goldstein, R. Attar, and A. Khan, "Real-time occupancy detection using decision trees with multiple sensor types,"

in *Proceedings of the 2011 Symposium on Simulation for Architecture and Urban Design*, ser. SimAUD '11. Society for Computer Simulation International, 2011, pp. 141–148. [Online]. Available: http://dl.acm.org/citation.cfm?id=2048536.2048555

[102] J. Bordoy, J. Wendeberg, C. Schindelhauer, and L. M. Reindl, "Single transceiver device-free indoor localization using ultrasound body reflections and walls," in *2015 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Oct 2015, pp. 1–7.

[103] H. Zou, Y. Zhou, J. Yang, W. Gu, L. Xie, and C. Spanos, "Freedetector: Device-free occupancy detection with commodity wifi," in *2017 IEEE International Conference on Sensing, Communication and Networking (SECON Workshops)*, June 2017, pp. 1–5.

List of Figures

List of Tables