UNIVERSITY OF CALGARY

Low Cost Indoor Localization Within and Across Disjoint Ubiquitous Environments using Bluetooth Low Energy Beacons

by

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A THESIS

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Abstract

The objective of this thesis was to design and explore the implementation of an indoor positioning and tracking technique that was low in cost, relying on Bluetooth Low Energy (BLE) sensors, and to integrate it into the Society of Devices Toolkit (SoD-Toolkit) developed at the Agile Surface Engineering lab at the University of Calgary. The resulting system maintains a database of all tracked and untracked users, and uses the signal strengths of pre-positioned BLE beacons to estimate the user's location in an indoor environment.

Through an evaluation of the proposed technique, we observed an accuracy of approximately 0.86 meters when a user's average distance to each Bluetooth beacon was less than 1.5 meters. The technique was, also, successful in achieving an 80% tracking accuracy across disjoint tracked spaces when the user density in the space is kept below 0.17 users per square meter, suggesting it could prove to be a practical alternative and/or complement to existing indoor positioning systems.

Acknowledgements

This work would not have been possible without the guidance and support of many extraordinary individuals that I have come to know and work with throughout the past four years (and prior).

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Dedication

One long year since my dear dad passed away, l dedicate this to him.

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List of Symbols, Abbreviations and Nomenclature

Symbol	Definition
ANOVA	Analysis of Variance
BLE	Bluetooth Low Energy
CPU	Central Processing Unit
dBm	Decibels per Milliwatt
DOLPHIN	Distributed Object Locating System for Physical Space Internetworking
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
HSD	Honest Significant Difference
IMU	Inertial Measurement Unit
IoT	Internet of Things
LED	Light-emitting Diode
OS	Operating System
PDR	Pedestrian Dead Reckoning
REST	Representational State Transfer
RF	Radio Frequency
RFID	Radio Frequency Identification
RSSI	Received Signal Strength Indication
SD	Standard Deviation
SoD	Society of Devices
TCP	Transmission Control Protocol
TOF	Time-of-Flight

Epigraph

The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it.

Mark Weiser

CHAPTER 1: INTRODUCTION

As computers become more miniaturized, more affordable, and more powerful, it has become possible to equip our everyday environments with a wide range of interactive and inter-connected smart objects that can bridge the gap between the physical world and the information world. Microcomputers have now become embedded in everyday objects such as light switches, locks, toasters, coffee machines, fridges, microwaves, and motor vehicles. This growing trend towards creating intelligent, connected environments is known as ubiquitous computing, which was first introduced by Mark Weiser in the late 1980s. Weiser states in his influential paper on the subject that "The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it." (Weiser, 1991).

The last few years have seen a growing interest in building novel ubiquitous systems and applications that can provide interactive and context-aware experiences. These systems allow for content and interaction to flow across and span a wide range of devices, harnessing the unique affordances (e.g. size, mobility) supported by each device. An important factor for providing such interactive experiences is enabling such systems to become spatially-aware and, thus, utilizing the rich spectrum of spatial information (i.e. location, orientation, direction, proximity, etc.) in order to support cross-device interactions, such as flicking (Dachselt & Buchholz, 2009), or picking and dropping (Rekimoto, 1997).

Ubiquitous computing environments in which the primary source of context is the user's or the device's spatiality is often referred to as location-aware computing (Hazas, Scott, & Krumm, Location-Aware Computing Comes of Age, 2004), with the most universal example of location-aware computing nowadays being satellite navigation. In satellite navigation, a detailed navigational map of the road links is used together with a Global Navigation Satellite System (GNSS) to obtain the location information and provide turn-by-turn navigation for a pedestrian or a motor-vehicle (Gleason & Gebre-Egziabher, 2009).

While the Global Navigation Satellite Systems have been very effective in creating interactive, spatially-aware applications for outdoor environments, they do fall short when it comes to indoor environments due to signal attenuation as signals propagate through buildings. Although a number of indoor positioning techniques have been researched and developed, each of these techniques does come with its shortcomings and imposed restrictions. For instance, systems that rely on low-end depth cameras or WiFi beacons are relatively inexpensive and easier to deploy. They do, however, provide lower precision tracking compared to their more expensive, highly-accurate, high-maintenance Vicon[1] and ultrasound based counterparts.

Furthermore, the majority of existing indoor tracking techniques do not support tracking across disjoint tracked spaces (Figure 1), demanding users to remain within the range of the tracking sensors at all times. This results in further instrumentation and/or calibration overhead when attempting to identify users as they become invisible to the system while transiting across multiple spaces.

This work aims to propose and analyze a low cost indoor positioning and tracking technique relying on Bluetooth Low Energy sensors, and to integrate it into the Society of Devices Toolkit (SoD-Toolkit) (Seyed, Azazi, Chan, Wang, & Maurer, 2015). The proposed technique can be

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[1] Vicon - www.vicon.com

used as a standalone indoor localization solution, and can be integrated with existing indoor localization systems to provide a cost effective solution for extending the range of such systems across disjoint tracked spaces.

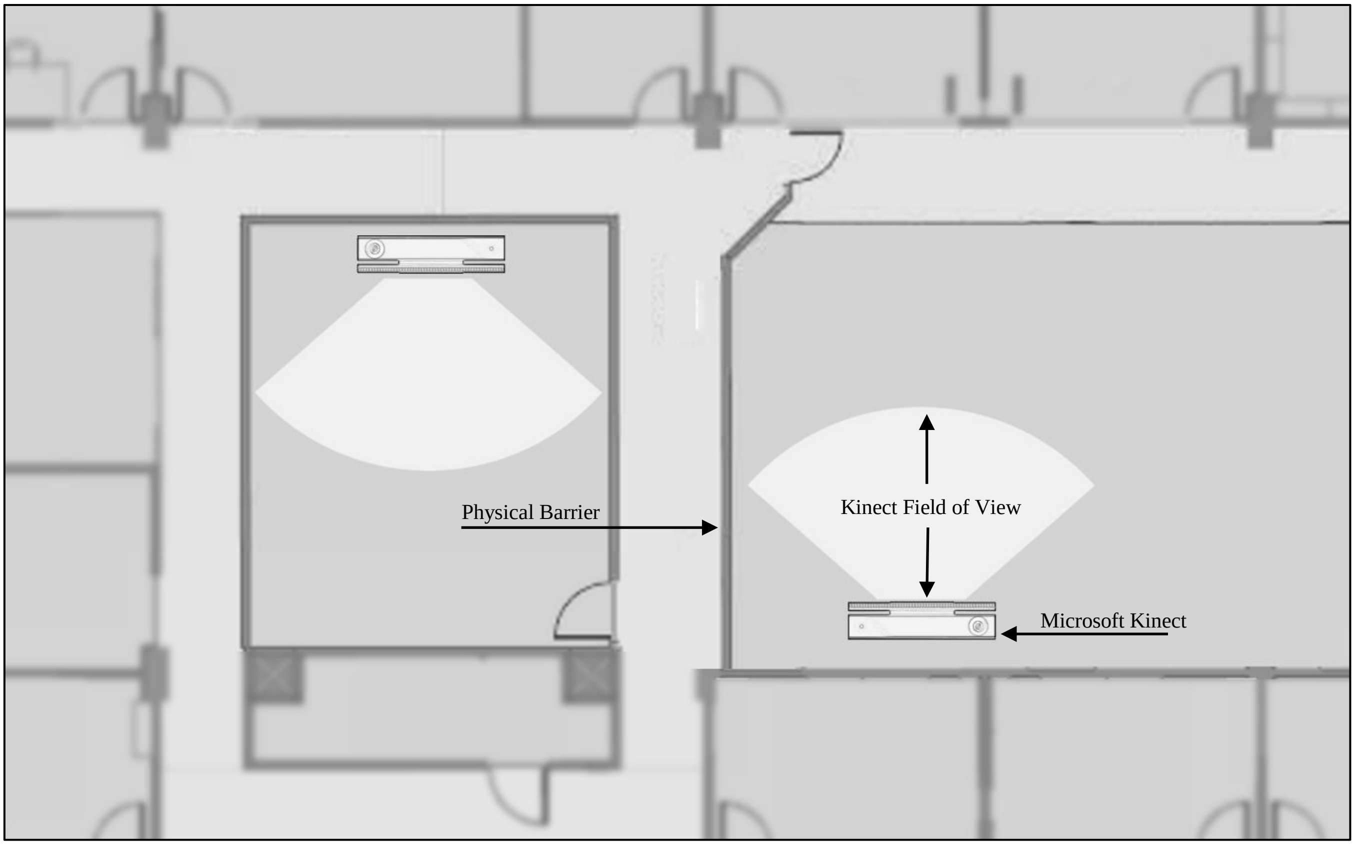

Figure 1 - An example of a disjoint tracked environment consisting of two Microsoft Kinect sensors covering non-overlapping fields of view (two rooms), and separated by a physical barrier (wall). As users transit in the untracked area between the two sensors, they become invisible to the system and lose their tracked status.

This chapter provides an introduction for this thesis. Section 1.1 provides a brief overview into indoor positioning, while Section 1.2 discusses disjoint environments. The motivation behind this thesis is then discussed in 1.3 and serves as the basis for the research questions in Section 1.4. Section 1.5 discusses the goals of this thesis. The contributions of this thesis are then detailed in Section 1.6, which is followed by an overview of the structure of this thesis in Section 1.7.

1.1 Indoor Positioning

Indoor positioning and navigation technologies provide the ability to locate and track users as well as objects within an indoor environment in real-time (Curran, et al., 2011). Many indoor positioning systems have been developed over the last few years, relying on a wide variety of technologies such as ultrasound (Addlesee, et al., 2001) (Hazas & Ward, A Novel Broadband Ultrasonic Location System, 2002) (Priyantha, Chakraborty, & Balakrishnan, 2000), infra-red (Want, Hopper, Falcão, & Gibbons, 1992), and radio (Gezici, et al., 2005) (Bahl & Padmanabhan, 2000) (which utilize the measured distance to nearby pre-positioned beacons), magnetic fingerprinting (Haverinen & Kemppainen, 2009), as well as dead-reckoning (Hu & Evans, 2004). Nonetheless, the research area of indoor positioning and tracking has not matured enough yet for a *de facto* solution to emerge despite extensive research. This is largely due to the constraints imposed by the unique requirements for different scenarios and use cases. Section 1.3 of this thesis discusses the major challenges encountered in the field of indoor positioning.

1.2 Disjoint Environments

We define a disjoint indoor setting as an environment that is comprised of two or more non-overlapping tracked spaces, across which a user cannot travel without becoming invisible to the positioning system in use. Disjoint environments span a wide range of settings and sizes and can be categorized as follows:

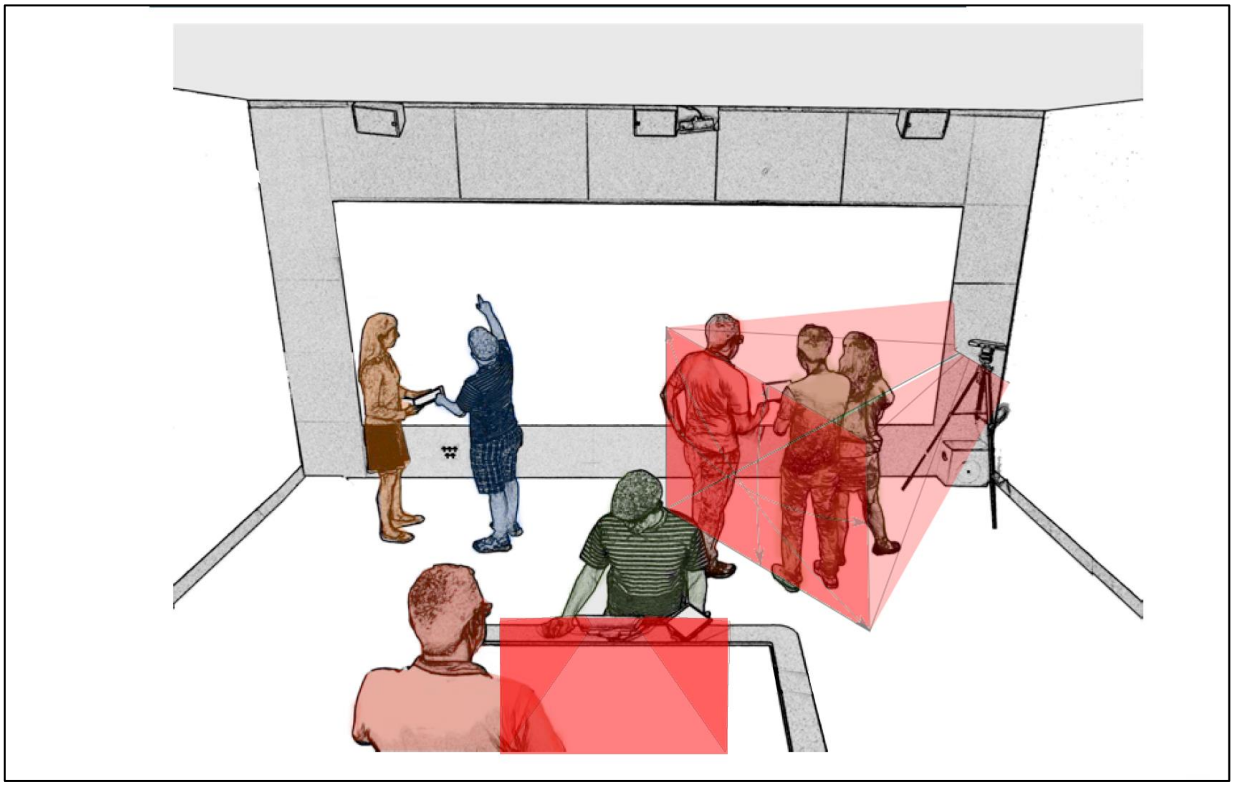

Figure 2 - Multi-surface Emergency Operations Center. The space in red is tracked by the Microsoft Kinects, while the rest of the space remains outside the tracked area of the system.

1.2.1 Sparse vs. Adjoining Environments

Sparse disjoint environments cover large areas and are usually separated by physical constraints and barriers, such as thick walls, and hallways. Examples of such sparse environments include tracking users across different stores within a shopping mall, tracking users across separate floors, or non-adjacent rooms within a building.

Adjoining environments, on the other hand, tend to cover more compact areas, usually covering non-overlapping regions of a continuous, visible space. An example of such an environment is shown in Figure 2. The figure shows Chokshi et al.'s multi-surface emergency operations center

(Chokshi, Seyed, Marinho Rodrigues, & Maurer, 2014), where two Microsoft Kinects[2] are used to track the areas immediately adjacent to the large display and the digital tabletop, which constitute the crucial areas of the environment, however leaving large parts of the environment untracked.

1.2.2 Congested vs. Scarce Environments

Another factor that plays a role in the classification of disjoint environments is related to the density of users and devices in relation to the total area of the environment.

This factor, in contrast with the previous one, is however transitory as users flow constantly into and out of the environment. Figure 3.1 illustrates an example of a congested disjoint environment

[2] Microsoft Kinect - https://developer.microsoft.com/en-us/windows/kinect

(a large crowded room during a presentation), while Figure 3.2 presents an example of a scarce disjoint environment using the same meeting room at different time of the day.

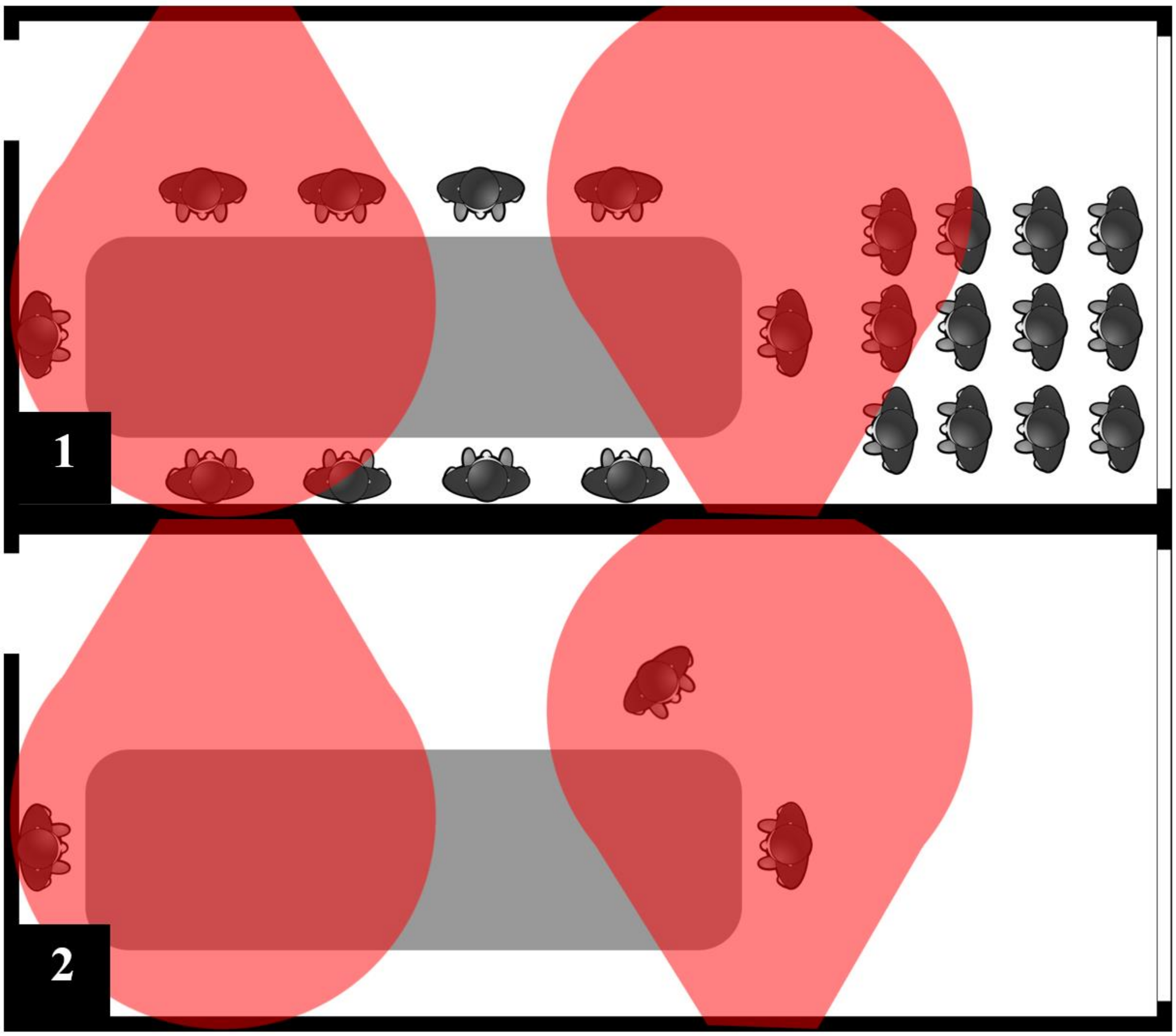

Figure 3 - An example of congested vs. scarce environment: 1) illustrates a user dense environment during a presentation in a large room. The red ellipses represent the tracked area of the environment, while 2) shows the same space but in a more scarce state at a different time of the day.

1.3 Motivation

Choosing the right technique and sensors for tracking an indoor environment is vital. It, however, is not an easy task because of the variety of factors that need to be considered, leading to the following challenges and providing the motivation for this thesis.

1.3.1 Accuracy vs. Cost

Factors such as the targeted application, the level of accuracy and precision, the complexity of system deployment and calibration, scalability, and overall system cost cannot all be met in one single solution. For instance, instrumenting the environment with high precision tracking sensors such as the Vicon camera or ultrasonic sensors can provide sub-millimeter tracking accuracy, but do require an intensive amount of deployment and calibration efforts, and come with a cost-prohibitive price tag for most use cases.

Similarly, the cost and the system complexity could be traded off through the usage of lower precision tracking technologies that may fall short of achieving the target accuracy required for the use case in hand.

1.3.2 Zombie Rising

A key challenge that motivates the work presented is related to the scalability of the indoor positioning system. In most usage scenarios, the tracking hardware and sensors are deployed and calibrated to provide user tracking within a continuous indoor environment which requires users to remain within the range of the tracking sensors. However, ensuring that every inch of the environment is within the range of the sensors is not always reasonably achievable because of

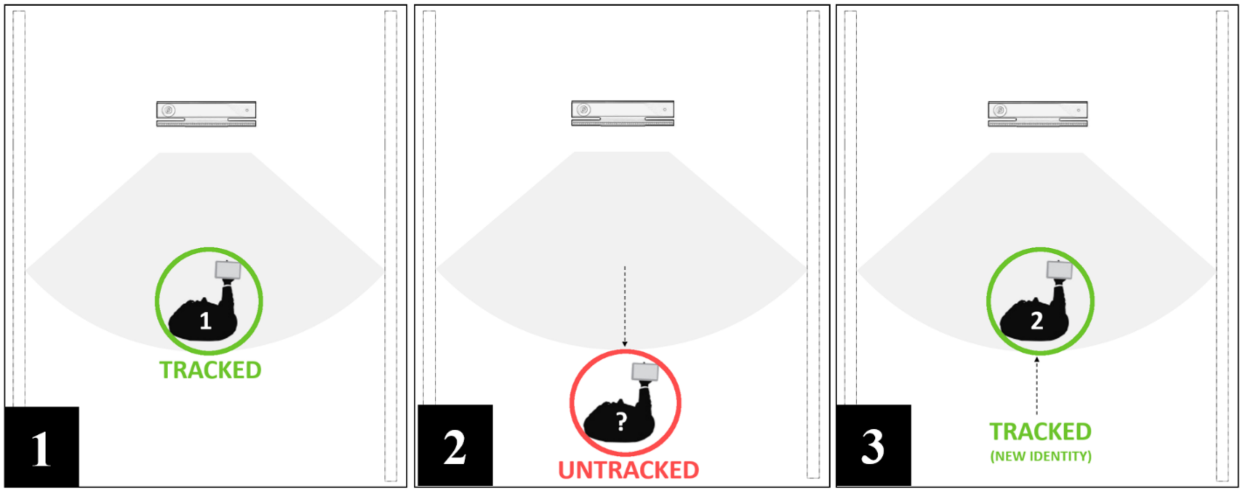

Figure 4 - An example of a Zombie rising scenario: 1) A user (user ID# 1) starts within the tracked area, 2) As the user leaves the tracked area, they become untracked, losing their identification with the system, and 3) The user moves back to the tracked area of the environment, but gets recognized as a new user and is assigned a new identity (user ID# 2).

physical constraints such as walls, furniture, and narrow hallways, as well as the cost associated with heavily instrumenting non-crucial areas of the environment.

While a few of the existing systems can be configured to track multiple disjoint indoor environments, identifying users as they transit across these environments becomes problematic. This is mainly due to the tracked user (user 1) becoming untracked as they leave the range of the sensors, and being registered as a new tracked user (user 2) as they re-enter the tracked range, which leaves user 1 in a registered but untracked state, or a ***Zombie state***. Figure 4 illustrates an example of a Zombie rising scenario. Ensuring that ***Zombie users*** are re-mapped (re-paired) to their respective tracked users requires repeated calibration which results in extra overhead for the system engineers and the end users alike.

1.4 Research Questions

This thesis investigates the development of an indoor positioning technique based on Bluetooth Low Energy beacons. In doing so it aims to answer the following questions:

1. What is the current state of research in indoor positioning and navigation, particularly within the context of ubiquitous computing environments? The aim here is to understand the existing research space and learn about the various indoor positioning and navigation techniques, as well as the trade-offs associated with current approaches.

2. How accurately can the relative movement of a user be measured using the signals of the Bluetooth Low Energy beacons? The aim here is to determine the extent and the precision to which it is possible to track the relative movement of users and their devices in an indoor environment using Bluetooth Low Energy beacons.

3. How accurately can the proposed technique identify and re-pair users as they transit across disjoint environments? This question differs from the one above because it deals specifically with the tracking and identification of users as they leave one tracked environment, travelling through a previously untracked area, and entering another tracked environment.

4. What is the infrastructure required to track users and their devices sufficiently in an indoor environment using Bluetooth Low Energy beacons? The aim here is to determine the amount (and cost) of the infrastructure that is required to be installed to provide an adequately accurate tracking in an indoor environment.

1.5 Research Goals

The thesis has two primary research goals. The first goals is to develop and evaluate the accuracy of an indoor positioning and tracking technique based on Bluetooth Low Energy beacons. Chapters 3 and 4 discuss the design, implementation, and evaluation of the technique that addresses this goal.

The second goal of this thesis is to answer the previous research question. That is, we aim to determine the amount of instrumentation and infrastructure necessary to provide a sufficient tracking accuracy in indoor environments when using the proposed technique.

1.6 Thesis Contribution

The contributions of the work discussed in this thesis for the field of indoor positioning and navigation are as follows:

1. A literature review of previous work in the area of indoor positioning and navigation. This review provides an overview of existing indoor positioning technologies and systems, alongside the affordances and limitations of these technologies.

2. The second major contribution provided in this thesis is the proposed indoor positioning technique. The proposed technique, based on Bluetooth Low Energy beacons, meets all the design considerations documented in Chapter 3 as it is low cost, provides a streamlined process for instrumenting the environment with beacons, can be used both as a standalone technique or as a complementary module when integrated with other indoor positioning system, and supports tracking users and their devices across disjoint environments.

3. In addition, two experiments were conducted to providing evidence that the proposed indoor positioning technique is a practical alternative and complement to existing indoor positioning systems in sufficiently sparse disjoint environments.

1.7 Thesis Structure

This introductory chapter presents a background of the research for this thesis. It, also, discusses the motivation, research questions, research goals, and the contributions of the thesis. The remaining chapters for this thesis are organized as follows:

- *Chapter Two: Related Work*

The next chapter provides an overview of research related to indoor positioning and tracking technologies, which includes current approaches and existing indoor positioning systems, alongside the advantages and limitations of these approaches and technologies.

- *Chapter Three: Modelling of the Positioning Technique*

This chapter details the design and the implementation of the indoor positioning techniques proposed in the thesis. The chapter discusses the design considerations of the technique, its integration with the Society of Devices Toolkit, alongside the algorithms and procedures used to implement it.

- *Chapter Four: Evaluation*

This chapter describes two experiments that investigated the accuracy of the proposed technique for tracking users and their devices across and within indoor ubiquitous environments. The chapter starts by detailing the design, procedures, and results of each experiment, and presents the implications of the results on standalone and integrated implementations, associated limitations, and provides suggested usage settings and scenarios.

- *Chapter Five: Conclusion & Future Work*

This chapter wraps up the work on the thesis and provides direction for future work in this area.

CHAPTER 2: RELATED WORK

The research space of indoor tracking and localization has been well defined in the past few years, with a significant amount of research conducted from the system engineering perspective and the human computer interaction perspective. Generally, indoor positioning techniques can be categorized, based on the sensor technologies used, into two categories: infrastructure-based, and infrastructure-free techniques. They can, also, be categorized based on the underlying environment model that indoor positioning techniques use to provide a spatial context into two categories: relative positioning techniques, and absolute positioning techniques.

The first section of this chapter outlines the sensor technologies that have been used to develop infrastructure-based positioning systems. Sensor technologies used for creating infrastructure-free positioning systems are, then, described in Section 2.2. Finally, sections 2.3 and 2.4 of this chapter describe and contrast relative and absolute positioning techniques, providing examples of systems that utilize the two approaches.

2.1 Infrastructure-based Positioning

Infrastructure-based techniques rely heavily on instrumenting the environment using customized hardware and sensors such as RF transmitters, ultrasound speakers, LED lights, and magnetic resonators to track users or marked objects within the environment. This section outlines the major technologies used in infrastructure-based indoor positioning, with examples from the literature of systems that utilize these technologies.

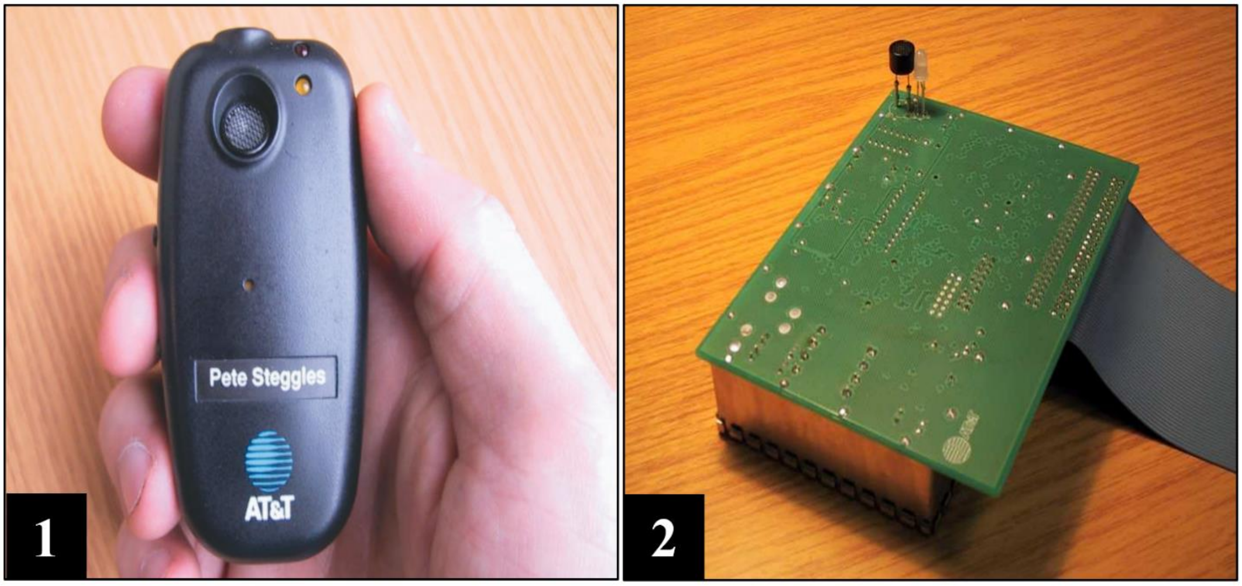

Figure 5 - Active Bat System: 1) Active Bat, 2) Ceiling mounted bat.

2.1.1 Ultrasound

Ultrasonic indoor positioning systems use Time-of-Flight (TOF) of ultrasonic signals to compute the distance between tracked users of devices and pre-positioned transmitter nodes, and estimate their positions in three dimensions, with accuracies down to a few centimeters.

An example of such a system is the Active Bat system (Addlesee, et al., 2001), which uses an infrastructure of small fixed narrowband beacons positioned on the ceiling of the tracked environment (known as bats), as shown in Figure 5.2. Tracked devices, known as active bats (shown in Figure 5.1), are carried by users and are positioned in the environment by multi-trilatering the times-of-flight of the ultrasonic signals to nearby bat beacons. The position measurements computed by the Active Bat system reported accuracies to within 3 centimeters (Addlesee, et al., 2001).

Although the system achieves a high tracking accuracy, a drawback of the Active Bat system is that its accuracy could be greatly affected by ultrasonic noise produced by typical everyday objects (such as chiming keys) in home and office environments. Additionally, instrumenting an environment with bat sensors requires positioning the bats one at a time in order to avoid signal collisions. A more recent example of ultrasonic indoor positioning systems is the DOLPHIN system (Fukuju, Minami, Morikawa, & Aoyama, 2003). The system uses two broadband ultrasonic transducers, one for transmitting and one for receiving. This allows for multiple beacons to be positioned simultaneously regardless of surrounding ultrasonic noise, and thus overcoming the limitations of the Active Bat system.

2.1.2 Infrared (IR)

Infrared based indoor positioning systems use infra-red light to provide room-level location information. That is, such systems narrow-down the location of the tracked user or device to a single room or area. Infrared-based system detect the location of a tracked user or a device by transmitting infrared signals from previously positioned sensors. When these signals are received by a device, the system reports the room locality in which the device is most likely located. Additionally, as infrared signals do not pass through and are reflected by physical barriers, such as walls, these systems do not require the establishment of a line-of-sight between the transmitter and receiver sensors.

A popular example of an infrared-based indoor positioning system is the Active Badge system (Want, Hopper, Falcão, & Gibbons, 1992), which was intended to aid telephone receptionists at the Olivetti research laboratory in routing incoming telephone calls to their intended recipients anywhere in the building. The Active Badge system used a network of infrared sensors that were mounted in the offices and common areas to detect employee-assigned badges (Figure 6). Each badge emitted a distinct infra-red code identifying the employee carrying the badge. The system

Figure 6 - Active Badge System: Active Badge.

reported the likelihood of locating an employee at a location as a percentage. A likelihood that is less than 100% indicated that the person is not stationery. If an employee could not be reached by the system for 5 minutes, the system reports the last time and location at which they were last sighted.

Although infrared-based positioning systems cannot be used to provide accurate localization of users an devices in indoor environments, infrared sensors are small, power efficient and can be made very cheaply, thus making them ideal for providing room-level location information.

2.1.3 Vision

Vision-based positioning systems rely the use of multiple camera views to track users and devices within an indoor environment. Proximity Toolkit, by Marquardt et al (Marquardt, Diaz-Marino, Boring, & Greenberg, 2011) is an example of a proxemic interaction framework that relies on a vision-based indoor positioning system. It provides accurate positioning of users and

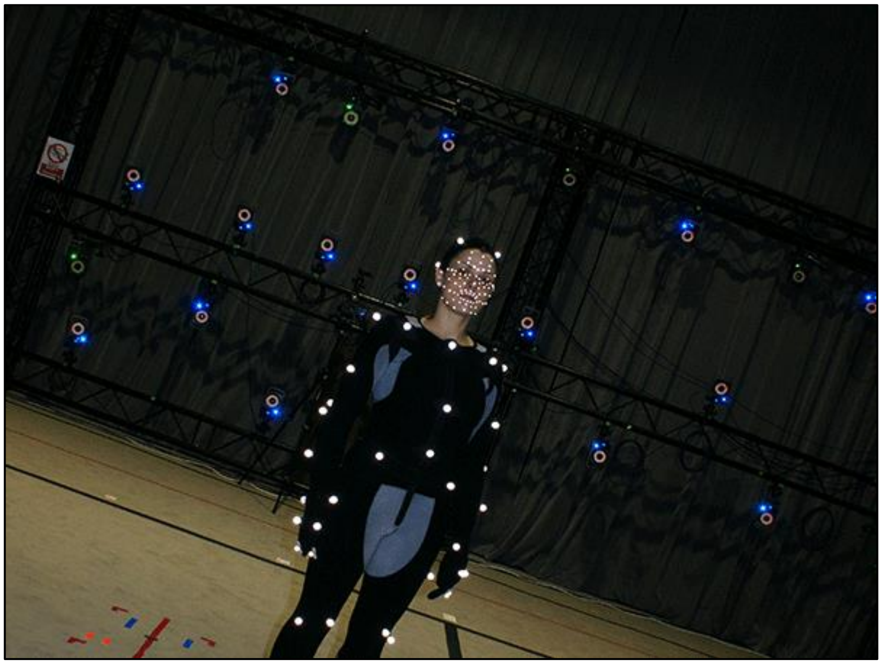

Figure 7 - Vicon Motion Capture Suit & Markers (Vicon Motion Systems Ltd., 2016).

devices within the environment by instrumenting the room with the Vicon Motion Capture system and instrumenting users with physical tracking markers (Figure 7). This allows users and devices to interact with each other using spatial information and proxemic relationships. Marquardt et al (Marquardt, Diaz-Marino, Boring, & Greenberg, 2011) defined proxemics relationships as the "distance and orientation towards others". According to Marquardt et al, Proximity Toolkit has "sub-millimeter tracking accuracy." (Marquardt, Diaz-Marino, Boring, & Greenberg, 2011).

A drawback of Proximity Toolkit, however, is its use of the Vicon Motion Capture system which requires physical markers, and thus limiting its practicality in real-life settings. The Vicon system is also very expensive and is time consuming to instrument a room with. While the toolkit is capable of using a single Microsoft Kinect sensor, there is a loss in the tracking accuracy in addition to the occlusion problems that arise when users are blocking the field of view of the Kinect sensor. The tracking area is limited to a small room with furniture, and it is infeasible to scale to a larger room because of the high cost of the Vicon cameras. Proximity Toolkit also requires an initial calibration of the various sensors in the room before using it for tracking purposes.

The EasyLiving system, by Krumm, is another example of a vision-based system that tracks users within an environment using two stereo cameras (Krumm, et al., 2000). The system is capable of tracking users with an accuracy within 10 centimetres without requiring users to wear visual markers. It maintains the identity of the users based on colour histograms that are captured as users move throughout the tracked environment. These identities are, however, not consistent as they do not always reflect the accurate identity of the user. As a result, a user who has left the field of view of the cameras might be assigned a new identity when re-entering the tracked environment, which relates closely to the Zombie rising issue discussed in section 1.3.2.

The Society of Devices (SoD) Toolkit, developed by Seyed et al (Seyed, Azazi, Chan, Wang, & Maurer, 2015), achieves marker-free tracking through the use of multiple Microsoft Kinect sensors to track users within an indoor environment (Figure 8). By using multiple overlapping Kinects, SoD improves the tracking accuracy of users and devices in the environment by mitigating the occlusion problem, and increasing the area of the tracked environment (Seyed,

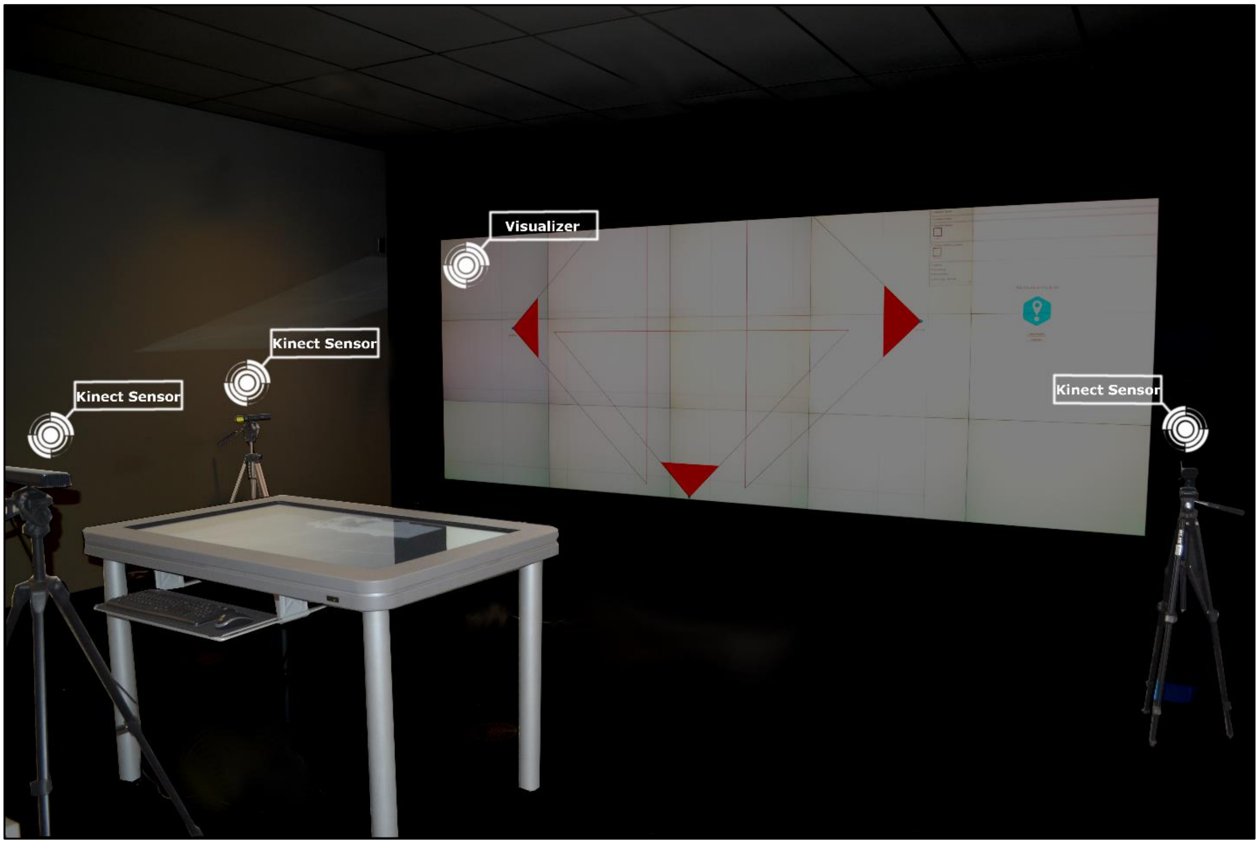

Figure 8 - SoD Toolkit Setup.

Azazi, Chan, Wang, & Maurer, 2015). SoD, however, suffers scalability issues although it uses consumer accessible Kinect sensors, and is still infeasible to scale to a large-sized room. This is because each Kinect optimally tracks “a range of 1.2 to 3.5 meters” (Satyavolu, Bruder , Willemsen, & Steinicke, 2012) and, therefore, a large number of Kinects would be required to track a room of a size that exceeds a few meters. Calibration, which is the procedure of establishing a standardized unit baseline to map the sensor readings to, would, also, be required for each Kinect sensor, increasing the amount of time needed to setup a room.

2.1.5 Summary

Currently, the choice of sensors in infrastructure-based indoor positioning depends on the requirements of the system being designed, and the level of accuracy it aims to achieve. For instance, infrared based Active Badge Location System (Want, Hopper, Falcão, & Gibbons, 1992) is relatively inexpensive and is easy to deploy. The system, however, achieves a lower precession than the higher-end indoor tracking systems that rely on far more sophisticated technologies. For example, systems such as the ultrasound based Active Bat System (Addlesee, et al., 2001) and Cricket Location-Support System (Priyantha, Chakraborty, & Balakrishnan, 2000), as well as the Vicon based Proximity Toolkit (Marquardt, Diaz-Marino, Boring, & Greenberg, 2011) can achieve very high precision, but are more expensive and do require extensive instrumentation efforts.

A notable drawback of infrastructure-based techniques, however, is that such approaches requires continuous instrumentation and calibration of the environment and the applications that use it, and therefore making such approaches difficult to scale to larger areas. Another drawback that is more specific to vision based tracking techniques is that prior research has shown that users do feel unfamiliar and uncomfortable with intrusive tracking technologies (Seyed, Costa Sousa, Maurer, & Tang, 2013).

2.2 Infrastructure-free Positioning

Alternatively, infrastructure-free implementations do not require instrumenting the environment with custom hardware and sensors to track users and objects, but rather rely on either leveraging the already existing infrastructure in the environment, or on instrumenting the users and their devices instead.

Most of these techniques combine the signals from existing infrastructure with device-embedded sensors such as accelerometer, gyroscope, and compass (which have become a standard in off-the-shelf mobile devices) to achieve better tracking precision in a process known as sensor fusion. The motivation behind sensor fusion is to combine the outputs of different sensors and technologies utilizing the unique capabilities of individual sensor technologies, while mitigating their individual weaknesses.

This section outlines the major approaches and technologies used in infrastructure-free indoor positioning, with examples from the literature of systems that utilize these technologies.

2.2.1 Leveraging Existing Infrastructure

Due to the large number of Wi-Fi access points that are already installed in all sorts of indoor environments, indoor positioning systems that rely on the received signal strength indication (RSSI) measurements of Wi-Fi signals have gained a growing popularity in the past few years. Such systems use the received signal strengths on the user's device in order to estimate the distance between the user and multiple base Wi-Fi stations in the environment.

Examples of such systems include RADAR (Bahl & Padmanabhan, 2000), which uses multiple Wi-Fi base stations positioned specifically to provide overlapping coverage of the indoor environment. RADAR uses the observed signal strengths and a radio map of the environment to estimate the user's position, achieving an accuracy within 9 meters 95% of the time. A similar approach, by Wan et al. (Wang, Lenz, Szabo, Bamberger, & Hanebeck, 2007), was able to obtain an accuracy of 6.44 meters using a similar algorithm.

Both of the systems mentioned above are deterministic in the sense that they produce the single best estimation of the user or the device within the environment. Another approach is to compute the probability distribution of the user's position rather than estimating a single coordinate. The

Horus (Youssef & Agrawala, 2005) and Mawi (Zhang, Luo, & Wu, 2014) systems use such an approach, with the Horus system reporting an accuracy of 1.4 meters in 95% of the samples collected, and Mawi reporting to have outperformed the Horus system.

Another example of an indoor positioning technique that leverages existing infrastructure, but is not Wi-Fi based, is the Acoustic Background Spectrum technique (Tarzia, Dinda, Dick, & Memik, 2011) which uses sound signals to create a fingerprint database of the environment. The technique estimates the user's location by measuring the present fingerprint and contrasting it to the fingerprint database, selecting the one that most resembles the current fingerprint. The technique, however, reported an overall success rate of only %69.

2.2.2 Instrumenting for Users and their Devices

Instrumenting the user and the device is an alternative technique for tracking indoor environments. It relies on equipping the users and their devices with specialized sensors - such as inertial measurement units containing accelerometers, gyroscopes, compass, and other sensors, in order to provide means of tracking and navigation within the environment.

According to Savage (Savage, 1998), Inertial Measurement Units (IMU) are devices which are "typically composed of an orthogonal three-axis set of inertial angular rate sensors and accelerometers." Savage provides an optimized algorithm for indoor inertial navigation using an accelerometer. However, an issue with inertial navigation systems is that error tends to build up over time because each new sensor reading is added onto the previous readings. An error in a previous sensor reading affects all subsequent calculations and, thus, produces erroneous results.

Kim et al (Kim, Cho, Kim, Kim, & Kee, 2011) introduces an approach to solving the problem of user tracking using a low-cost pedestrian navigation system that overcomes the signal blockage problems that arise in urban environments when using standalone Global Positioning Systems (GPS). The Pedestrian Dead Reckoning (PDR) algorithm with step length correction integrates GPS navigation with the accelerometer signal pattern to compensate for the GPS signal blockage error. The algorithm models the step length as a linrar combination of constants and step frequency, and corrects for accumulated error by using the user's GPS position.

Project Tango[3] - a project by Google, is another example of this approach. Project Tango is a mobile device equipped with customized sensors and software that track the motion of the device in 3D space. This custom design allows the device to compute over a quarter million measurements every second, providing real-time position and orientation information of the device. It uses computer vision, in combination with other smartphone sensors, to create a 3D model of a room, tracking the location of the device within that room. InstantLoc (Jain, Manweiler, & Roy Choudhury, 2015) is an example of a system that uses Google's project Tango to scan and store a depth-map relative to the user's initial position, and uses the produced map to identify the location of users in environments of arbitrary sizes.

2.3 Absolute Positioning Techniques

Absolute indoor positioning techniques rely on constructing a map model of the environment to constrain the interpretation of the motion of the users and their devices. In the simplest sense, mapping an environment creates a spatial graph of an indoor space, such as a floor plan, that

[3] Project Tango - http://www.google.com/atap/projecttango/

features a variety of constraints such as walls and entrances that limits the allowable interpreted movement of the user within the environment. For example, a user cannot transit between two separated spaces through walls, and can only reach an area through its entrance. More complex map types provide additional sensor-specific features, such as the coordinates of pre-positioned signal transmitters and receivers and radio fingerprints.

Combining the positional information obtained by the tracking sensors with the constraints provided by the map model of the environment, the system then attempts to estimate the most likely trajectory (i.e. the trajectory that violates none or the fewest constraints) of the users as they move throughout the environment. An example of such a system is MapCraft (Xiao, Wen, Markham, & Trigoni, 2014), which uses a map matching technique based on the application of conditional random fields. MapCraft uses dead-reckoned trajectories alongside a floor plan of the tracked environment to compute user's position with an average accuracy of 1.14 meters (Xiao, Wen, Markham, & Trigoni, 2014).

2.4 Relative Positioning Techniques

Alternatively, relative positioning techniques, which are also known as dead reckoning systems, do not require constructing a map model of the environment prior to using the system, but rather track the positions of users and their devices relative to their initial state (i.e. location, orientation, direction, etc.), relying solely on user and device instrumented tracking sensors. Existing implementations of relative positioning systems can be categorized into two major groups: step detection based implementations, and inertial navigation based implementations.

Step detection based systems use an accelerometer that could be mounted on the user's body (foot (Cho & Park, 2006), or waist (Alvarez, Gonzalez, Lopez, & Alvarez, 2006)) or on the user's wear (helmet (Beauregard, 2006), or backpack (Groves, et al., 2007)) to estimate a user's position. Step detection based algorithms are composed of three phases: 1) Step detection phase, during which the body-mounted sensors sense that the user has moved, 2) Step length estimation phase, during which the system estimates the length of the movement performed by the user, and 3) Step heading estimation phase, during which the system estimates the heading (orientation) of the user, and updates the position of the tracked user.

Inertial navigation based systems require the use of a full inertial measurement unit (consisting normally of 3 orthogonal accelerometers and 3 gyroscopes aligned with the accelerometers). To avoid the rapid accumulation of drift of the tracked position in such implementations, which is due to the propagation of measurement errors through the integration calculations, the inertial measurement unit must be mounted on the user's foot, and thus correcting the system state every time the foot is grounded (Foxlin, 2005) (Godha, Lachapelle, & Cannon, 2006).

Although both techniques use body-mounted sensors, step detection based systems can leverage a variety of sensors that could be mounted in different positions of the user's body, while systems that are based on inertial navigation can only be effective if foot-mounted sensors were used. Nonetheless, inertial navigation based systems can correctly recognize and handle sidesteps and vertical displacement (i.e. when climbing the stairs), and thus proving to be more accurate than their step detection based counterparts.

2.5 Conclusion

In this chapter, a set of the major techniques and approaches for implementing indoor positioning systems were discussed. Some of these techniques achieve high accuracies, but require extensive instrumentation efforts, and provide limited support for the consistent identification of users as they transit into and out of the environment. In this thesis, I propose an indoor positioning and tracking technique based on Bluetooth Low Energy beacons, and I then evaluate the proposed technique in the form of two experiments examining the accuracy of the technique in tracking users within and across indoor environments.

CHAPTER 3: MODELLING OF THE POSTIONING TECHNIQUE

As shown, there is a significant amount of work in the indoor positioning and navigation space, however, existing implementations still do suffer from various limitations. To attempt to address these limitations, we designed an indoor positioning technique based on Bluetooth Low Energy sensors. Mainly, we developed and evaluated an indoor navigation technique that addresses the problem of identifying and re-pairing zombie uesers to the respective tracked users as they transit across disjoint ubiquitous environments.

The first section of this chapter outlines the design considerations of the proposed positioning technique. Bluetooth Low Energy technology is then described in section 3.2, followed by the positioning algorithms used that were used in section 3.3. Finally, section 3.4 of this chapter describes the architecture of the positioning technique, outlining its various components, and the technical decisions that led to its design.

3.1 Design Considerations

While reviewing the literature, we iterated over three main considerations in the design of our proposed technique, which are: providing a cost-extensible model, a simple instrumentation and deployment process, and a versatile model that could be used as standalone or as part of an integrated system. Each of these considerations is described in more details in the next three sections.

3.1.1 Cost-extensible Model

The first consideration is related to supporting a wide range of cost-accuracy permutations based on the requirements of the system, and thus creating a cost-wise flexible system. This means accommodating the different settings required for different applications (i.e. low-cost low-precession vs higher-cost higher-precession), while providing painless means for switching between these settings as necessary.

3.1.2 Simple Instrumentation and Deployment

The second consideration is related to reducing the amount of effort required to set-up and instrument the environment. This means designing a streamlined sensor calibration process, allowing for an easy and quick deployment of new sensors as required.

3.1.3 Versatile Standalone and Integrated Model

The last consideration aims to create a system model that can be used as a standalone system, or integrated with existing indoor-positioning implementations. This consideration is of importance as it adds to the overall flexibility of the system. The ability to integrate with existing implementations provides means for addressing the issue of tracking and identifying users and their devices across disjoint tracked environments.

3.2 Bluetooth Low Energy

The proposed positioning technique uses Bluetooth Low Energy (BLE), also known as Bluetooth Smart, beacons as the means for tracking users and their devices within an environment. Bluetooth Low Energy is a relatively new (BLE was introduced in June 2010 (Townsend, Cufí, Akiba, & Davidso, 2014)) low-power RF-based technology that was developed for close-range communication (Gomez, Oller, & Paradells, 2012). It was introduced by the Bluetooth Special Interest Group as part of the version 4.0 of the Bluetooth Core specification.

Bluetooth Low Energy has seen an increased popularity in the past few years as a durable and reliable communication mechanism for Internet of Things (IoT) implementations (Siekkinen, Hiienkari, Nurminen, & Nieminen, 2012), and has emerged as a feasible indoor positioning technology due to the recent surge in the number of BLE-enabled devices. It, however, is worth noting that Bluetooth, in its classic standard, which has been around for a number of years is not directly compatible with Bluetooth Low Energy since the applications and the upper protocol layers are different amongst the two technologies. Table 1 contrasts the compatibility of different versions of Bluetooth devices with the Bluetooth classic version and the BLE version.

Device	**Classic Bluetooth Support**	**Bluetooth Low Energy Support**
Pre-4.0 Bluetooth	Yes	No
4.x Single-Mode (Bluetooth Smart)	No	Yes
4.x Dual-Mode (Bluetooth Smart Ready)	Yes	Yes

Table 1 - Compatibility of versions of Bluetooth devices with classic Bluetooth and Bluetooth Low Energy.

According to its specification, BLE has a modulation rate of 1Mbps, however this limit is significantly lowered in practice due to a variety of factors, such as protocol overhead, bidirectional traffic, CPU and radio limitations, as well as artificial software restrictions. BLE focuses on short-range communication, with its transmission power configurable over a range between -30 and 4dBm. Increasing the transmission power, however, reduces the durability of the BLE device's battery cell. Additionally, although it is possible to configure a BLE device to reliably transmit beyond 30 meters, a practical operating range is probably within the range of 2 to 5 meters (Townsend, Cufí, Akiba, & Davidso, 2014).

In this work, we used the consumer-grade Estimote[4] Bluetooth Low Energy beacons as our choice of BLE beacons, which will be discussed in further detail in section 3.4.4.2.

3.3 Indoor Positioning Algorithms

In this thesis, the location of users and their devices will be estimated on the basis of nearby Bluetooth Low Energy beacons and their received signal strength. The system employs the concepts of Free Space Path Loss and Trilateration to estimate the user's location based on the distance from BLE-enabled devices to at least three pre-positioned BLE beacons in combination with the calibrated positions of the BLE beacons.

3.3.1 Free Space Path Loss

Before we could estimate a user's device location using the Bluetooth beacons, the distance from the device to each of these beacon must be computed. To achieve this, we use the Free Space Path Loss (Saunders & Aragón-Zavala, 2007) relationship between the signal strength and the distance to the Bluetooth beacon through free space, as shown in Equation 1 below.

$$\log_{10}(d) = \frac{p_t - p_r + 20\log_{10}\frac{\lambda}{4\pi}}{10n} \quad (1)$$

Where:

- d is the distance between the device and the Bluetooth beacon (in meters)

[4] Estimote - http://www.estimote.com

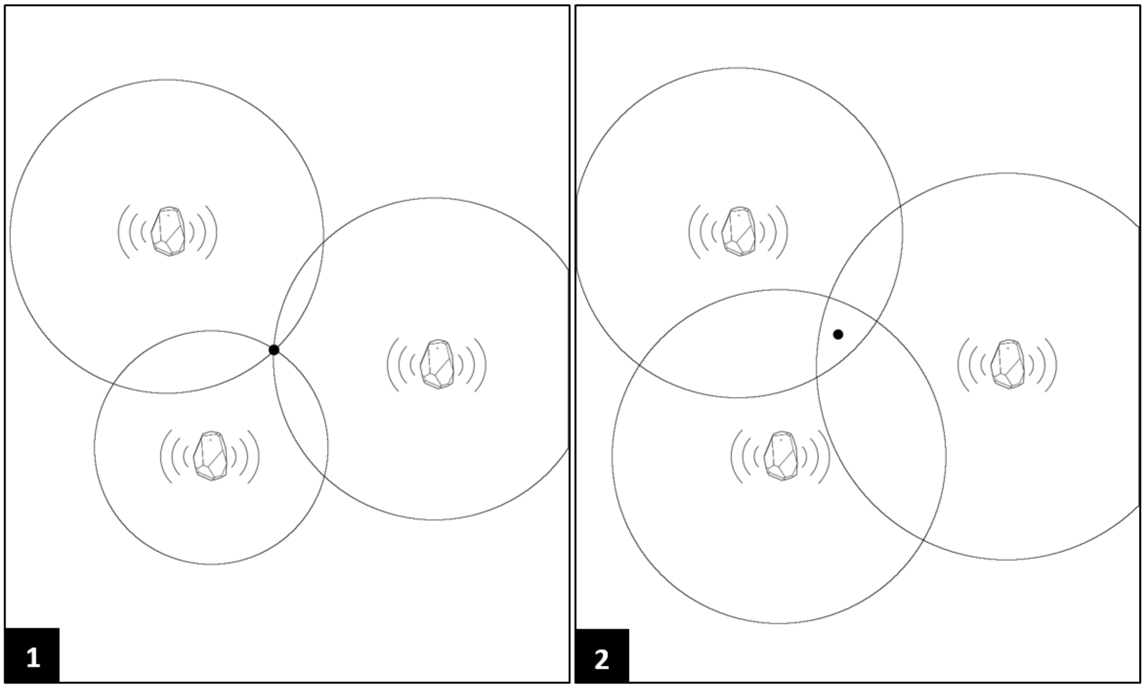

Figure 9 - Beacon Trilateration: 1) Optimal case where the three circles intersect in exactly one point, 2) Usual case where the three circles intersect in more than one point.

- $\boldsymbol{p_t}$ is the broadcasting power of the Bluetooth beacon (in $\boldsymbol{dBm}$)
- $\boldsymbol{p_r}$ is the power level of the received signal (in $\boldsymbol{dBm}$)
- $\boldsymbol{n}$ is the path loss constant (2 in free space)
- $\boldsymbol{\lambda}$ is the wavelength, which is given by equation 2 below

$$\boldsymbol{\lambda} = \frac{\boldsymbol{c}}{\boldsymbol{f}} \quad (2)$$

Where

- $\boldsymbol{c}$ is the speed of light (in meters per second)
- $\boldsymbol{f}$ is the frequency of signal (in hertz)

3.3.2 Trilateration

To compute the estimated location using the Bluetooth beacons, the device scans for nearby BLE beacons. When three or more beacons are visible, the user's device reports the closest three Bluetooth beacons alongside the signal strength of each of these beacons. These updates are sent to the SoD locator service once per second, which is the minimum scanning interval on iOS. The decision to use iOS as the client platform is discussed in detail in section 3.4.4.1.

Using the distances computed from the Free Space Path Loss equation to each Bluetooth beacon, one could represent each of these beacons as a circle centered at its registered location, with a radius equal to its distance to the device, as shown in Figure 9.

As shown in Figure 9.1, the three circles optimally intersect in one point, which can be computed by formulating the equations of the three circles. Nonetheless, due to measurement and approximation errors, it is often the case that the three circles do not intersect in one single point, as presented in Figure 9.2.

A trilateration algorithm that minimizes the distance to all three beacons was implemented. Given the computed distances to each of the beacons $\boldsymbol{d_1}$,$\boldsymbol{d_2}$, and $\boldsymbol{d_3}$, and the registered locations of these beacons ($\boldsymbol{x_1}$,$\boldsymbol{y_1}$), ($\boldsymbol{x_2}$,$\boldsymbol{y_2}$), and ($\boldsymbol{x_3}$,$\boldsymbol{y_3}$), the estimated location of the device ($\boldsymbol{x, y}$) is computed by solving the three resulting non-linear equations (equations 2, 3, and 4 below) simultaneously to eliminate one of the coordinates, and thus, finding the approximated intersection point.

$$x^2 + y^2 - 2xx_1 - 2yy_1 = d_1^2 - x_1^2 - y_1^2 \quad (2)$$
$$x^2 + y^2 - 2xx_2 - 2yy_2 = d_2^2 - x_2^2 - y_2^2 \quad (3)$$
$$x^2 + y^2 - 2xx_3 - 2yy_3 = d_3^2 - x_3^2 - y_3^2 \quad (4)$$

3.4 Architecture

Since the proposed positioning technique was to be integrated into the Society of Devices (SoD) Toolkit (Seyed, Azazi, Chan, Wang, & Maurer, 2015), which was developed at the Agile Surface Engineering lab at the University of Calgary, this section gives a brief overview of Society of Devices Toolkit, and the modifications that were introduced to integrate the proposed BLE-based positioning technique into the toolkit.

3.4.1 Society of Devices (SoD) Toolkit

To simplify the implementation process as well as to satisfy the third design consideration, we leveraged the Society of Devices (SoD) Framework (Seyed, Azazi, Chan, Wang, & Maurer, 2015), which provides convenient means for tracking users' spatial attributes using multiple Microsoft Kinect[5] cameras.

The SoD Toolkit was designed to aid developers and interaction designers in the development of ubiquitous environments by abstracting the collection of spatial information from a wide range of sensors into a plug-and-play architecture.

The software architecture of the SoD Toolkit consists of four main components: the SoD Locator service, the SoD Kinect client, the SoD Visualizer, and the client libraries, each of which will be discussed in more detail in this section.

[5] Microsoft Kinect - https://developer.microsoft.com/en-us/windows/kinect

3.4.1.1 SoD Locator Service

The SoD Locator service is the central component of the SoD Toolkit. It maintains spatial information about tracked devices and entities in the environment (such as position, orientation, direction, proximity, etc.), which can be queried for or filtered by using the client libraries.

The locator service is designed to obtain raw positional data from the connected devices and the distributed sensor clients over the local area network, and transform that data into a coherent model of the environment. It utilizes an event-driven approach, in which clients can subscribe to events advertised by the locator service. Examples of such events include subscribing to events as users and devices enter the environment, leave the environment, or get within an certain proximity of a range.

3.4.1.2 SoD Kinect Client

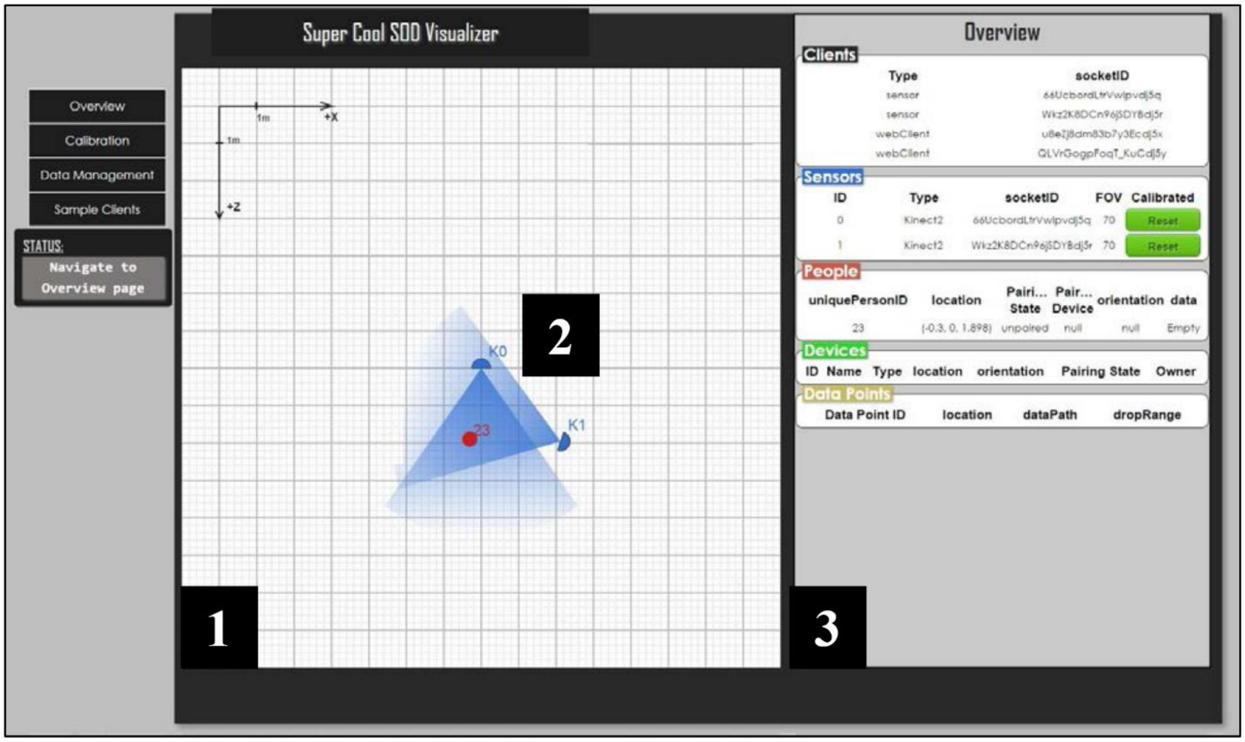

Figure 10 - SoD Vizualizer: 1) The tracked environment, 2) Movable user, device and sensor components, and 3) List of devices, users, and sensors currently in the system.

The SoD Kinect Client uses a single Microsoft Kinect (version 1 or 2) sensor to collect positional data (skeletal) of the users in the environment. Collected data is sent over the network using TCP connections at a rate of 30 skeleton frames per second to the locator service. The Kinect Client also allows the SoD Toolkit to incorporate an arbitrary number of Kinect sensors by running multiple instances of the Kinect client component, each connected to a Kinect sensor covering a range from 1.2 to 3.5 meters per sensor. The locator service collects tracking data from the distributed sensors over the local area network, and uses the received data to generate an interpretation of the entities in the room space.

3.4.1.3 SoD Visualizer

The SoD Visualizer assists developers and researchers to picture and understand the locator service interpretation of the spatial information of devices and users being tracked in the environment. It also provides easy means for creating simulated ubiquitous environments, which can be useful for testing various settings without having to instrument the environment or the users with tracking sensors.

As shown in Figure 10.1, the SoD Visualizer presents a 2D visualization of the environment, which is updated in real-time and shows:

- The approximate area of the environment as a 2D grid, with drag-able Kinect, user and device components allowing developers and researchers to dynamically remap the environment in real-time (Figure 10.2)
- The location and field of view of Kinect clients that are currently tracking the environment depicted on the 2D grid
- A list of device clients that are currently connected to the system (Figure 10.3),
- A list of tracking sensors that are registered with the locator service (Figure 10.3), and
- A list of tracked users within the environment, detailing their location, orientation, and device assignment (Figure 10.3)

3.4.1.4 SoD Client Libraries

SoD provides developers and researchers with native client libraries in Objective-C, JavaScript, and C# to aid developers in integrating a wide range of devices running on different platforms into ubiquitous environments. The client libraries utilize the device-embedded sensors (such

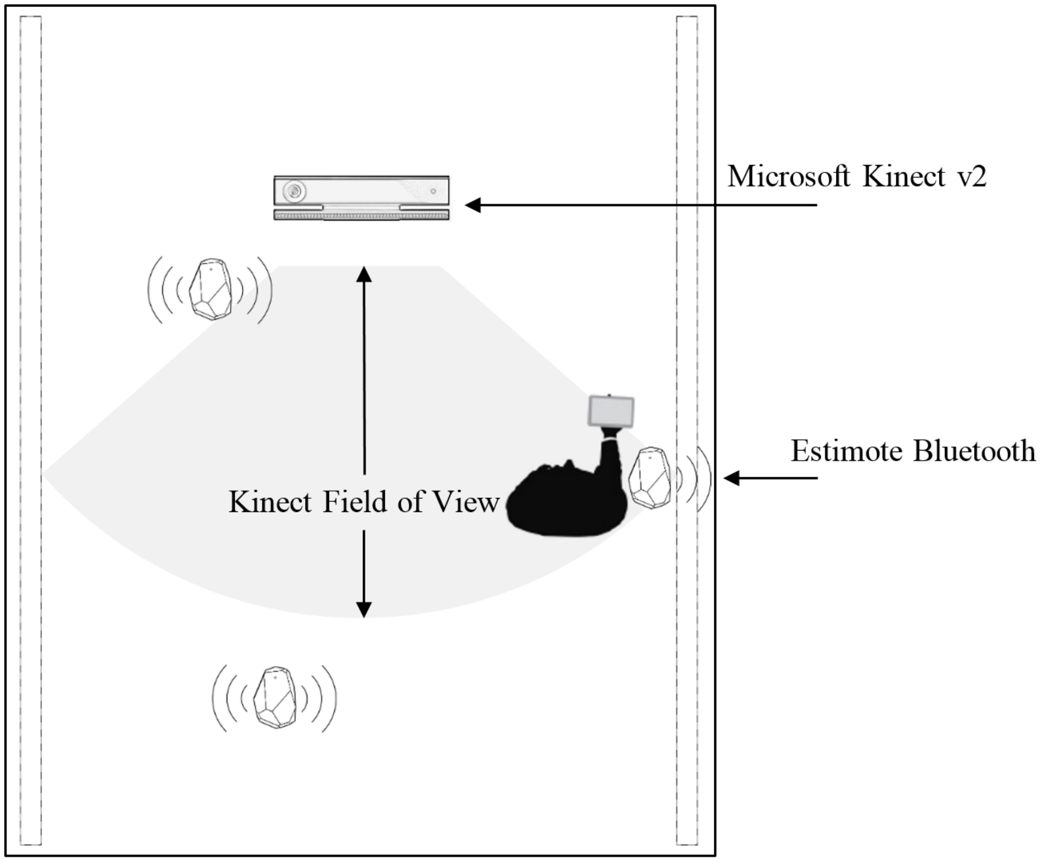

Figure 11 - User attempting to register the location of a Bluetooth beacon with the SoD locator service.

accelerometers and gyroscopes) by capturing spatial information such as orientation and direction, and sending this data to the locator service over frequent intervals.

The SoD client libraries, also, provide a simple REST based interface for developers to perform spatial queries (such as devices in range, devices in view, devices within certain proximity, etc.). This allows inexperienced developers to send and receive data across different platforms without having to handle the low-level specifics of message serialization, encoding and deserialization.

3.4.2 Calibration Component

The registration of the beacon locations could be done in a number of ways: 1) Dragging a visual control resembling a BLE beacon on the SoD visualizer to the approximate location of the beacon, which is the simpler but less accurate approach or 2) Entering the coordinates of each of the beacons manually in the system (SoD locator service), which provides a more accurate estimation of the position of the users and their devices, but is more tiresome to set up.

For the purposes of this thesis, a calibration component was introduced into the SoD toolkit in order to position the BLE beacons in the environment, and register the location of each beacon with the SoD locator service using Kinect sensors. The calibration component relies on placing the BLE beacons within the field of view of a Kinect sensor to provide an accurate position for the BLE beacon, as well as to allow for using the Kinect-based user location as a basis to compare the beacon-based location to, as will be discussed in chapter 4.

To register the location of a beacon with the SoD locator service, a user holding an iOS device, running a custom application that was built to find the nearest BLE beacon, must stand next to the beacon, and within the field of view of the Microsoft Kinect, as shown in Figure 11. The Kinect was connected to a Microsoft Surface Pro III, running an instance of the SoD Kinect Client application. The application uses the connected Microsoft Kinect to scan for any users in its field of view, and reports any users it finds to the SoD locator service. These updates are sent from the Kinect Client to the SoD locator at a rate of 30 frames per second.

Once the user becomes visible to the Microsoft Kinect, the user is assigned a numeric Person ID, which is displayed on the Microsoft Surface Pro III connected to the Kinect. The user is, then, prompted to enter the Person ID on the custom iOS application and press calibrate. Once the user has pressed calibrate, the Person ID along with the data of the closest Bluetooth beacon are sent to the SoD locator service, which registers the received beacon with the location of the person with the provided Person ID.

3.4.3 Zombie Identification Component

The second component that was introduced into the SoD toolkit handles the identification and re-pairing of Zombie users to a tracked state. To achieve this, the SoD locator service maintains a database of the real-time Kinect-based and BLE beacon-based locations of all users and devices currently using the system (tracked users), while constantly checking for changes in the number of tracked users (Figure 12.1).

Upon recognizing that a user has left the field of view of the SoD Kinects, the system notifies the user's device that it is no longer tracked by the Microsoft Kinects. The SoD locator service, then, invalidates the user's Kinect-based location, relying solely on the BLE-based location, and changes the user's state to a **Zombie state** (Figure 12.2).

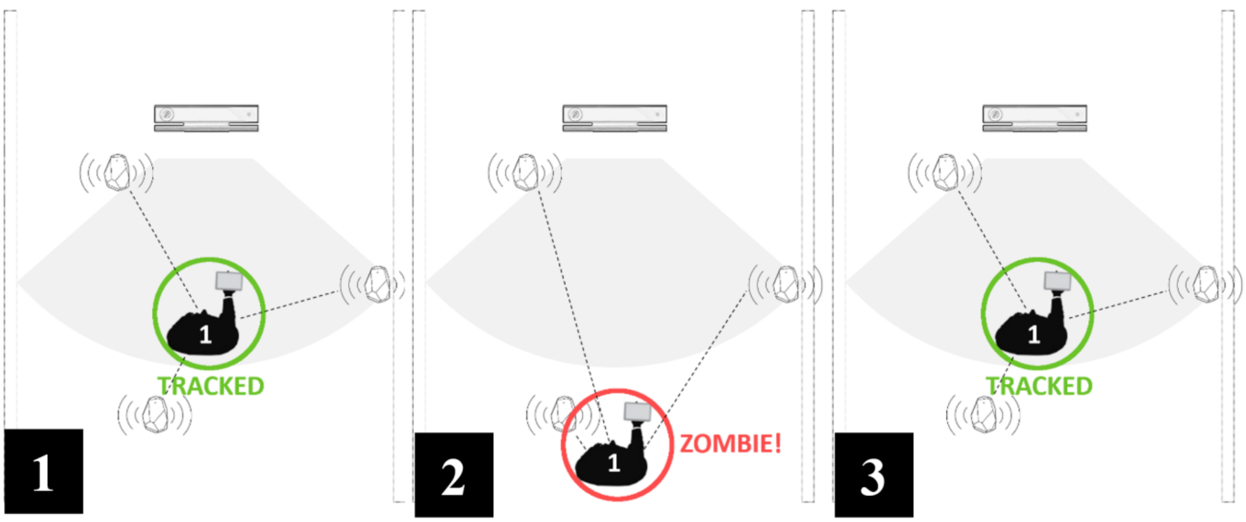

Figure 12 - Zombie Identification: 1) Locator service maintains a Kinect-based and a BLE-based location for each user. 2) Relying on BLE-based location as users transit to a Zombie state. 3) User is repaired to the closest new user observed by the Kinect.

As the user transits back to the field of view of the SoD Kinects, the system scans its database for the BLE-based location closest to the new user's Kinect-based location, using an empirical threshold of 40 centimeters. If a match is found, the new user is re-paired to the Zombie user that reported the closest BLE-based location. The system, finally, re-validates the Kinect-based locations for that user, and changes the user's state to a **tracked state** (Figure 12.3). If a match was not found, however, the user is treated as new user.

3.4.3.1 User Counting

To assist with the issue of re-pairing Zombie users, the system supports the use of an external user-counter sensor. Such a sensor could be mounted at the entrance of the tracked environment to update the system as users join and/or leave the space. This reduces the guess work the system needs to do when a user leaves the field of view of the SoD Kinects but stays within the tracked environment. In such a case, as the user re-joins the field of view of the SoD Kinects, the need for searching the system's database for the user with the closest BLE-based location is eliminated since there is only one re-pairing option.

To simplify the implementation of the system, while allowing for the external user-counter sensor mechanism to be evaluated, we implemented a simulated user-counter sensor component. The simulated user-counter is accessible through the SoD Visualizer and can be turned off or on, specifying the number of users within the environment at any given time.

3.4.4 Technical Decisions

This section outlines the technical design decisions and choices that were made with respect to the choice of development platform for the client side, as well as the choice of Bluetooth Low Energy beacon.

3.4.4.1 Client Platform

For the purposes of this thesis, Apple's iOS was chosen as the platform on which the client side of the proposed indoor positioning technique was implemented.

At first, Google's Android alongside Apple's iOS were both considered since they have both dominated an aggregated 95% share of the entire smartphone market throughout the past two years, as shown in Table 2. However, to narrow the two choices down to one, another aspect had to be evaluated, which is BLE support on the Android and iOS platforms.

Period	**Android**	**iOS**	**Windows Phone**	**BlackBerry OS**	**Others**
2015Q2	82.8%	13.9%	2.6%	0.3%	0.4%
2014Q2	84.8%	11.6%	2.5%	0.5%	0.7%
2013Q2	79.8%	12.9%	3.4%	2.8%	1.2%
2012Q2	69.3%	16.6%	3.1%	4.9%	6.1%

Table 2 - Worldwide Smartphone OS Market Share (IDC, 2015).

Apple's support for Bluetooth Low Energy gained popularity when iBeacon was introduced as part of the iOS 7 launch. In essence, iBeacon is a proprietary protocol that leverages the Bluetooth Low Energy standard to estimate a device's location on the basis of its proximity to beacons. Along with the protocol, Apple provided developers with managed SDKs allowing users to turn any iOS device into an iBeacon transmitter and receiver, amongst other features that made it an ideal choice for the development of BLE based systems.

Following to the successful introduction of Apple's iBeacon, a number of libraries were developed to support iBeacon on Android (as well as on other platforms). However, Apple has recently introduced their iBeacon License Program, which required developers and vendors to remove any references or connection between Android devices and iBeacon protocols from their libraries and products. This resulted in many of the previously available Android iBeacon libraries being discontinued, and thus making it less desirable and more difficult for developers to program Android devices to work with iBeacon.

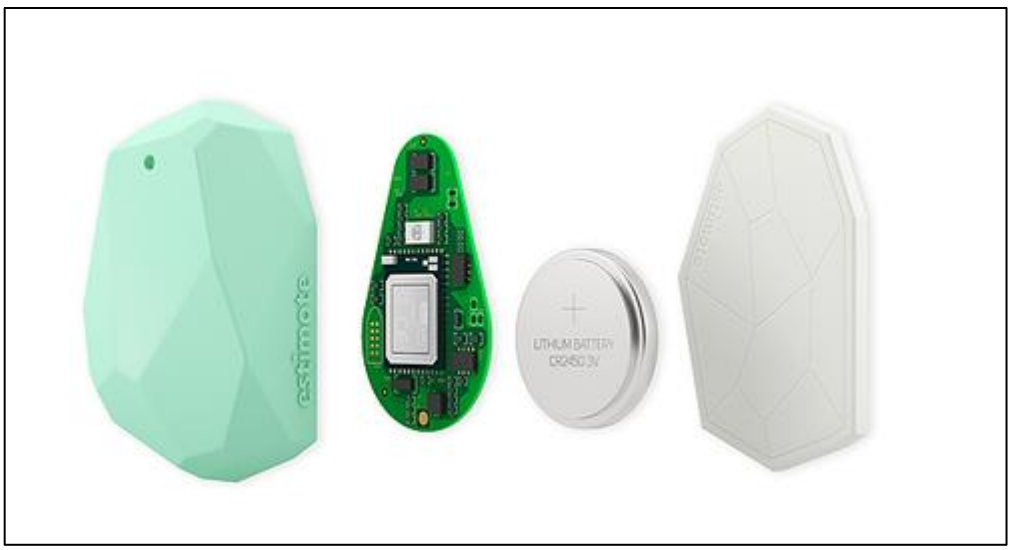

Figure 13 - Estimote Beacon.

As a result, and to simplify the implementation process, Apple's iOS was chosen as the platform on which the client side of the proposed indoor positioning technique was implemented.

3.4.4.2 BLE Hardware

In this work, we used the consumer-grade Estimote Bluetooth Low Energy beacons as our choice of BLE beacons (Figure 13). Estimote was decided on as the BLE hardware through a review of a number of commercially available BLE beacons. The reviewed beacons were inspected with certain criteria in mind, including cost, power type, range, configurability, and broadcast rate. Table 3 summarizes the results of the review.

The main advantages of Estimote over the reviewed alternatives were its higher range (70 meters in contrast with a maximum of 50 meters in all other alternatives), and frequent broadcast rate (200 ms in contrast with 250 ms for the closest alternative), and thus making it the best choice amongst the surveyed BLE beacons.

Manufacturer	StickNFind	Estimote	RedBearLabs	KST	GeLo
Device	Enterprise Beacon	Estimote Beacon	Beacon B1	Particle	Beacon
Retail cost each	\$25.00 US	\$33.00 US	\$30.00 US	\$60.00 US	\$35.00 US
iBeacon protocol supported	Yes	Yes	yes	Yes	no
Power type	Battery	battery	battery	battery	battery
Reported operating life	3 years	2 years	1 year	6 months	2 years
Radio range	50 meters	70 meters	50 meters	50 meters	10 meters

Battery capacity	240 mAh	640 mAh	~1000 mAh	240 mAh	~1000 mAh
Configurable radio output power	yes	No	yes	No	unknown
Configurable (RSSI)	yes	Yes	yes	No	unknown
Default beacon broadcast rate	1000 ms	200 ms	250 ms	unknown	unknown
Configurable advertising interval	yes	No	yes	No	No

Table 3 - A review of commercially available BLE Beacons.

3.5 Conclusion

The proposed positioning technique in this chapter utilizes Bluetooth Low Energy (BLE) for positioning and tracking users and devices within and across adjoint and disjoint environments. The technique was designed with three major considerations in mind: cost-extensibility, easy instrumentation, and support for standalone and integrated deployments, which were discussed in more detail in section 3.1. The technique was integrated with the Society of Devices Toolkit through the introduction of the beacon calibration and zombie identification components, as outlined in sections 3.4.1, 3.4.2, and 3.4.3. Finally, section 3.4.4 demonstrated the technical decisions that were made throughout the design and modelling of the positioning technique.

CHAPTER 4: EVALUATION

Two experiments were conducted to investigate the accuracy of the proposed technique for providing spatial awareness in ubiquitous environments. Specifically, the experiments investigated the accuracy of the location measurements estimated using the BLE beacons and its precision and impact on identifying and re-pairing users across disjoint ubiquitous environments.

4.1 First Experiment

The first experiment was used to evaluate the proposed technique as a standalone indoor positioning and tracking system by investigating the accuracy of the location measurements computed using the BLE beacons. The beacon location estimates were compared to the actual location measurements returned by a Microsoft Kinect treated as a benchmark.

4.1.1 Apparatus

The experiment was conducted using three consumer-grade Estimote Bluetooth beacons set to broadcast at a signal strength of **+4 dbm** and running Estimote's 3.1 OS. The beacons were placed at the boundaries of the tracking area of a 2nd generation Microsoft Kinect to ensure that the Bluetooth signals cover the entire tracking area as shown in Figure 14. The Microsoft Kinect

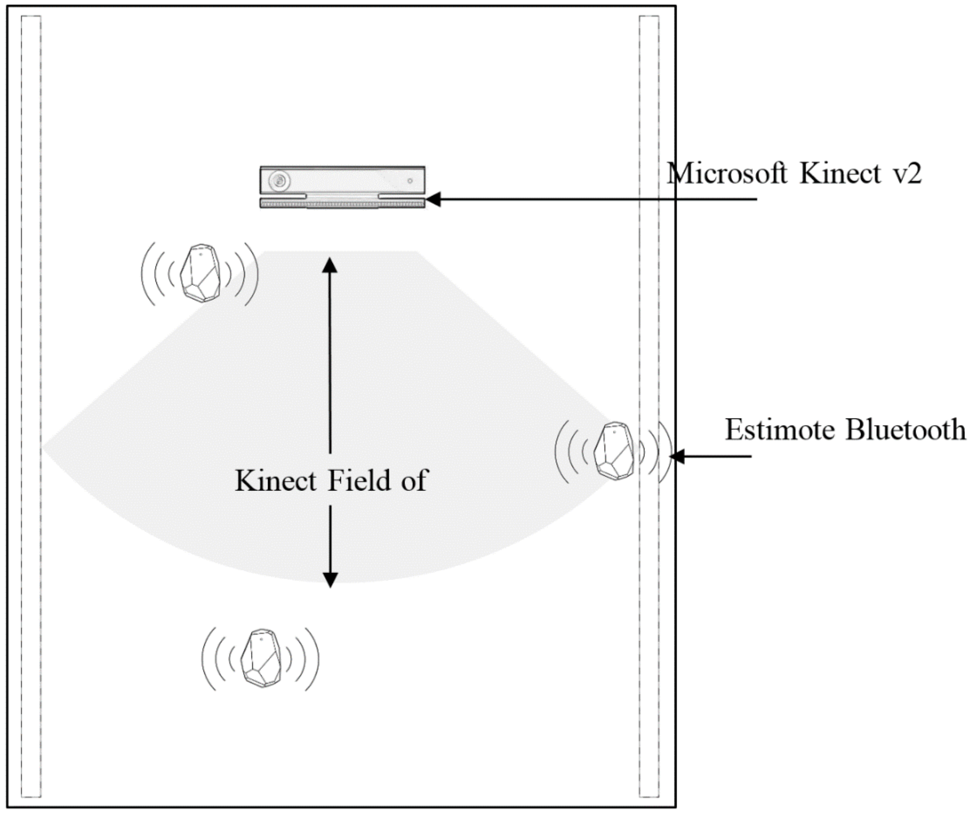

Figure 14 - Placing Estimote Bluetooth beacons at the boundaries of a Microsoft Kinect's field of view.

was used to provide the benchmark for the location measurements estimated from the Bluetooth beacons.

4.1.2 Design

As basis for comparison, the measure of Euclidean distance was used to contrast the beacon-based device location against the actual Kinect-based user location.

4.1.3 Experiment Variables

The experiment examined a single independent variable which is the average distance from the device to each Bluetooth beacon. Distances $\boldsymbol{d_1}$,$\boldsymbol{d_2}$, and $\boldsymbol{d_3}$ were computed by calculating the Euclidean distance between the user's actual location, provided by the Microsoft Kinect, and the

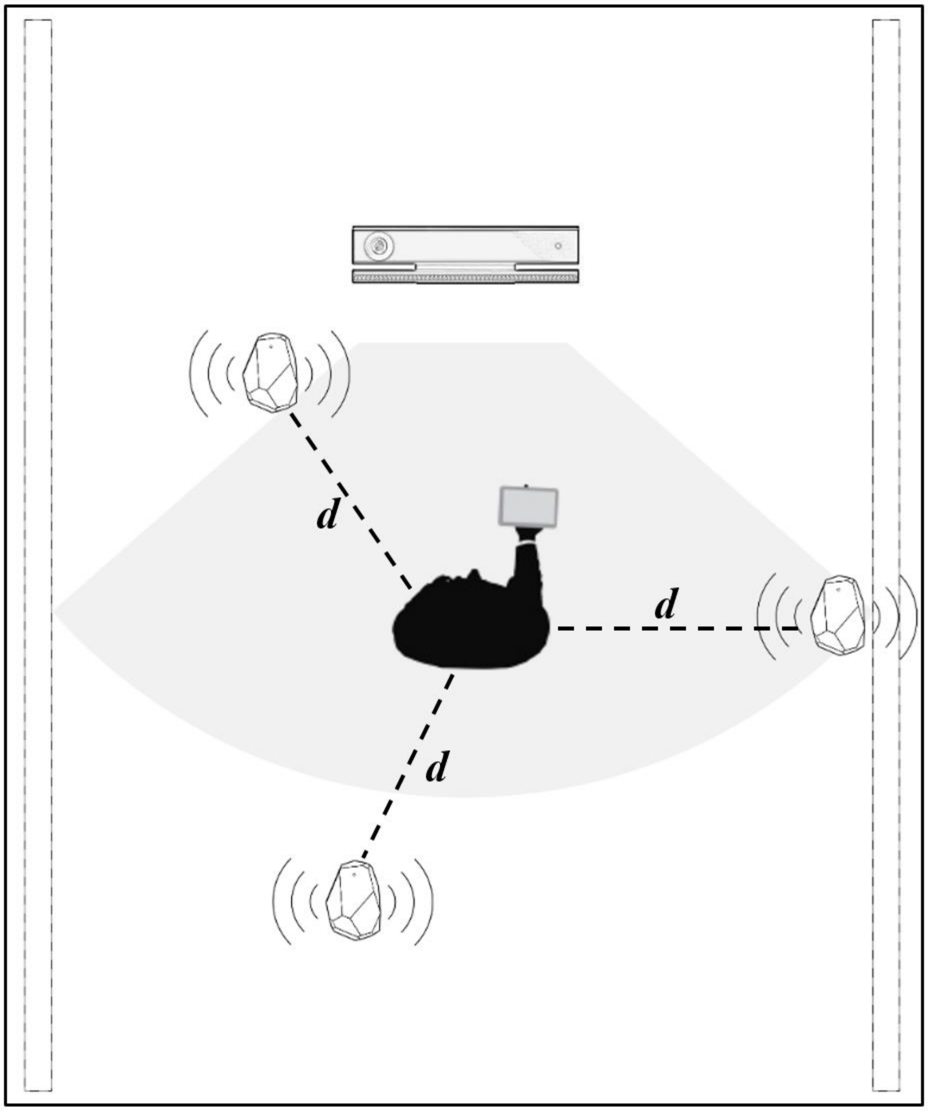

Figure 15 - Computing the average distance by averaging the user's distance to the closest three Bluetooth beacons.

registered location of each of the three closest Bluetooth beacons, as shown in Figure 15. The average distance ***d*** is computed, then, by dividing the sum of these three distances by three.

Given the range of the Microsoft Kinect, which spans approximately **4** meters in front of the Kinect and a view angle of **70º**, and the placement of the Bluetooth beacon in this experiment, the average distance ***d*** to each of the beacons produced values ranging from 1.3 to 4.3 meters.

The dependent variable was the accuracy of the location estimated by trilateration the Bluetooth beacon signals. The Accuracy was assessed by computing the Euclidean distance between the beacon-based device location and the actual Kinect-based user location, which is referred to as the ***Measurement Error***.

4.1.4 Procedure

At the start of the experiment, the SoD locator service is started alongside an instance of the SoD Kinect Client, a mobile application is started on an iOS device, and a user is asked to stand in the field of view of the Kinect while holding the mobile device. The user is instructed to enter the Person ID assigned to them by the Kinect Client in the mobile application to pair the device with the user.

Once paired with the device, the user is instructed to move within the field of view of the Microsoft Kinect for about **6** minutes while data is collected from the Microsoft Kinect and the beacons.

4.1.5 Results

The ***Measurement Error*** produced by trilaterating the Bluetooth beacon signals was measured as the Euclidean distance between the beacon-based device location and the actual Kinect-based user location. We collected a total of **381** observations (**6** minutes and **21** seconds × **1** observation per second). The grand mean ***Measurement Error*** was **1.83** meters (**SD = 1.29** meters).

The experiment observations were organized into **7** categories based on the user’s average distance to each beacon. The categories covered distances from **1** meter to **4.5** meters, spanning

0.5 meters each. The initial analysis revealed that there was a significant effect of the average distance to each beacon upon measurement error ($F_{6,374} = 277.1, p < .001$).

Running post hoc comparisons using the Tukey HSD test indicated that the mean score for the first three categories [1, 1.5] (**M = 0.86**, **SD = 0.51**), [1.5, 2] (**M = 1.35**, **SD = 0.56**), and [2, 2.5] (**M = 1.94**, **SD = 0.30**) were significantly different than each other and the rest of the categories. The four remaining categories did not significantly differ otherwise. Figures 16 through 22 outline the measurement error distribution corresponding to each of the seven categories[6].

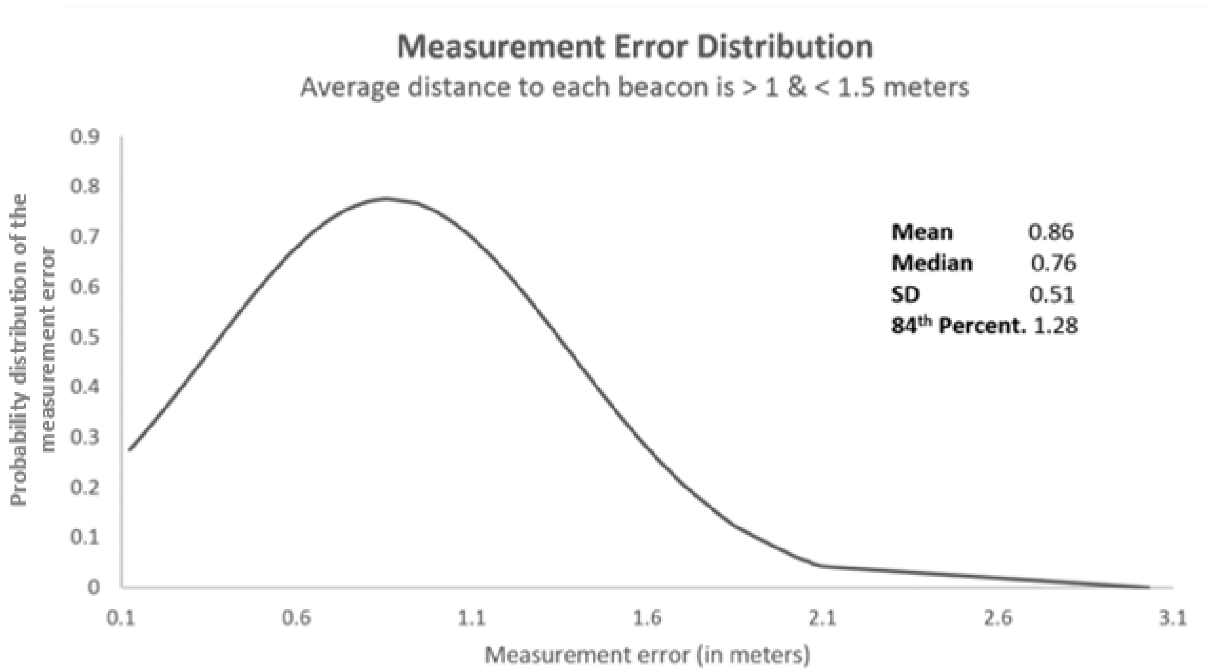

Figure 16 - Measurement error distribution for the [1, 1.5] category.

[6] The integral of the average distance over any interval is the probability that the measurement error specified by it will lie within that interval.

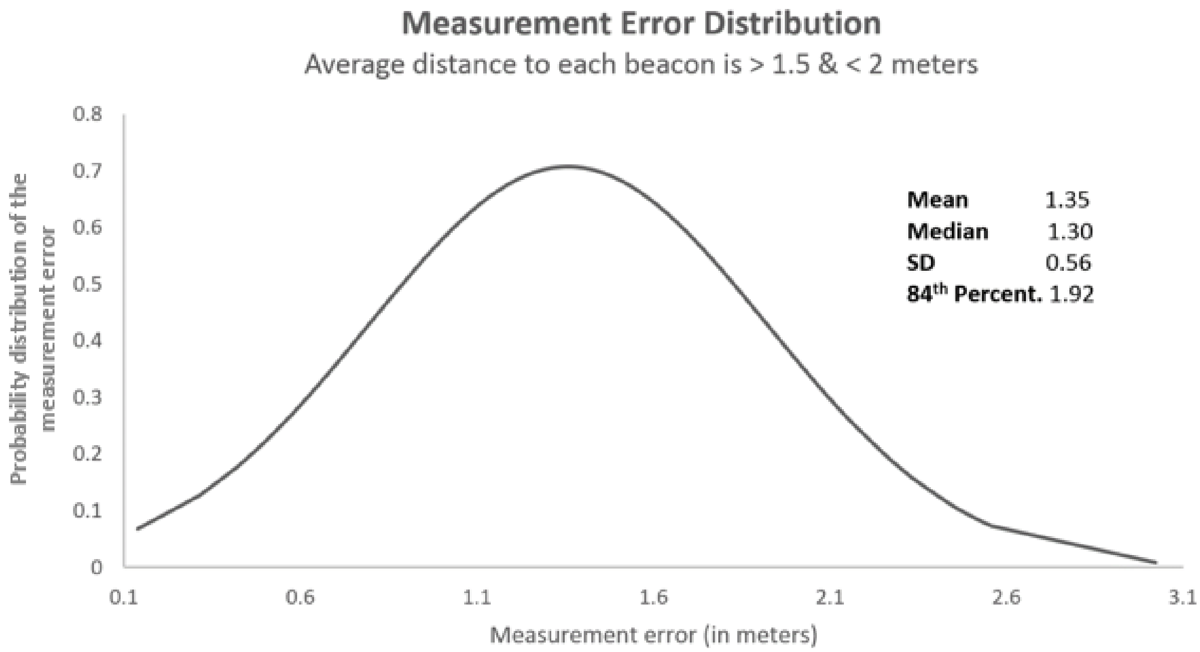

Figure 17 - Measurement error distribution for the [1.5, 2] category.

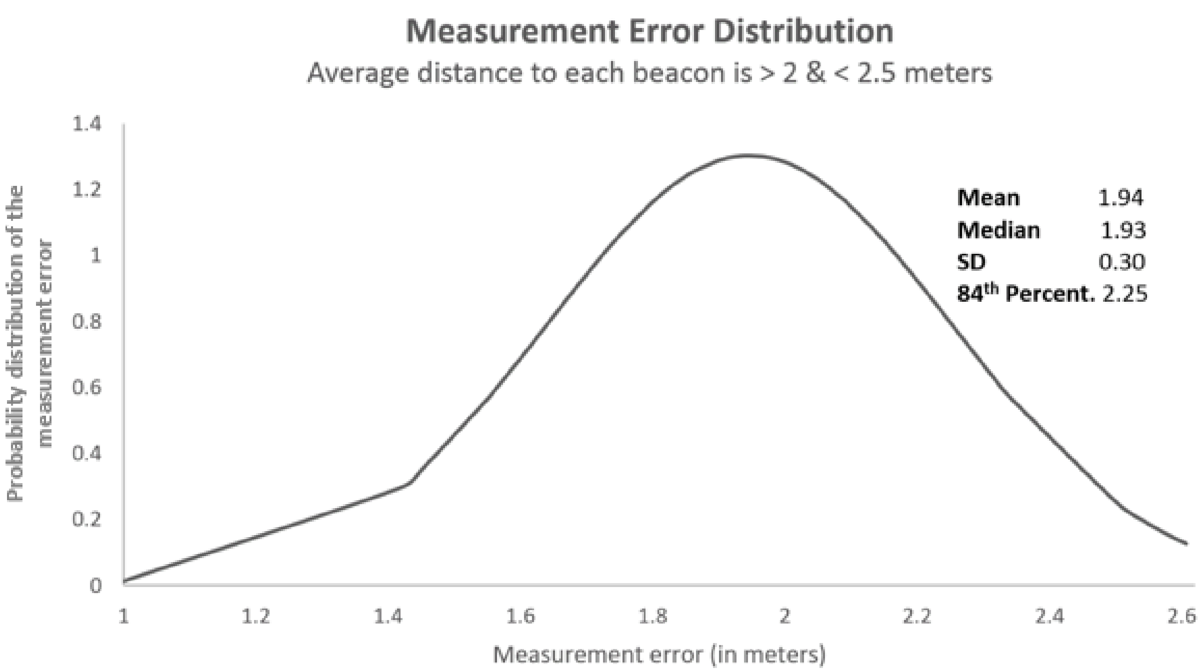

Figure 18 - Measurement error distribution for the [2, 2.5] category.

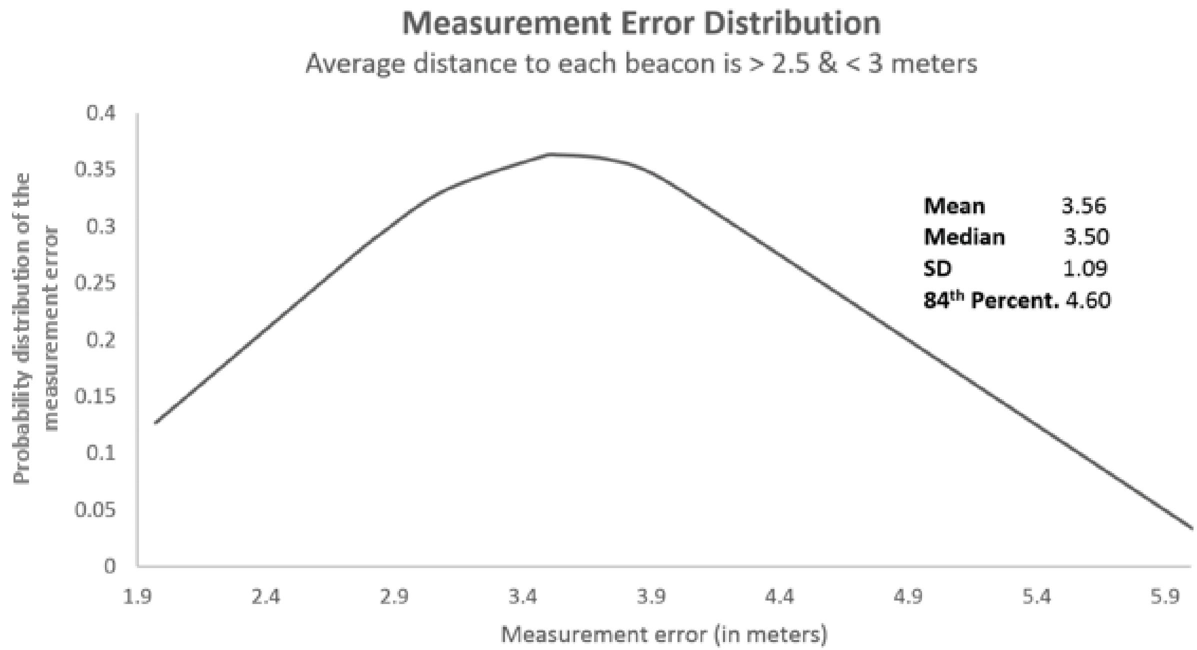

Figure 19 - Measurement error distribution for the [2.5, 3] category.

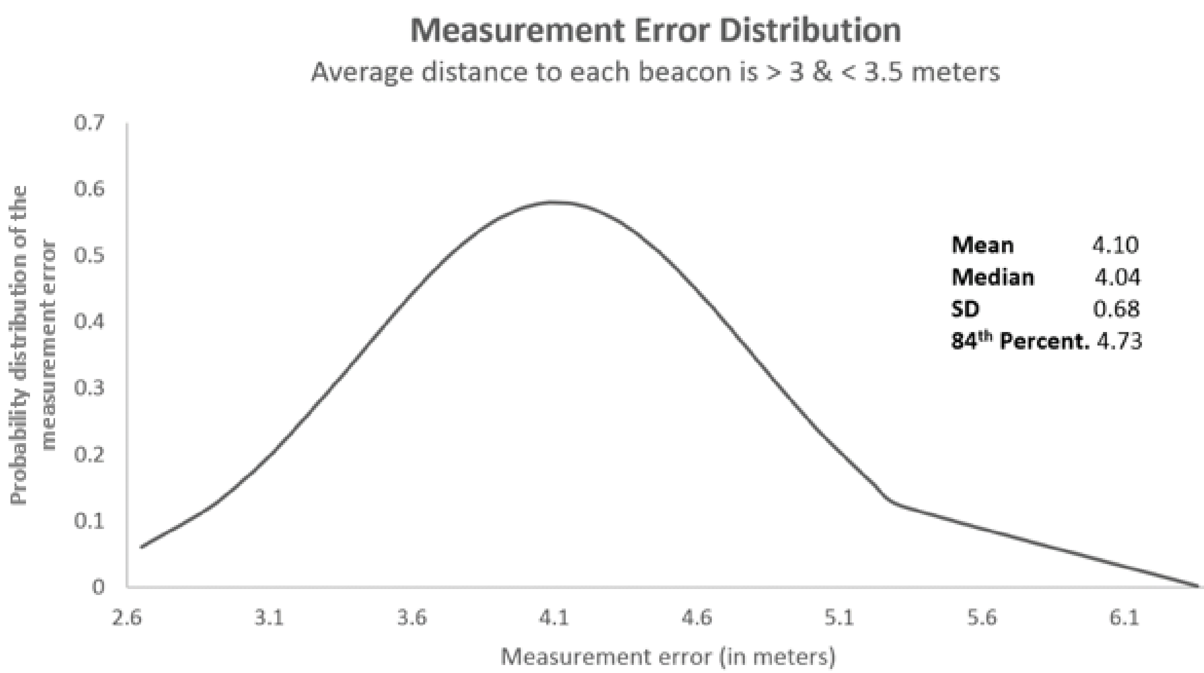

Figure 20 - Measurement error distribution for the [3, 3.5] category.

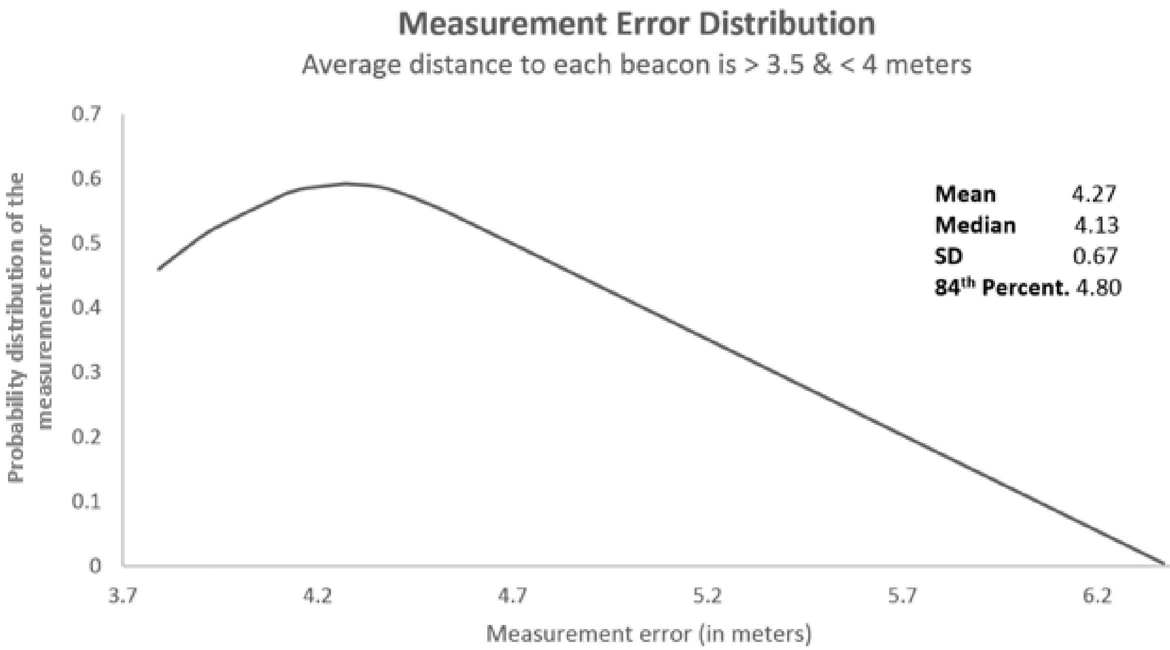

Figure 21 - Measurement error distribution for the [3.5, 4] category.

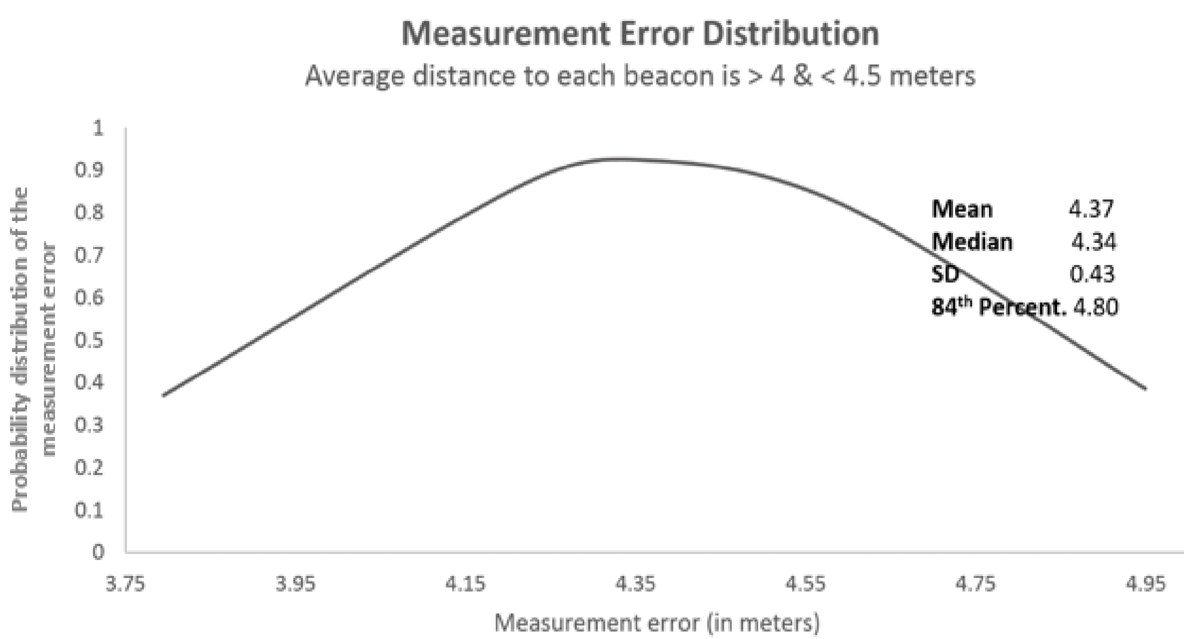

Figure 22 - Measurement error distribution for the [4, 4.5] category.

4.1.6 Discussion

This section discusses the implications of the results of the first experiment with respect to the standalone implementations category. The section details the implications of the results on standalone implementations, reflecting on the research questions and goals of the thesis, and provides sample recommended use cases in which the technique performs well as a standalone implementation.

4.1.6.1 Standalone Implementations

The results of the first experiment indicate that most of the statistical significance that was reported stemmed from observations that had a high average distance to each BLE beacon. More specifically, it was observed that the measurement error grew linearly in the area of interest and quadratically otherwise as the user moved further from the BLE beacons (Figure 23). By studying the chart, it can be observed that achieving a measurement error of less than **1** meter becomes highly unlikely when the average distance to each Bluetooth beacon becomes larger than **2** meters.

To better understand the implications of the experiment results on the overall accuracy, the **84th** percentile of the measurement error for each of the seven categories was computed and plotted,

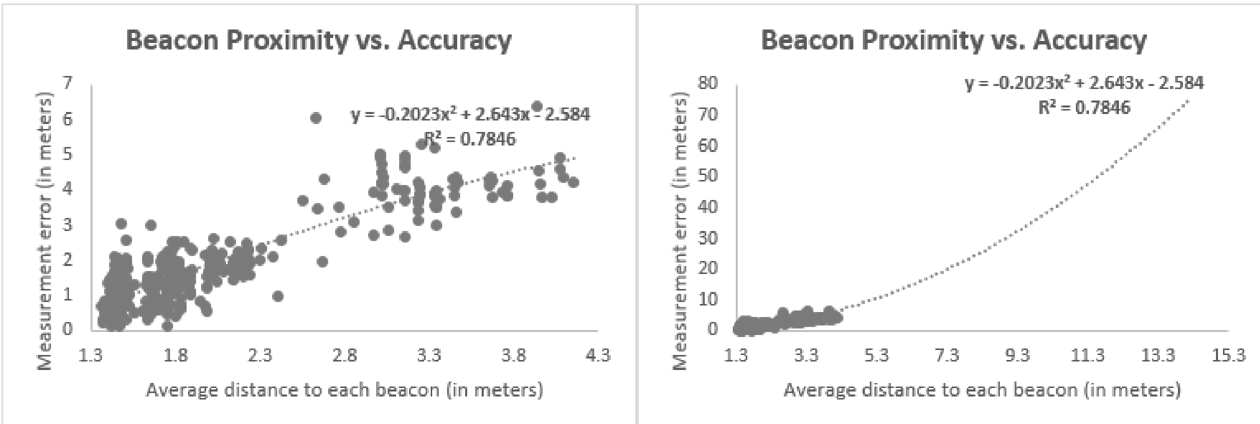

Figure 23 - Beacon proximity vs accuracy: A chart outlining the correlation between the users distance from the beacons and accuracy of the beacon-based location measurements.

as seen in Figure 24. Reading the chart, it can be observed that the **84%** of the observations achieved a measurement error that was within the **0** and **2** meters range as the average distance to each beacon remains below **3** meters.

4.1.6.2 Comparison to Existing Techniuqes

A recent study by Lymberopoulos et al. (Lymberopoulos, et al., 2015), comparing the accuracy of a diverse set of 22 indoor positioning and tracking technologies revealed that only 3 of the 22 tested technologies achieved a measurement error below 3 meters. In particular, the lowest measurement error (0.72 meters) was achieved by Reimann et al.'s *ArgusNetViewer* (Reimann,

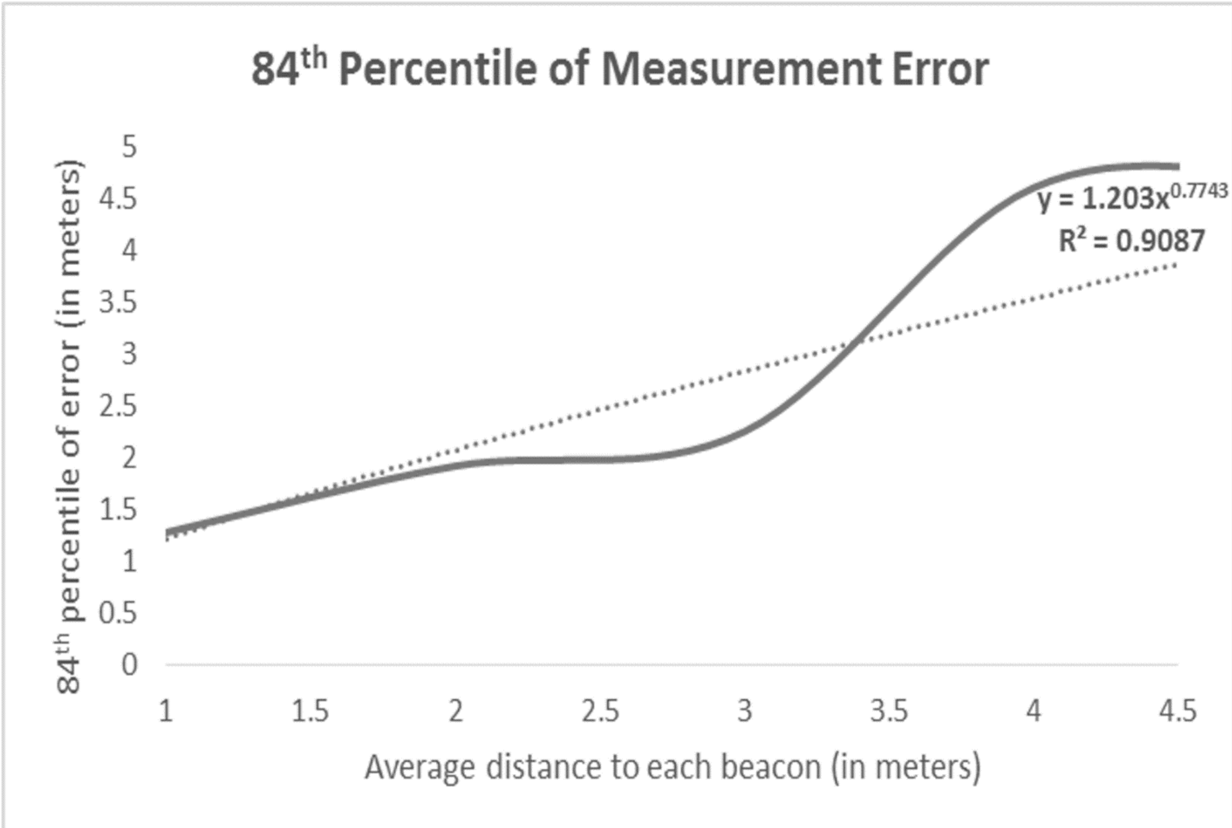

Figure 24 - 84th Percentile of measurement error: A chart outlining the maximum measurement error that occurs 84% of the time as a function of the user's average distance to each beacon.

Bestmann, & Ernst, 2013), followed by Beder et al.'s Wifi fingerprinting-based localization technique (1.56 meters) (Beder & Klepal, 2012).

Based on the results of our first experiment, our approach shows to be capable of achieving an average accuracy of 0.86 meters by keeping the average distance to the closest three beacons between 1 and 1.5 meters, which suggests that the proposed technique does score higher than the vast majority of the indoor positioning technologies put to test in the referenced study.

4.1.6.3 Beacon Placement

The results of this experiment becomes of particular interest to system engineers and users when attempting to determine the number of BLE beacons required to achieve the target accuracy in an

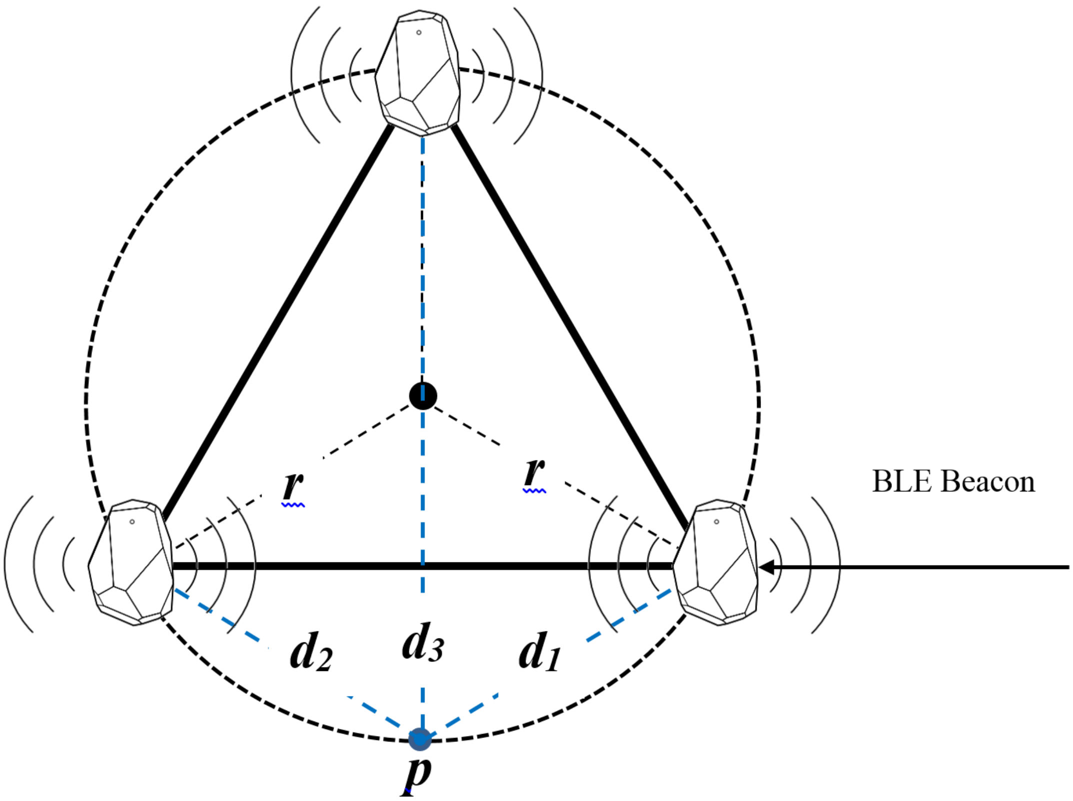

Figure 25 - Beacon Placement Model, where *r* is the radius of the tracking area, *p* is the point furthest from the beacons, and d_1, d_2, and d_3 are the distances from point *p* to each of the beacons.

environment. By using the properties of Equilateral Triangles (Euler, 1767), a model for the placement of the BLE beacons has been constructed.

As shown in Figure 25, the model relies on placing the BLE beacons at the vertices of an equilateral triangle, which provides a tracking radius that is equal to the radius ***r*** of the circumscribed circle (Kay, 1969) containing the triangle, and guarantees a maximum average distance ***m*** to the three beacons of ***4r/3*** as a worst case scenario when the user is at point ***p*** (furthest point to the BLE beacons), as shown in Equations 5, 6 and 7 below:

$$m = (d_1 + d_2 + d_3)/3 \text{ meters} \quad (5)$$

Since d_1, r, and the segment connecting the point p to the center of the circumscribed circle construct a smaller equilateral triangle, Equation 5 becomes:

$$m = (r + r + 2r)/3 \text{ meters} \quad (6)$$

$$m = 4r/3 \text{ meters} \quad (7)$$

OR

$$r = 3m/4 \text{ meters} \quad (8)$$

By consulting Figure 24, the maximum tolerable measurement error E is used to determine the maximum average distance using the formula:

$$E = 1.203 \times m^{0.7743} \text{ meters} \quad (9)$$

Using the value of m, it is possible to use Equation 8 to determine the radius r at which the beacons need to be placed, and accordingly the maximum area that could be tracked using three BLE beacons while remaining within the required maximum tolerable measurement error E, as follows:

$$\text{Maximum accurately trackable area} = (2r)^2 = 4r^2 \text{ meters} \quad (10)$$

For example, to accurately track an environment with a maximum tolerable measurement error E of ***2 meters***, Equation 9 is used first to obtain the maximum average distance m, as follows:

$$2 = 1.203 \times m^{0.7743}$$

$$m = 1.93 \text{ meters}$$

The radius r is found by plugging the computed maximum average distance m into Equation 8, which is then used to find the maximum trackable area (Equation 10), as follows:

$$r = 3m/4 = 1.45 \text{ meters}$$

$$\text{Maximum trackable area} = 4r^2 = 5.8 \text{ meters}$$

Which is the maximum trackable area up to an accuracy of 2 meters, using three Bluetooth Low Energy beacons.

4.1.6.4 Cost Estimation

Using the constructed beacon placement model, it is possible to track a **diameter of 2.25 meters** (approximately an area of **5 square meters**) at an accuracy of **1.65** meters at a cost of just below $100 dollars (since a three beacon pack costs between $75 - $99 US as shown in Table 3). As a result, the system proves to be more economically viable compared to other Kinect based or RF-based low end/low cost systems, as shown in Table 4.

Technology	Sensor Type	Infrastructure to Track 5 meter^2	Approximate Cost
Kinect-based	Microsoft Kinect	1x Microsoft Kinect	$140
WiFi-based	Wi-Fi AP	3x Wi-Fi Access Points	$150

Table 4 - Approximate cost of tracking a 5 meter^2 space using low-end low cost tracking technologies.

4.2 Second Experiment

We conducted a second experiment to evaluate the integration of the proposed technique with an existing indoor positioning system (the SoD toolkit) by investigating the precision of the re-pairing process as recently lost users (zombie users) attempt to transit through disjoint environments.

4.2.1 Apparatus

The apparatus for this experiment were almost identical to the previous one, with the following differences:

• The experiment was conducted using two 2nd generation Microsoft Kinects, covering disjoint fields of view, to simulate two non-overlapping environments (e.g. two separate rooms in a building). This allowed us to simulate two environment sizes: 1) a smaller 6 × 2 meters area covered by one Microsoft Kinect (Figure 26), and 2) a larger 6 × 4 meters area covered by the two Microsoft Kinects (Figure 27)

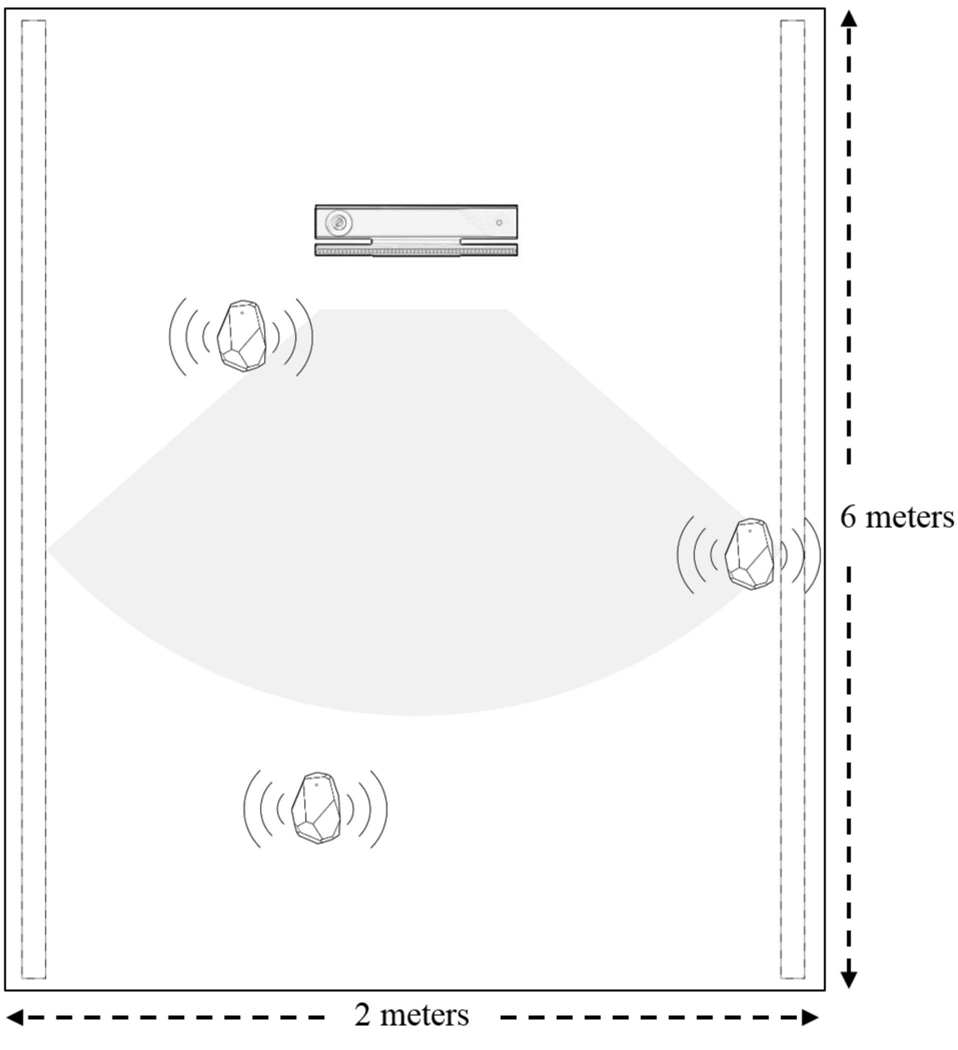

Figure 26 - A small simulated environment covering a 6x2 meters area.

• Seven BLE beacons, placed at the boundaries of the tracking areas of the two Microsoft Kinects, were used rather than three to cover a larger area across the fields of view of the two Kinects, as shown in Figure 27

The number and the placement of Bluetooth beacons in this experiment were inspired by the results of the preceding one. To reduce the measurement error, the seven Bluetooth beacons were placed to guarantee that the average distance between any point within the field of view of the two Microsoft Kinects and the closest three beacons is within 2.5 meters.

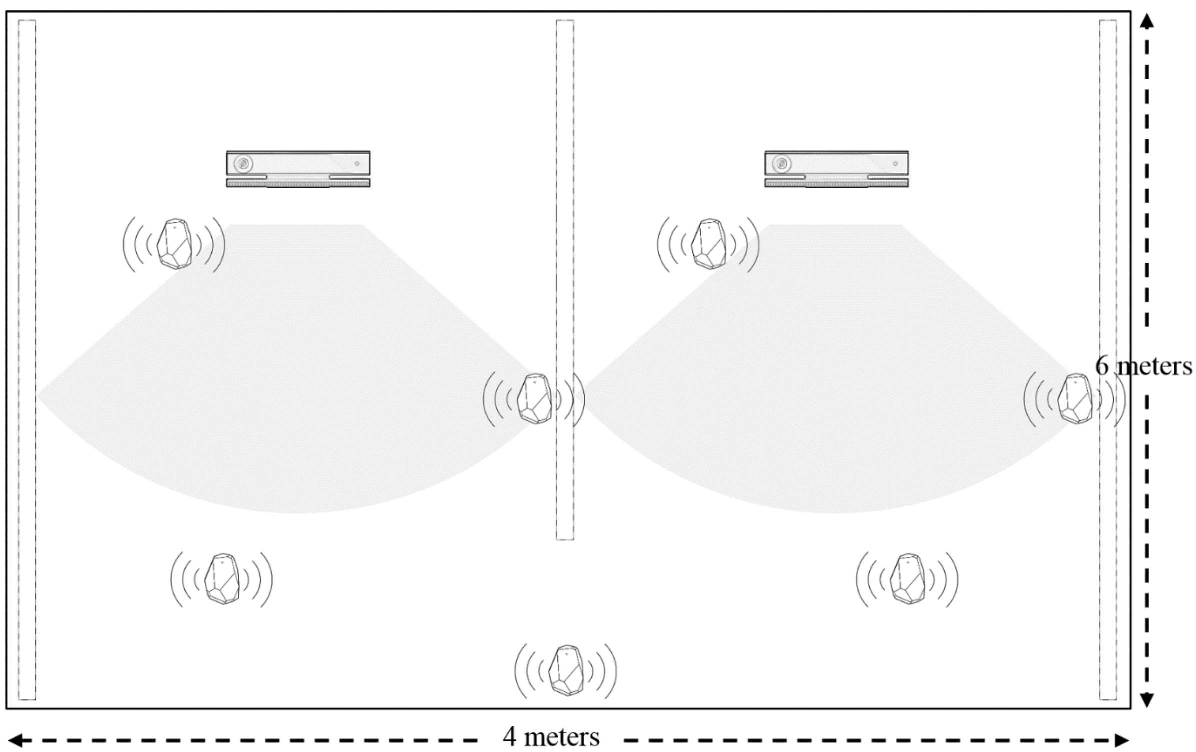

Figure 27 - A larger simulated environment (6x4 meters): two Microsoft Kinects covering two disjoint spaces (24 square meters in total), and seven Bluetooth beacons placed across the room to reduce the average distance of a user standing in the field of view of either Kinect.

4.2.2 Design

The experiment used a between-subjects factorial ANOVA design. Independent variables were the number of users seen by the Microsoft Kinect ($\boldsymbol{U}$ = 1, 2, 3, and 4 users), the number of new untracked users to the area of the tested environment (***Density*** = 0.042, 0.083, 0.125, 0.167, 0.25, 0.333 person per square meter), the number of devices in the zombie state to the number of new untracked users ($\boldsymbol{Z_{ratio}}$ = 1, 0.75, 0.66, 0.5, 0.33, and 0.25), and the use of an external user-counter to track the number of users in the room ($\boldsymbol{C}$ = T or F) (Table 5).

The Density was chosen as an independent variable to test the accuracy of the technique in different user-congestion settings, while the Z_{ratio} was chosen to test the accuracy of the technique in mapping zombies to their respective users in variable difficulties. The number of users was chosen between one and four as the Microsoft Kinect can recognize up to a maximum of four users at one time. The dependent variable was the precision of re-paring a device in the zombie state to its respective user once it is seen by one of the Microsoft Kinects. The number of users was chosen between one and four as the Microsoft Kinect can recognize up to a maximum of four users at one time. The dependent variable was the precession of re-paring a device in the zombie state to its respective user once it is seen by one of the Microsoft Kinects.

The dependent variable takes one of four possible values: True Positive (***TP***) which indicates that a device in the zombie state has been successfully re-paired to its corresponding user, True Negative (***TN***) which indicates that a device in the zombie state was not paired with the wrong user, False Positive (***FP***) which indicates that a device in the zombie state has been re-paired to the wrong user, and False Negative (***FN***) which indicates that a device in the zombie state was not paired with its corresponding user. An observation is considered as a ***TN*** or a ***FN*** if **10** seconds (the time required for 10 beacon-based location updates) have elapsed since the user has become visible to the Microsoft Kinect.

4.2.3 Procedure

At the start of the experiment, the SoD locator service is started alongside two instances of the SoD Kinect Client, a mobile application is started on each iOS device held by the users, and users are asked to stand in the field of view of the Kinect while holding the mobile device. Users are instructed to enter the Person ID assigned to them by the Kinect Client in the mobile application to pair their devices with the user.

Once paired with their devices, patches of 1, 2, 3, or 4 users were instructed to move around the room, leaving and entering the field of view of the Microsoft Kinect (becoming zombies and then becoming re-paired) 10 times per $\boldsymbol{Density} \times \boldsymbol{Z_{ratio}} \times \boldsymbol{U} \times \boldsymbol{C}$ configuration, while data is collected from the Microsoft Kinect and the beacons.

Figure 28 shows an example configuration, in which the total number of new users visible to the Kinect ***U = 3***, the number of **Zombie users = 2**, and the $\boldsymbol{Z_{ratio}}$ **= 0.66**. The example configuration shows the smaller environment setting, with an area of ***6 × 2 meters*** (***12 square meters***) and a ***User Density = 0.33 users per square meter***. For the purposes of the example configuration, we assume that an external user counter sensor is present (***C = True***).

In Figure 28.1, two users start in the field of view of the Kinect, registering their devices with their own Kinect based locations, and thus becoming **tracked** within the system. Once paired with their devices, the users are instructed to move around the environment. As the users leave the field of view of the Kinect, the system invalidates the user's Kinect-based location, relying solely on the BLE-based location, and changes the user's state to a **Zombie state** (Figure 28.2).

Figure 28.3 demonstrates the case as a new untracked user approaches the field of view of the Kinect around the same time during which the two other users are transiting back to the field of view of the Kinect, moving from the Zombie state to the Tracked state. In such a case, a number of scenarios are possible. Figure 28.4 shows the best case scenario, in which devices corresponding to users 1 and 2 are re-paired to their corresponding owners, with the new user being assigned a new user ID. Figure 28.5 shows yet another possible scenario, in which user 1 gets correctly re-paired, but user 2 gets mismatched with the new user re-pairing their device to the wrong user. Finally, Figure 28.6 shows the worst case scenario for this configuration, in which the all users get mismatched, assigning the two Zombie users as well as the new user incorrectly.

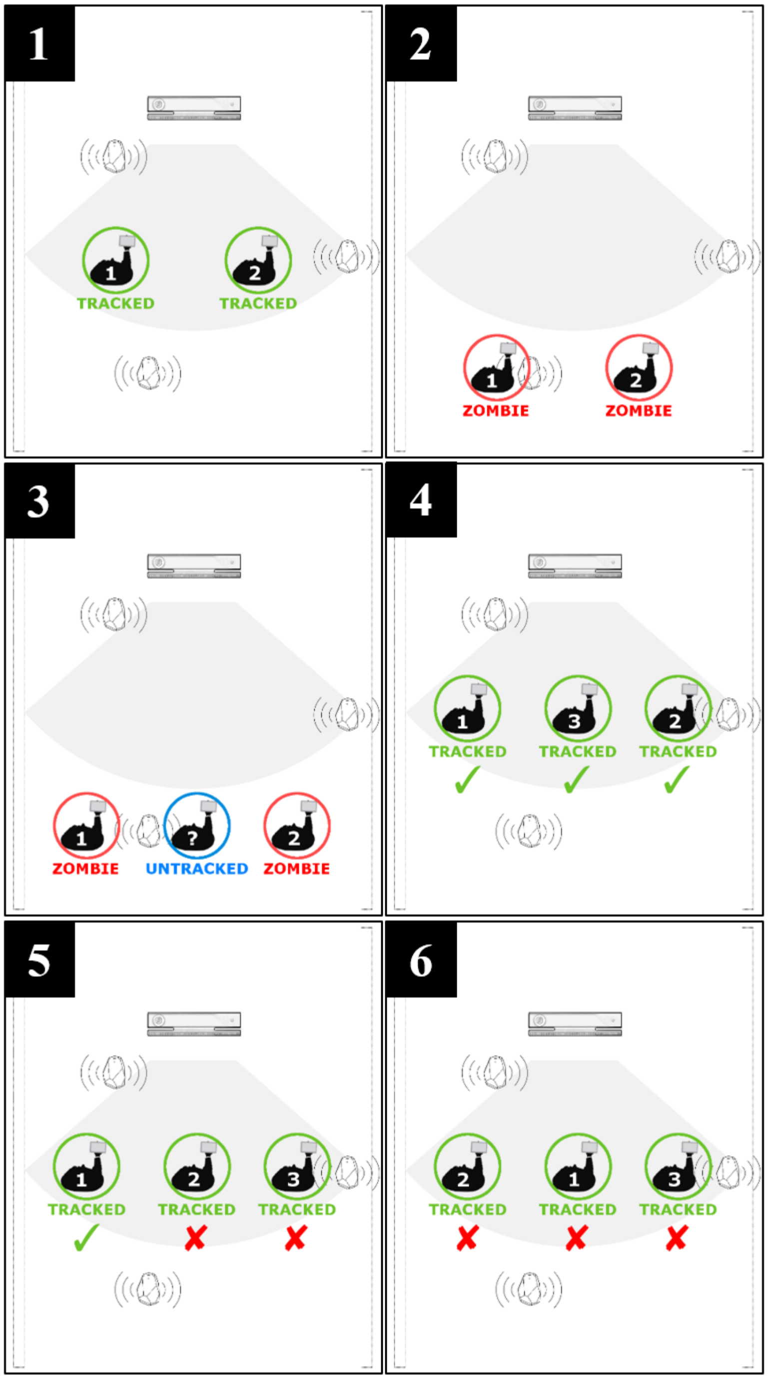

Figure 28 - Example configuration for the second experiment. Independent variables are U=3, $Z_{ratio} = 0.66$, Density=0.33, and C=True.

New Users	Zombie Users	Density	Z_{ratio} $(\frac{zombie\ users}{new\ users})$	User Counter
4	1	0.167 0.333	0.25	T F
	2	0.167 0.333	0.5	T F
	3	0.167 0.333	0.75	T F
	4	0.167 0.333	1	T F
3	1	0.125 0.25	0.33	T F
	2	0.125 0.25	0.66	T F
	3	0.125 0.25	1	T F
2	1	0.083 0.167	0.5	T F
	2	0.083 0.167	1	T F
1	1	0.042 0.083	1	T F

Table 5 - Independent variables: Z_{ratio} is the quotient of the number of devices in the zombie state to the number of new users visible to the Microsoft Kinect at a given time, and Density is the quotient of the number of new users to the area of the tracked environment (12 & 24 square meters).

4.2.4 Results

The **success rate** of the re-pairing process was measured as the ratio of ***TP*** and ***TN*** to the total number of observations. We collected a total of **1200** observations (**10** observations $\times$ $\boldsymbol{U}$ $\times$ $\boldsymbol{Density} \times \boldsymbol{Z_{ratio}} \times \boldsymbol{C}$).The results of the second experiment corresponding to each of the performed permutations can be found in Table 6. The grand mean **success rate** was **68.73%** (**SD = 19.56%**). Figure 29 outlines the percentage of each ***TP***, ***TN***, ***FP***, and ***FN*** observation with respect to the number of users ***U***.

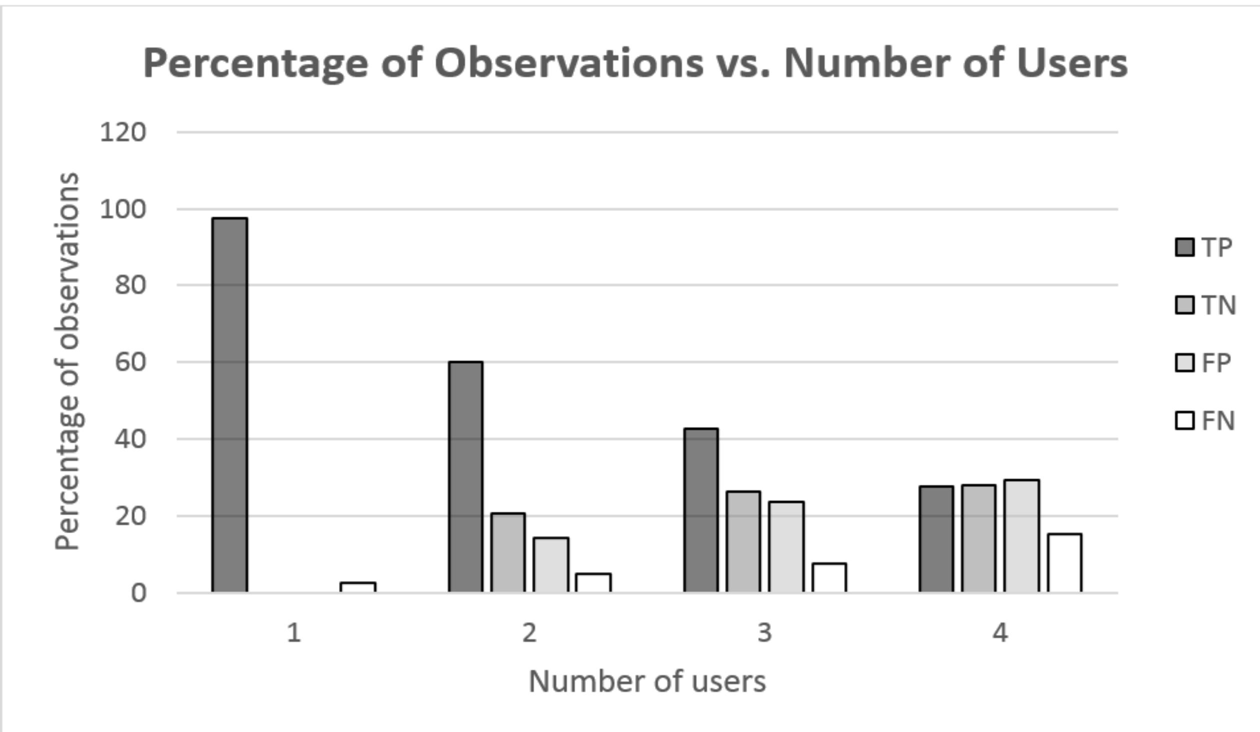

Figure 29 - Percentage of TP, TN, FP, and FN observations for each of the different U categories.

The initial analysis revealed that there was a significant effect of the ***Density*** of users within the tracked environment upon the success rate ($F_{1,24} = 159.56, p < .001$). There was, also, a significant effect of the number of zombie users to the number of new untracked users $\mathbf{Z_{ratio}}$ on the success rate ($F_{1,24} = 16.70, p < .001$). There was, however, no significant effect of ***U*** or ***C*** on the re-pairing process success rate.

Running post hoc comparisons indicated that the different ***Density*** categories were significantly different than each other ($F_{1,38} = 117.51, p < 0.001$). The comparisons, however, reported no significant differences in the means of the $\boldsymbol{Z_{ratio}}$ categories. Figure 30 outlines the mean and standard deviation of the re-pairing success rate corresponding to each of the four ***Density*** categories.

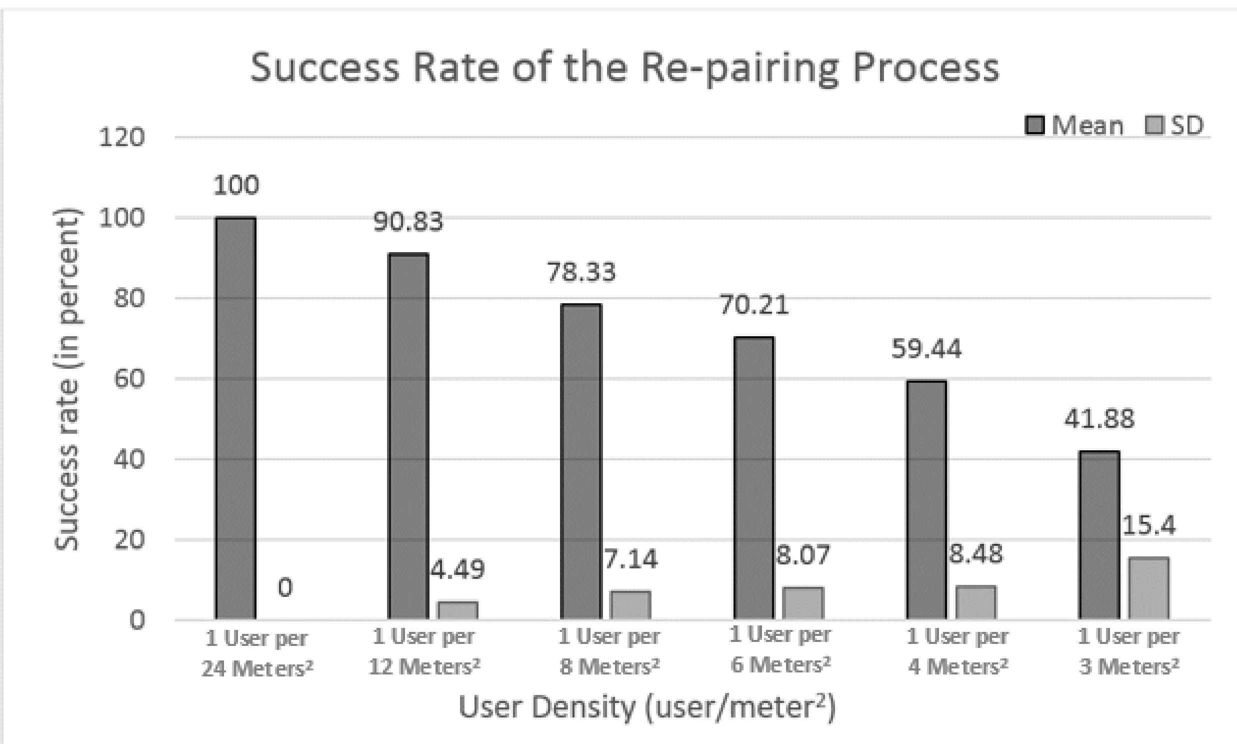

Figure 30 - Success rate of the re-pairing process: A chart outlining the mean and standard deviation for each of the density groups.

Area	User Density	# Users	# Zombie Devices	C	TP	TN	FP	FN
12	0.083	1	1	T	10	0	0	0
24	0.042	1	1	T	10	0	0	0
12	0.083	1	1	F	9	0	0	1
24	0.042	1	1	F	10	0	0	0
12	0.167	2	1	T	7	7	3	3
24	0.083	2	1	T	9	9	1	1
12	0.167	2	1	F	8	8	2	2
24	0.083	2	1	F	9	9	1	1
12	0.167	2	2	T	14	0	6	0
24	0.083	2	2	T	18	0	2	0
12	0.167	2	2	F	14	0	6	0
24	0.083	2	2	F	17	0	2	1
12	0.25	3	1	T	6	16	4	4
24	0.125	3	1	T	8	18	2	2
12	0.25	3	1	F	5	15	5	5
24	0.125	3	1	F	7	17	3	3
12	0.25	3	2	T	10	5	13	2
24	0.125	3	2	T	16	10	4	0
12	0.25	3	2	F	10	5	9	6
24	0.125	3	2	F	15	8	5	2
12	0.25	3	3	T	18	0	12	0
24	0.125	3	3	T	22	0	8	0
12	0.25	3	3	F	17	0	11	2
24	0.125	3	3	F	20	0	9	1
12	0.333	4	1	T	3	23	7	7
24	0.167	4	1	T	7	27	3	3
12	0.333	4	1	F	2	22	8	8
24	0.167	4	1	F	6	27	2	5
12	0.333	4	2	T	9	9	11	11
24	0.167	4	2	T	13	15	7	5
12	0.333	4	2	F	8	8	12	12
24	0.167	4	2	F	12	13	7	8
12	0.333	4	3	T	9	0	21	10
24	0.167	4	3	T	10	17	10	3
12	0.333	4	3	F	7	0	23	10
24	0.167	4	3	F	9	17	9	5
12	0.333	4	4	T	19	0	21	0
24	0.167	4	4	T	25	0	15	0
12	0.333	4	4	F	15	0	18	7
24	0.167	4	4	F	23	0	14	3

Table 6 - Results of the second experiment. Table shows the different permutations performed as part of the experiment. Ten permutations were performed of each row.

4.2.5 Discussion

This section discusses the implications of the results of the second experiment with respect to the integrated implementations category. The section details the implications of the results on integrated implementations, reflecting on the research questions and goals of the thesis, and provides recommended integrated implementations where the technique could be used to mitigate the issue of tracking users across disjoint environments.

4.2.5.1 Integrated Implementations

The results of the second experiment suggest that most of the statistical significance rose from observations that had a higher user density. Analyzing the results with respect to the ***Density*** variable, it was observed that the accuracy of the re-pairing process degraded exponentially as the density of users in the environment grows (Figure 31). By studying the chart, it can be observed that achieving a re-pairing accuracy of more than **80%** requires the density of users in the environment to be smaller than **0.17** users per square meter.

Based on the results of the second experiment, there is a significance degrade in the success of the re-pairing process in settings where there was more than one user in a 6 square meters area (0.17 users per square meter), which proves to be problematic and unusable in crowded settings.

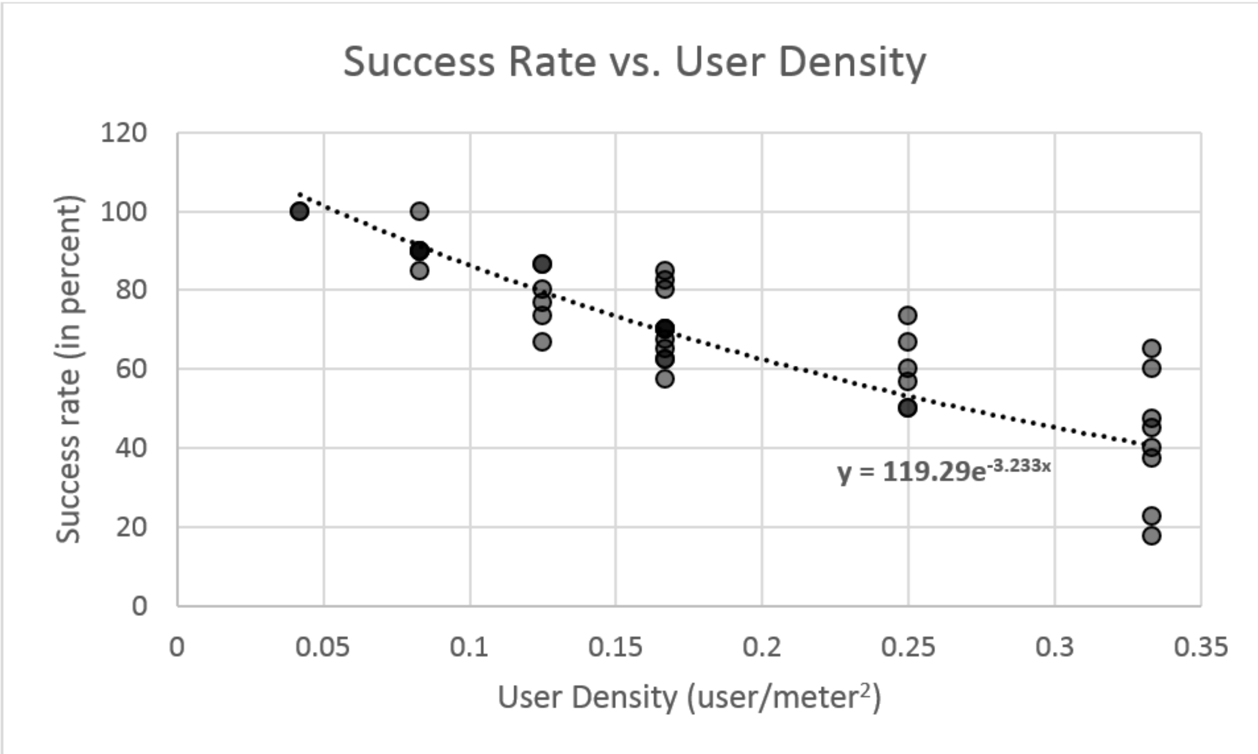

Figure 31 - The success rate of the re-pairing process as a function of the user density in the environment.

Nonetheless, with a re-pairing success rate of more than 80% for less dense settings, the system promises to overcome the problem of tracking users across sparse disjoint environments.

<u>4.2.5.2 Recommendations</u>

An example of such sparse environments where the proposed technique could be used is a setting where an indoor positioning and tracking system is required to track the interior of a set of rooms in a building with high accuracy, while allowing users to be correctly identified as they move through the hallways of the building from one room to another.

To achieve this, a high-end indoor tracking system could be used to accurately track the interior of the rooms, and extending its functionality by integrating the proposed technique. This will ensure an adequate level of accuracy within the rooms, while allowing users to be correctly identified and re-paired as they transit between these rooms, eliminating the extensive instrumentation overhead and high installation costs associated with high accuracy tracking technologies. The user identification and re-pairing accuracy can also be improved through the introduction of physical constraints such as allowing users to enter or leave a tracked room one user at a time, which can be easily implemented as most room doors can reasonably fit only one person at a given time.

4.3 Limitations

Although an indoor positioning and tracking technique was developed throughout this thesis, it is important to note that the aim was not to develop a complete system that is usable in any given scenario. Instead, this thesis focuses on the development and the evaluation of the technique's major components and algorithms, with the objective of answering the research questions and meeting the research goals discussed earlier.

This section describes the limitations in the scope of the thesis and the capabilities of the proposed technique within two categories: technique related limitations, and evaluation related limitations.

4.3.1 Technique Limitations

This section discusses the key shortcomings and challenges of using Bluetooth Low Energy beacons as the means of positioning and tracking users and devices within an environment.

4.3.1.1 Accuracy

It's worth noting that although the proposed technique scores higher, when used in standalone implementations, than many of the existing indoor positioning systems, using Bluetooth Low

Energy beacons as the sole mean of positioning and tracking within indoor environments still is not suitable for accuracy-critical settings. As a result, the proposed technique is suggested to only be used to provide a rough estimation of the position of users and their devices within an indoor environment, using the beacon placement model to estimate the level of measurement error a specific setting normally yields.

Nonetheless, the technique proves, as revealed in the results of the evaluation of the technique, to be a practical complement to existing indoor positioning systems when support for tracking across disjoint environments is required.

4.3.1.2 Interference

As with any radio-frequency (RF) based technology, Bluetooth Low Energy is also prone to electromagnetic interference, which results in faulty signal strengths, and thus erroneous position estimations.

Sources of interference are often unavoidable in a home or office environment as many of our everyday devices and machines (such as microwaves, wireless gadgets, satellite service, baby monitors, etc.) operate over the same radio frequency as Bluetooth Low Energy. Different Bluetooth receivers and transmitters could, also, theoretically interfere with one another, although such a scenario is unlikely since Bluetooth Low Energy uses frequency hopping (Townsend, Cufí, Akiba, & Davidso, 2014) to thwart narrowband interference problems.

Nonetheless, the effects of RF interference could be minimized by freeing the indoor environment of external interference sources, such as defective or poorly shielded cabling, high voltage power lines, as well as concrete and metal barriers.

4.3.2 Evaluation Limitations

This following subsections discuss two major aspects of evaluation that were left out of the scope of this thesis during the two experiments conducted: usability evaluation, and the evaluation of the technique in multiple real-world settings.

4.3.2.1 Usability

The evaluation of the proposed technique intended to mainly assess the accuracy of the technique in tracking users and devices within and across indoor environments. However, an important aspect that was not addressed nor discussed during the design of the evaluation of the technique is its usability.

While usability testing has been left out of the scope of this thesis, a usability study is due in order to better understand the users' perception of and experience with the technique in general and the level of accuracy it provides in contrast with the low cost it requires.

4.3.2.2 Multiple Real-world Settings

Another limitation of the experiments conducted is that in both of the experiments, users were tracked within a controlled lab environment that simulated a room setting, which gives insight only into a limited sample of the potential indoor environments in which this technique could be applied.

Therefore, a more comprehensive experiment needs to be performed to examine the proposed technique in a wide range of real-world environment settings. Examples of such settings include wall separated spaces of different barrier materials, different furniture arrangements within the same space, and spaces spanning separate rooms or floors.

CHAPTER 5: CONCLUSION & FUTURE WORK

This thesis has demonstrated an approach for indoor positioning and tracking using BLE sensors, to ultimately help in the facilitation of the development and deployment of spatially-aware environments. The approach is adaptable to disjointed environments, and deals with situations such as zombie users in environments, a common challenge for engineering ubiquitous environments. This was achieved by combining a Bluetooth Low Energy based positioning approach with existing indoor positioning and navigation techniques.

The indoor positioning and navigation technique that has been proposed in this thesis was discussed in two parts: the modelling and design of the positioning technique, and the evaluation of the technique. The proposed technique was designed with three major considerations in mind: cost extensibility, and versatility of implementation, and follows a multi-lateration approach to positioning users and their devices using the measured signal strength to pre-positioned Bluetooth Low Energy beacons in the environment. The technique was integrated into the Society of Devices Toolkit to demonstrate its versatility as well as evaluate the accuracy of the proposed technique in re-pairing zombie users as they transit across disjoint environments.

The second part of the thesis presented an evaluation of the proposed technique in the form of two experiments, assessing the accuracy of the BLE based location measurements and the precision of the technique in identifying zombie users across disjoint indoor environments respectively. The results of the experiments showed that this solution is both a practical alternative for indoor positioning at the room level, as well as a viable means of handling disjointed spaces in a low-cost manner. Analyzing the results of the evaluation phase led to the development of a beacon placement model that allows system engineers and users to determine the placement, cost and number of Bluetooth Low Energy beacons necessary to achieve the required accuracy in an environment.

5.1 Research Contribution

The purpose of developing the proposed indoor positioning and tracking technique outlined was to answer the research questions posted in section 1.4. These questions are repeated below and are addressed in the following sections, which also summarizes the main contributions and conclusions of this thesis.

1. What is the current state of research in indoor positioning and navigation, particularly within the context of ubiquitous computing environments?

2. How accurately can the relative movement of a user be measured using the signals of the Bluetooth Low Energy beacons?

3. How accurately can the proposed technique identify and re-pair users as they transit across disjoint environments?

4. What is the infrastructure required to track users and their devices sufficiently in an indoor environment using Bluetooth Low Energy beacons?

5.1.1 Research Question 1: Current State of Research

The first research question posed at the beginning of this thesis concerned the current state of research within the field of indoor positioning and navigation, which was aimed to better understand the different approaches and challenges encountered in the field. Chapter 2 demonstrated an overview of the current research space, provided in the form of a taxonomized literature review, categorizing the different approaches to indoor positioning and navigation. The categorization was based upon the infrastructure and instrumentation requirements, as well as upon the requirement of an absolute model of the environment. This categorization is intended to help system engineers in determining the most suitable approach for the use case at hand by outlining the advantages and drawback of each approach.

5.1.2 Research Question 2: BLE Based Location Accuracy

One of the most important conclusions of this work is that indoor positioning using Bluetooth Low Energy beacons can be a practical alternative to existing approaches at the room level. The answer to the second research question was presented in Chapter 4, section 4.1.5 and discussed in further detail in section 4.1.6. The results of the first experiment, which examined the accuracy of the BLE based locations, indicated a negative correlation between the accuracy of location estimates and the average distance to the BLE beacons. However, the results suggest that the proposed technique is capable of achieving an average accuracy of 0.86 meters when the user's average distance to the BLE beacons is kept below 1.5 meters.

5.1.3 Research Question 3: Zombie User Re-pairing Accuracy

Due to the limitations of tracking and identifying zombie users as they transit across disjoint indoor environment, it is necessary to seek cost effective techniques to automatically re-associate these users with the system. In section 3.4.3, a zombie identification component was introduced for identifying zombie users. The introduced approach is lightweight and can be integrated with existing indoor navigation systems. The results of the evaluation of the zombie identification component are presented in section 4.2.4 and are discussed in section 4.2.5, which indicates an inverse correlation between the precision of the zombie identification success rate and the user density of the environment, and thus addressing the third research question.

5.1.4 Research Question 4: Infrastructure Requirement

The answer to the fourth research question of this work is dependent on the second and third questions. That is, the infrastructure required to achieve the necessary level of accuracy tracking users and devices within and across indoor environment using the proposed approach is dependent on the accuracy of the BLE based locations and the precision of the zombie identification process. To address this question, a beacon placement model was developed and presented in section 4.1.6 to aid system engineers and users determine the amount of infrastructure (and cost) to achieve a desired level of accuracy using the proposed technique.

5.2 Future Work

Despite being extensively discussed in the literature, indoor navigation and positioning, particularly with respect to ubiquitous environments is yet to be solved. There are a number of avenues of future work that need be explored before a comprehensive system based on the positioning technique discussed in this thesis can be deployed. In the following sections, these avenues will be divided into two broad categories: enhancements to the internals of the implementations of the technique, and more extensive evaluation of the technique.

5.2.1 Technique Related

There are a number of directions of future work that could be taken in order to enhance the internals of the implementation of the proposed technique. This section outlines further work that has been identified in this area.

5.2.1.1 Positioning Algorithm Enhancement

There are numerous possible enhancements that could be introduces to the algorithms presented in this thesis. Positioning algorithms could be categorized into two groups: probabilistic and deterministic.

Probabilistic algorithms consider input signals as random values drawn from a distribution that is based on a known model, and produces a distribution of possible outcomes, outlining the likelihood (probability) of each outcome. Deterministic algorithms, on the other hand, use the input signals, without making any assumptions of the distribution or the model of the data, and produces a single solution that best represents the outcome of the inputs.

For the purposes of the work done as part of this thesis, the proposed technique utilized a deterministic algorithm that relies on trilaterating the signal strength to nearby pre-positioned BLE beacons. However, a future direction for future work is to use a probabilistic approach to indoor positioning. Such an approach may be useful for representing the various constraints in the environment (such as movable objects, interference sources, etc.), and is easier to work with as the number of variables in the model becomes cumbersome to be addressed individually.

5.2.1.2 Android Client

Another direction for future work is related to integrating the proposed technique with the Society of Devices Toolkit. As discussed in section 3.4.4.1, iOS was chosen as the target platform for integrating the proposed technique with the SoD Toolkit due to the recent complications with BLE and iBeacon Android libraries. However, considering that these limitations will be removed in the future, it would be possible to integrate the technique with SoD's Android client library.

5.2.2 Evaluation Related

As the evaluation of the proposed technique, for the purposes of this thesis, focused mainly on assessing the accuracy, this leaves room for multiple directions of future work and more comprehensive evaluation of the proposed positioning technique to be carried on, as described below.

5.2.2.1 Usability Evaluation

Although usability testing has been left out of the scope of this thesis, it would be useful to incorporate a usability evaluation of the technique from the perspective of system engineers as well as end users. This will lead to a better understanding of the users' perception and experience with the technique, and will guide the design and development of existing and future features.

The results of such a usability evaluation should, also, be contrasted to those of other indoor positioning and navigation systems to assess how the proposed technique compares in usability as well as in functionality to existing implementations and technologies.

5.2.2.2 Real World Setting Evaluation

A major question that must be addressed is how the proposed technique might be deployed and how it would perform if evaluated in real-world settings. This is important as different indoor environments impose various constraints and often require variable levels of tracking accuracy. As a result, a more comprehensive evaluation of the proposed technique must be conducted to consider a wide range of real-world constraints and settings, such as wall separated spaces of different barrier materials, different furniture arrangements within the same space, and spaces spanning separate rooms or floors.

REFERENCES

Addlesee, M., Curwen, R., Hodges, S., Newman, J., Steggles, P., Ward, A., & Hopper, A. (2001, August). Implementing a Sentient Computing System. *IEEE Computer, 34*, 50 - 56. doi:10.1109/2.940013

Alvarez, D., Gonzalez, R., Lopez, A., & Alvarez, J. (2006). Comparison of Step Length Estimators from Weareable Accelerometer Devices. *International Conference of the IEEE Engineering in Medicine and Biology Society* (pp. 5964 - 5967). New York: IEEE.

Bahl, P., & Padmanabhan, V. (2000). RADAR: an in-building RF-based user location and tracking system. *INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies. 2*, pp. 775 - 784. Tel Aviv: IEEE. doi:10.1109/INFCOM.2000.832252

Beauregard, S. (2006). A Helmet-Mounted Pedestrian Dead Reckoning System. *International Forum on Applied Wearable Computing (IFAWC)* (pp. 1 - 11). Bremen: VDE.

Beder , C., & Klepal, M. (2012). Fingerprinting based localisation revisited: A rigorous approach for comparing RSSI measurements coping with missed access points and differing antenna attenuations. *International Conference on Indoor Positioning and Indoor Navigation (IPIN)* (pp. 1 - 7). Sydney: IEEE. doi:10.1109/IPIN.2012.6418940

Cho, S., & Park, C. (2006, January). MEMS Based Pedestrian Navigation System. *Journal of Navigation, 59*(1), 135 - 153. doi:10.1017/S0373463305003486

Chokshi, A., Seyed, T., Marinho Rodrigues, F., & Maurer, F. (2014). ePlan Multi-Surface: A Multi-Surface Environment for Emergency Response Planning Exercises. *Ninth ACM International Conference on Interactive Tabletops and Surfaces* (pp. 219 - 228). Dresden: ACM. doi:10.1145/2669485.2669520

Curran, K., Furey, E., Lunney, T., Santos, J., Woods, D., & McCaughey, A. (2011, June). An Evaluation of Indoor Location Determination Technologies. *Journal of Location Based Services, 5*, 61 - 78. doi:10.1080/17489725.2011.562927

Dachselt, R., & Buchholz, R. (2009). Natural Throw and Tilt Interaction Between Mobile Phones and Distant Displays. *CHI '09 Extended Abstracts on Human Factors in Computing Systems* (pp. 3253 - 3258). Boston: ACM. doi:10.1145/1520340.1520467

Euler, L. (1767). Solutio facilis problematum quorundam geometricorum difficillimorum. *Novi Commentarii academiae scientiarum Petropolitanae, 11*, 103 - 123.

Foxlin, E. (2005, November - December). Pedestrian tracking with shoe-mounted inertial sensors. *IEEE Computer Graphics and Applications, 25*(6), 38 - 46. doi:10.1109/MCG.2005.140

Fukuju, Y., Minami, M., Morikawa, H., & Aoyama, T. (2003). DOLPHIN: an autonomous indoor positioning system in ubiquitous computing environment. *IEEE Workshop on Software Technologies for Future Embedded Systems* (pp. 53 - 56). IEEE. doi:10.1109/WSTFES.2003.1201360

Gezici, S., Tian, Z., Giannakis, G. B., Kobayashi, H., Molisch, A. F., Poor, V., & Sahinoglu, Z. (2005, July). Localization via ultra-wideband radios: a look at positioning aspects for future sensor networks. *IEEE Signal Processing Magazine, 22*(4), 70 - 84. doi:10.1109/MSP.2005.1458289

Gleason, S., & Gebre-Egziabher, D. (2009). *GNSS Applications and Methods.* Boston, MA: Artech House.

Godha, S., Lachapelle, G., & Cannon, M. E. (2006). Integrated GPS/INS System for Pedestrian Navigation in a Signal Degraded Environment. *International Technical Meetings of the*

Satellite Division of the Institute of Navigation (pp. 2151 - 2164). Fort Worth: Institute of Navigation.

Gomez, C., Oller, J., & Paradells, J. (2012, August). Overview and Evaluation of Bluetooth Low Energy: An Emerging Low-Power Wireless Technology. *Sensors*, *12*(9), 11734 - 11753. doi:10.3390/s120911734

Groves, P., Pulford, G., Mather, C., Littlefield, C., Nash, D., & Carter, M. (2007). Integrated pedestrian navigation using GNSS, MEMS IMU, Magnetometer and Baro-altimeter. *Navigation Conference and Exhibition* (pp. 822 - 865). London: Royal Institute of Navigation.

Haverinen, J., & Kemppainen, A. (2009, October). Global Indoor Self-localization Based on the Ambient Magnetic Field. *Robotics and Autonomous Systems, 57*(10), 1028 - 1035. doi:10.1016/j.robot.2009.07.018

Hazas, M., & Ward, A. (2002). A Novel Broadband Ultrasonic Location System. *4th International Conference on Ubiquitous Computing* (pp. 264 - 280). Göteborg: Springer-Verlag. Retrieved from http://dl.acm.org/citation.cfm?id=647988.741478

Hazas, M., Scott, J., & Krumm, J. (2004, February). Location-Aware Computing Comes of Age. *IEEE Computer, 37*, 95 - 97. doi:10.1109/MC.2004.1266301

Hu, L., & Evans, D. (2004). Localization for Mobile Sensor Networks. *10th Annual International Conference on Mobile Computing and Networking* (pp. 45 - 57). Philadelphia: ACM. doi:10.1145/1023720.1023726

IDC, I. D. (2015). Smartphone OS Market Share, 2015 Q2. International Data Corporation (IDC). Retrieved July 14, 2016, from IDC: http://www.idc.com/prodserv/smartphone-os-market-share.jsp

Jain, P., Manweiler, J., & Roy Choudhury, R. (2015). User Location Fingerprinting at Scale. *21st Annual International Conference on Mobile Computing and Networking* (pp. 260--262). Paris: ACM. doi:10.1145/2789168.2795175

Kay, D. (1969). *College geometry.* New York: Holt, Rinehart and Winston.

Kim, Y., Cho, A., Kim, O., Kim, C., & Kee, C. (2011). A Low-cost Pedestrian Navigation System Including In-flight Parameter Correction. *International Technical Meeting of The Institute of Navigation*, (pp. 908 - 915). San Diego.

Krumm, J., Harris, S., Meyers, B., Brumitt, B., Hale, M., & Shafer, S. (2000). Multi-camera multi-person tracking for EasyLiving. *Third IEEE International Workshop on Visual Surveillance, 2000. Proceedings* (pp. 3 - 10). Dublin: IEEE. doi:10.1109/VS.2000.856852

Lymberopoulos, D., Liu, J., Yang, X., Choudhury, R., Handziski, V., & Sen, S. (2015). A Realistic Evaluation and Comparison of Indoor Location Technologies: Experiences and Lessons Learned. *14th International Conference on Information Processing in Sensor Networks* (pp. 178 - 189). Seattle: ACM. doi:10.1145/2737095.2737726

Marquardt, N., Diaz-Marino, R., Boring, S., & Greenberg, S. (2011). The Proximity Toolkit: Prototyping Proxemic Interactions in Ubiquitous Computing Ecologies. *24th Annual ACM Symposium on User Interface Software and Technology* (pp. 315 - 326). Santa Barbara: ACM. doi:10.1145/2047196.2047238

NI, L., LIU, Y., LAU, Y., & PATIL, A. (2003). LANDMARC: indoor location sensing using active RFID. *First IEEE International Conference on Pervasive Computing and Communications* (pp. 407 - 415). Fort Worth: IEEE. doi:10.1109/PERCOM.2003.1192765

Priyantha, N., Chakraborty, A., & Balakrishnan, H. (2000). The Cricket Location-support System. *6th Annual International Conference on Mobile Computing and Networking* (pp. 32 - 43). Boston: ACM. doi:10.1145/345910.345917

Reimann, R., Bestmann, A., & Ernst, M. (2013). Locating Technology for AAL Applications with Direction Finding and Distance Measurement by Narrow Bandwidth Phase Analysis. In S. Chessa, & S. Knauth, *Evaluating AAL Systems Through Competitive Benchmarking: International Competitions and Final Workshop, EvAAL 2012, July and September 2012. Revised Selected Papers* (pp. 52 - 62). Berlin, Heidelberg: Springer Berlin Heidelberg. doi:10.1007/978-3-642-37419-7_5

Rekimoto, J. (1997). Pick-and-drop: A Direct Manipulation Technique for Multiple Computer Environments. *10th Annual ACM Symposium on User Interface Software and Technology* (pp. 31 - 39). Banff: ACM. doi:10.1145/263407.263505

Satyavolu, S., Bruder , G., Willemsen, P., & Steinicke, F. (2012). Analysis of IR-based virtual reality tracking using multiple Kinects. *IEEE Virtual Reality Workshops (VRW)* (pp. 149 - 150). Costa Mesa: IEEE. doi:10.1109/VR.2012.6180925

Saunders, S., & Aragón-Zavala, A. (2007). *Antennas and Propagation for Wireless Communication Systems: 2nd Edition* (2 ed.). John Wiley \& Sons, Inc.

Savage, P. (1998, March - April). Strapdown Inertial Navigation Integration Algorithm Design Part 2: Velocity and Position Algorithms. *Journal of Guidance, Control, and Dynamics, 21*(2), 208 - 221. doi:10.2514/2.4242

Seyed, T., Azazi, A., Chan, E., Wang, Y., & Maurer, F. (2015). SoD-Toolkit: A Toolkit for Interactively Prototyping and Developing Multi-Sensor, Multi-Device Environments.

2015 International Conference on Interactive Tabletops & Surfaces (pp. 171 - 180). Madeira: ACM. doi:10.1145/2817721.2817750

Seyed, T., Costa Sousa, M., Maurer, F., & Tang, A. (2013). SkyHunter: A Multi-surface Environment for Supporting Oil and Gas Exploration. *ACM International Conference on Interactive Tabletops and Surfaces* (pp. 15 - 22). St. Andrews: ACM. doi:10.1145/2512349.2512798

Siekkinen, M., Hiienkari, M., Nurminen, J., & Nieminen, J. (2012). How low energy is bluetooth low energy? Comparative measurements with ZigBee/802.15.4. *IEEE Wireless Communications and Networking Conference Workshops* (pp. 232 - 237). Paris: IEEE. doi:10.1109/WCNCW.2012.6215496

Tarzia, S., Dinda, P., Dick, R., & Memik, G. (2011). Indoor Localization Without Infrastructure Using the Acoustic Background Spectrum. *9th International Conference on Mobile Systems, Applications, and Services* (pp. 155 - 168). Bethesda: ACM. doi:10.1145/1999995.2000011

Townsend, K., Cufí, C., Akiba, & Davidso, R. (2014). *Getting Started with Bluetooth Low Energy.* O'Reilly Media.

Vicon Motion Systems Ltd. (2016). Vicon Devices, Markers and Suits. Retrieved July 31, 2016, from https://www.vicon.com/products/vicon-devices/markers-and-suits

Wang, H., Lenz, H., Szabo, A., Bamberger, J., & Hanebeck, U. (2007). WLAN-Based Pedestrian Tracking Using Particle Filters and Low-Cost MEMS Sensors. *4th Workshop on Positioning, Navigation and Communication* (pp. 1 - 7). Hannover: IEEE. doi:10.1109/WPNC.2007.353604

Want, R., Hopper, A., Falcão, V., & Gibbons, J. (1992, January). The Active Badge Location System. *ACM Transactions on Information Systems (TOIS), 10*, 91 - 102. doi:10.1145/128756.128759

Weiser, M. (1991). *The computer for the 21st century.* Scientific American.

Xiao, Z., Wen, H., Markham, A., & Trigoni, N. (2014). Lightweight Map Matching for Indoor Localisation Using Conditional Random Fields. *13th International Symposium on Information Processing in Sensor Networks* (pp. 131 - 142). Berlin: IEEE Press. Retrieved from http://dl.acm.org/citation.cfm?id=2602339.2602355

Youssef, M., & Agrawala, A. (2005). The Horus WLAN Location Determination System. *3rd International Conference on Mobile Systems, Applications, and Services* (pp. 205 - 218). Seattle: ACM. doi:10.1145/1067170.1067193

Zhang, C., Luo, J., & Wu, J. (2014). A Dual-Sensor Enabled Indoor Localization System with Crowdsensing Spot Survey. *IEEE International Conference on Distributed Computing in Sensor Systems* (pp. 75 - 82). Marina Del Rey: IEEE. doi:10.1109/DCOSS.2014.14