CAPTURE:

Cooperatively Applied Positioning Techniques Utilizing Range Extension

Gary Cullen, M.Sc.

School of Computing & Intelligent Systems

Faculty of Computing & Engineering

Ulster University, Magee

A thesis submitted in partial fulfilment of the requirements for the degree of

Doctor of Philosophy

Table of Contents

Acknowledgments

Above all else, I would like to express my sincere and heartfelt thanks to my family, for all their support throughout my academic endeavours. Firstly, my mother and father for their unrelenting patience and encouragement, throughout my life and my siblings for basically, enduring me. My beautiful wife Linda, for her understanding, help and support, always. My children, who motivate me every day, Daragh who was 3 when this all began, Leah 2 and Oran who came along two years into the process, all knowing pretty much nothing but a life where Daddy disappears off to do "*PhD work*". Finally, to Shannon, my longest '*serving'* child, who provided the single biggest motivation to my initial journey back to education all those years ago. Thank you all, I can sincerely say, without you and your support and motivation, none of this would've been possible nor worth it.

There are many people who I would like to thank for their encouragement and support during the course of my PhD, unfortunately I can only mention a few of them here. I would like to thank my supervisor Professor Kevin Curran for his valuable support and guidance during the last six years. I would also like to thank my second supervisor Dr Jose Santos for his help. I would also like to acknowledge the help and support of my fellow staff members at LyIT especially the staff at the Library, the Department of Computing and the Development Office, for their unwavering support and invaluable experience.

"These people sail in those seas from Island to Island for several hundred leagues, the Sun serving them for a compass by day and the Moon and stars by night. When this comes to be prov'd we Shall be no longer at a loss to know how the islands lying in those Seas came to be people'd, for if the inhabitants of [Ra'iatea] have been at islands lying 2 or 300 Leagues to the westward of them it cannot be doubted but that the inhabitants of those western islands may have been at others as far to westward of them and so we may trace them from Island to Island quite to the East Indias."

Captain James Cook's journal during his First voyage around
the world made on-board H.M. Bark "Endeavour" 1768 – 71

Abstract

Access to location-based information in mobile devices, is now ubiquitous. This has been mostly possible in the outdoor arena via the Global Positioning System (GPS) providing near global coverage, barring some natural obstacles and manmade obstructions. The provision of accurate position estimations and broad coverage in the indoor environment has however proven somewhat more problematic to deliver.

The most commonly implemented Indoor Positioning Systems (IPSs) use existing Wi-Fi network components and infrastructure to locate devices. This technique offers obvious economic rewards, utilizing a preinstalled infrastructure. These topologies however were typically designed to provide network coverage, rather than deliver an indoor location-based solution.

Large areas without coverage are common in these networks, because network designers were not typically concerned with providing 100% coverage for mobile data. Hallways, toilet areas or other general-purpose areas that ordinarily would not require network coverage, were not provided with dedicated Wireless Access Points (WAPs). Transient users, navigating these areas of the network were therefore, un-locatable using this infrastructure. Furthermore, the indoor arena is an especially noisy radio atmosphere as it hosts other wireless devices such as Bluetooth Headsets, Cordless Phones and Microwave Ovens which operate at the same frequency as a Wi-Fi signal. Considering users spend more time in an indoor environment, the need for a solution is clear.

The hypothesis of this research is that mobile devices at the boundaries of IPSs which have themselves been located by an IPS, can assist in a cooperative fashion, to locate mobile devices beyond the range of the IPS but within range of the cooperating devices. The primary research question is whether the range of indoor positioning solutions can be extended using cooperating devices at their extremities.

To solve the hypothesis, this work designed and implemented a framework using cooperative techniques using range extension (CAPTURE) which works with any IPS irrespective of the technology it utilised to locate. The framework can plug into existing solutions to extend their range into areas of indoor environments that cannot be reached without the need for any additional infrastructure. Results show CAPTURE can extend the range of an existing IPS by up to 180m using Wi-Fi and Bluetooth.

List of Acronyms

AoA	Angle of Arrival
AP	Access Point
API	Application Programming Interface
AR	Augmented Reality
ARPANET	Advanced Research Projects Agency (ARPA) Computer Network
BLe	Bluetooth Low Energy
BluFi	Bluetooth\Wi-Fi Devices
BS	Base Station
CAPTURE	Cooperatively Applied Ranging Techniques Utilizing Range Extension
CDF	Cumulative Distribution Functions
CRB	Cramér Rao Bound
CRLB	Cramér Rao Lower Bound
dB	Decibels
DoA	Direction of Arrival
ESS	Ekahau Site Survey
FCC	Federal Communications Commission
GIS	Geographical Information System
GPRS	General Packet Radio Service
GPS	Global Positioning System
GSM	Global System for Mobile Communications
HDD	Hard Disk Drive
IMU	Inertial Measurement Unit
INS	Inertial Navigation System
IoT	Internet of Thing
IPS	Indoor Positioning System
IR	Infra-Red
JCGM	Joint Committee for Guides in Metrology
LANDMARC	**L**oc**A**tio**N** i**D**entification based on dynamic **A**ctive **R**fid
LBAs	Location-Based Applications
LBS	Location Based Service
LBS	Location Based Solution
LED	Light Emitting Diodes
LoS	Line of Sight

LyIT	Letterkenny Institute of Technology
MAC	Media Access Control
MEMS	Micro-Electro-Mechanical Systems
NFPA	National Fire Protection Association
NIC	Network Interface Card
PAN	Wireless Personal Area Network
PDA	Personal Digital Assistant
PDR	Pedestrian Dead Reckoning
RADAR	**Ra**dio **D**etection **A**nd **R**anging
RF	Radio Frequency
RFID	Radio Frequency Identification
RH	Relative Humidity
RSS	Received Signal Strength
RSSI	Received Signal Strength Indicator
RTLS	Real Time Locating Systems
RTT	Round Trip Time
SONAR	**SO**und **N**avigation **A**nd **R**anging
SPAWN	**S**um-**P**roduct **A**lgorithm over a **W**ireless **N**etwork
SSID	Service Set Identifier (SSID)
TDoA	Time Difference of Arrival
TOA	Time of Arrival
UWB	Ultra-Wide Band
WALRUS	**W**ireless **A**coustic **L**ocation with **R**oom Level Resolution using **U**ltra**S**ound
WAP	Wireless Access Point
WGS-84	World Geodetic System
WLAN	Wireless Local Area network
WSN	Wireless Sensor Network

List of Tables

List of Figures

List of Contributions

This piece of research has contributed to seven publications, the details of these publications are as follows:

[1] **Cullen, G.**, Curran, K. & Santos, J. 2012. Dynamically Extending the Reach of Wireless Networks in Determining Movement of Individuals Between Cells. 13th Annual Post Graduate Symposium on the Convergence of Telecommunications, Networking and Broadcasting (PGNET 2012), 25th & 26th June 2012 Liverpool, UK. John Moores University, 323 - 327.

[2] **Cullen, G.**, Curran, K. & Santos, J. Cooperatively extending the range of Indoor Localisation. Signals and Systems Conference (ISSC 2013), 24th IET Irish, 20-21 June 2013 Letterkenny, Ireland, LyIT, 1-8.

[3] **Cullen, G.**, Curran, K. & Santos, J. CAPTURE - Cooperatively Applied Positioning Techniques Utilizing Range Extensions. In: IEEE, ed. 5th International Conference on Indoor Positioning and Indoor Navigation (IPIN 2014), 14-18 Nov. 2014, Busan, Korea. IEEE, 22-29.

[4] **Cullen, G.**, Curran, K., Santos, J., Maguire, G. & Bourne, "To wireless fidelity and beyond CAPTURE, extending indoor positioning systems," in Ubiquitous Positioning Indoor Navigation and Location Based Service (UPINLBS, 2014), 20-21 Nov 2014, Corpus Christi, Texas, USA, pp. 248-254.

[5] **Cullen, G.**, Curran, K., Santos, J., Maguire, G. & Bourne, D. CAPTURE - Extending the scope of self-localization in Indoor Positioning Systems. Indoor Positioning and Indoor Navigation (IPIN), 2015 International Conference on, 13-16 Oct. 2015 Banff, Canada 1-10.

[6] **Cullen, G.**, Curran, K. & Santos, J. CAPTURE–"Widening the Net"–Indoor Positioning using Cooperative Techniques. The Twelfth International Conference on Wireless and Mobile Communications (ICWMC), 8-12 Nov. 2016 Barcelona, Spain. ThinkMInd, 70-74.

[7] **Cullen, G.**, Curran, K., Santos, J. & Toman, M. Using Cooperatively Applied Positioning Techniques Utilizing Range Extension to Manage Passengers in Crowded Environments. Indoor Positioning and Indoor Navigation (IPIN), 2018 International Conference on, 24-27 Sept. 2018. Nantes, France, 1-10.

1 Introduction

Navigation or wayfinding is the activity of ascertaining one's position, planning and following a route (Willim, 2007). Navigation began with maritime exploration, through the art of seamanship, where vessels were directed on the open sea using geometry, astronomy, or special instruments. The starting point for any navigation is determining ones starting position as precisely as possible. Localisation is *"a determination of the place where something is" (Atyabi and Nefti-Meziani, 2016).* Positioning and Localisation are sometimes used interchangeably however positioning can be more accurately defined as determining the position of oneself, whereas location is more related to the position of another object (Sharp and Yu, 2018). Another difference between position and location is that position is nearly always a precise value while location is not as precise (Kirson, 1992). Location is concerned with locating a place on a map e.g. a street address or road while navigation is defining pathways to a position. Positioning determines coordinate values. For instance, this is what the 'P' in Global Positioning System (GPS) and an Indoor Positioning System (IPS) relates to. A tracking system is concerned with determining the location of a mobile object with or without the consent of the object being tracked (Sharp and Yu, 2018). An example of tracking is using radar to monitor aircraft in the sky. This is distinct from the navigation systems used by pilots to control aircraft.

Navigation and positioning are important for many everyday activities. GPS has unlocked the world of accurate navigation by offering near centimeter level accuracy (Bossler *et al.,* 2010). GPS coverage is global apart from some obstacles that can impede the signal from a satellite such as the urban canyon effect (Xie and Petovello, 2015) where large high rise buildings create urban canyons that block signals from satellites impacting coverage. The Global Positioning System is considered a global solution to the outdoor positioning problem. However, as the radio signal from a satellite has travelled approximately 22,200 kilometers (Kals, 2010) to earth, its signal strength has attenuated to such a degree that it cannot penetrate a buildings infrastructure. This renders it unusable for indoor positioning. Considering up to 88% of our time is spent indoors, (Matz *et al.,* 2014), the requirement for a solution is obvious.

Indoor positioning must cope with issues such as multipath errors which are more pronounced inside. These signals used to determine range, bounce off themselves as well as any obstacles that are nearby (Chen and Guinness, 2014). For instance, the human body is made up of 60% water and radio signals commonly operate at frequencies that resonate in water. This causes attenuation issues with the propagation of signals. The numerous walls, doors, ceilings, floors and furniture that make up the indoor environment are also challenging obstacles for radio signals to propagate through or around. The horizontal trajectory of most indoor signals struggle to circumvent most of these obstacles. When positioning outdoors, applications can generally function adequately with a reasonable range of location errors but the indoor setting typically demands a much more precise position fix.

Indoor position accuracy is a problem that has mostly been solved (Grossmann et al., 2007; Gezici, 2008; Gu et al., 2009; Hijikata et al., 2009; Guvenc et al., 2009; Kranz et al., 2010; Chen et al., 2016), barring some niche areas that require a fine grain of precision, however the problem of coverage has been somewhat overlooked. Indoor positioning solutions can at times struggle to locate devices due to positioning blind spots.

An example of blind spots in an indoor positioning scenario can be seen in Figure 1-1 which shows the pre-installed wireless infrastructure that is used to position. The coverage area for each Access Point (AP) is illustrated with a different coloured circle. Mobile Device X located in the stairwell cannot be positioned, because only 2 APs can *'sense'* it while Mobile Device A is covered by 3 of the APs and can be positioned by the IPS using Trilateration. Trilateration uses range estimates from reference devices (APs) to the lost device (Mobile Device X) to position requiring at least 3 range estimates as input. Mobile Device A is within range of Mobile Device X as illustrated with the small circular area covering it. The range from Mobile Device A to Mobile Device X can be estimated. This third range estimate can be used as input for the Trilateration algorithm. Mobile Device A is thereby cooperatively assisting with the positioning of Mobile Device X by becoming a mobile reference point replicating the static reference points of the APs. Such a cooperative methodology can be used to overcome the blind spot problem.

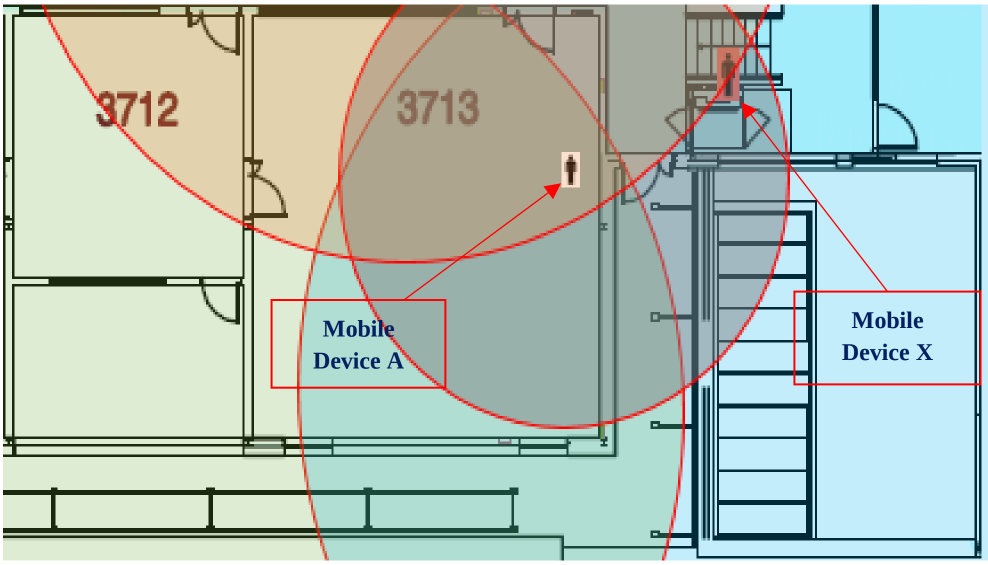


Figure 1-1: Cooperating to Position

The focus of this work is to identify positioning blind sport situations and solve them using a cooperative methodology. The study advocates the use of mobile devices at the boundaries of these areas which have already been located, to act as reference devices which in turn locate devices inside these 'blind spots'. This offers a unique contribution within the field of indoor positioning.

1.1 Thesis Hypothesis

The work presented in this thesis, CAPTURE (Cooperatively Applied Positioning Techniques Utilising Range Extensions) aims to provide a solution to the coverage issue in Indoor Positioning Systems. The thesis hypothesis is as follows:

> Mobile Devices, at the extremities of an IPS, which have been located, can in turn, assist in the determination of the position of devices beyond the range of that Indoor Positioning System.

The research questions that emanate from this hypothesis focus on the capabilities of mobile devices that *'know'* their position, to locate devices within their range. These are:

1. Can mobile devices be used to accurately measure range between devices?
2. What range can these mobile devices reach, i.e. how far can they possibly extend a system and can these range estimates be used to position devices?
3. Can a framework be designed to allow any device within an in-situ IPS, to cooperatively assist in the locating of other devices, effectively extending the range of the IPS?

The objectives of this thesis are to:

- Research current solutions in localising devices, specifically solutions in the IPS arena and by doing so, identify areas where further research is required.
- Investigate current techniques and methods to extend the range of IPSs.
- Describe the development of a CAPTURE framework in theoretical terms.
- Implement CAPTURE in a specific test case and to evaluate and measure the effectiveness of CAPTURE, therein.

1.2 Thesis Motivation

Location Based Services (LBSs) use information about the geographical position of a device or user, to deliver a set of services based on that information (Liu *et al.*, 2010). Many services and sectors can incorporate location information to provide a LBS (Yassin and Rachid, 2015) such as, disaster aid, agriculture, healthcare monitoring, child tracking, emergency services, and information services, (Zhao and Guibas, 2004; Zhao and Nehorai, 2007; Bullo *et al.*, 2009; Corke *et al.*, 2010; Ko *et al.*, 2010; Martinez, 2010; Nayak and Stojmenovic, 2010; Hlinka *et al.*, 2013; Nia *et al.*, 2013; Meyer *et al.*, 2015).

GPS can be used outdoors for accurate positioning information but is unable to provide the same functionality for positioning services within indoor environments (Kals, 2010). The demand by users for an accurate positioning service indoors (Bekö *et al.*, 2015; Odeh and Hussein, 2016) motivates this work. We concentrate within the niche area of indoor positioning coverage as opposed to the more common research field of positioning accuracy.

The solution proposed is heterogeneous in its implementation and provides a plug-in service to an in situ positioning system. The system model allows for the establishment of an ad-hoc positioning system, where mobile devices could set up a mobile cooperative positioning system in a location where a traditional positioning system could not normally exist. The solution also utilises everyday devices such as off the shelf smart phones, as positioning infrastructure which offers a more affordable accessible solution.

1.3 Thesis outline

This thesis is organised into 6 chapters. Chapter 1 introduces the subject area, details the hypothesis and the motivation of the thesis, concluding with this outline of the overall thesis document.

Chapter 2 provides a survey of the current literature in positioning and IPSs and outlines the various technologies and techniques used to implement IPSs. Both indoor and outdoor positioning systems are appraised, focusing on indoor based solutions. An overview of how things are positioned is provided, beginning with an insight into how humans have positioned historically. The chapter explains where these practices are mirrored in how technologies are used in today's positioning systems. Different ranging techniques, as well as positioning algorithms such as Trilateration and Triangulation are considered in this section. Some of the issues that affect positioning accuracy in the indoor arena, by interfering with the radio signals used to measure range, are investigated along with the performance metrics that are employed to evaluate a positioning system.

Chapter 3 provides an investigation into cooperative based positioning, offering an overview of the cooperative positioning methodology that is presented in this thesis. It begins by describing cooperation and the benefits therein, as well as cooperation or collaboration in computer systems. The chapter continues by outlining some of the issues surrounding a cooperative solution, such as device selection strategies and quantifying the truth of a device. The negative consequences for collaborating devices in a cooperative methodology is presented. The problem of positioning coverage is also described here, accentuating the preliminary experiments that were carried as evidence to back up this issue. This chapter concludes by portraying a picture of how CAPTURE can assist in the world of positioning, illustrating specific scenarios where it can accomplish this. Some of the inherent flaws with such a framework are highlighted, as well as emphasising the novel concept of using devices to extend localisation coverage.

Chapter 4 discusses the design and implementation of the proposed CAPTURE model, defining the framework that makes up the CAPTURE platform. The cooperative positioning algorithm used with

CAPTURE is also described here. Some of the mobile devices that could be used as part of a cooperative solution are defined, while issues with the heterogeneity of devices adopted in a cooperative solution are also presented and evaluated.

CAPTURE is evaluated and tested in Chapter 5. The equipment and preliminary tests are described. The main experiments, which attempt to address the research questions and evaluate the overall thesis hypothesis are presented. Five unique testing environments used to evaluate CAPTURE are described. The results of the experiments are presented. The four environments are areas within the LyIT Campus.

In Chapter 6, a synopsis of the overall findings and main contributions of this work are provided and evaluated as a solution to the indoor ranging problem. Relationships to this work and other research are presented. Some further areas of research that have spawned from this investigation are described as well as illustrating some novel implementations of CAPTURE. This chapter concludes with an appreciation of the limitations of CAPTURE whilst acknowledging its novel contribution to research within this field.

2 Positioning

This chapter motivates the need for positioning and outlines how human's position and how many of the techniques humans use to position are emulated in many of the positioning technologies employed today. The chapter explains why localising or positioning in the indoor arena differs from localising in the outdoor arena and highlights some of the obstacles to accurate positioning in an indoor environment. Indoor positioning technologies are investigated evaluating their inherent strengths and weaknesses, with a focus on the issue of coverage or yield of indoor positioning solutions. These technologies and techniques are discussed in relation to cooperative localisation techniques, underlining the benefits such an approach offers to indoor positioning.

2.1 Introduction

Figure 2-1 shows a 5-layer location stack with the components, technologies, devices, chipsets and sensors, operating systems and vendors that can be used when locating devices.

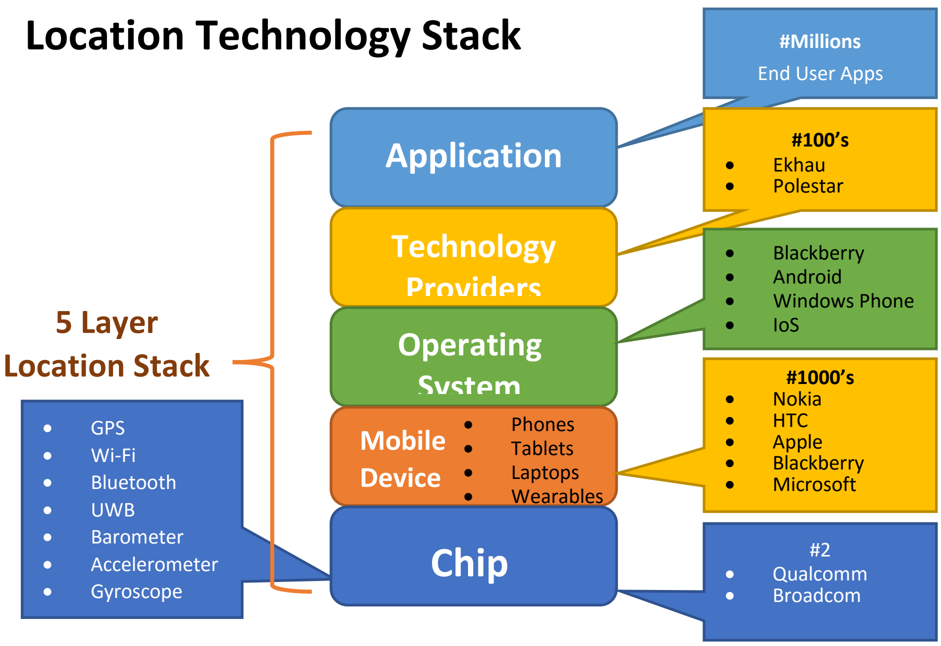


Figure 2-1: Location Technology Stack

The applications that use location services to provide location as a context sits at the top of the Location Technology Stack. These applications are omnipresent, being found within in-car navigation systems, friend finder applications, emergency responder apps and in games such as Pokémon Go. Indoor positioning technology providers such as Ekahau and Pole Star and outdoor positioning technologies like GPS provide the systems to locate users and devices. The Operating Systems (OS) layer of the Location Technology Stack defines the different mobile OS's which provide access to the hardware sensors that are used by the Technology Providers to derive a position fix. The Mobile Devices are typically positioned at Layer 2 of the stack and can be used indirectly to position users. Examples include Mobile Phones, Fitbits, Wireless headphones, Laptops and Smart Watches. The positioning chips reside at the bottom of the stack. These can be purpose-designed positioning sensors or chips that are re-purposed for positioning. The Location Technology Stack layers can operate in combination, to provide location-based information as is the case with Location Based Services, or independently to assist in a Location Based System (LBS).

2.2 Coordinate Systems

A positioning system can deliver an object's location with regard to a spatial reference system or to a defined symbolic space, such as a room a hallway or a building (Stojanović and Stojanović, 2014). A geometric location can be described in a geographic reference system, such as the World Geodetic System (WGS-84) used by GPS or a geometric reference system such as a local coordinate system (Kouba *et al.*, 1994). IPSs can use a local coordinate system to position lost devices where the position will be described in a 2-dimensional plane of x and y coordinate values. These values can be transferred to an IPS and used to track objects or transfer the location of an object onto a map of a building.

A coordinate system is a way to reference a point on any plane using some type of addressing. The most simplistic of these is the number line shown in Figure 2-2.

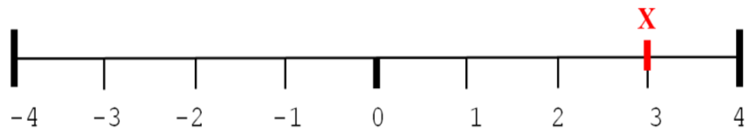


Figure 2-2: Number Line

A single dimensional location could for instance be the position of a town on a specific stretch of road where *x* would represent the position of the town relative to the road or at a given distance along the road. Only one scalar value *x* is needed to position the town on the road. This is the simplest coordinate system, *'the number line'*. To address or position the point X on this coordinate system, a value only needs to be applied to X as it appears relative to the line, or 3 in this particular example.

If the example is scaled up to consider the hypothetical town on a typical road map, consisting of multiple intersecting roads, the limitations of our single coordinate value can be imagined. Representing a position along two dimensions requires the incorporation of another scalar numerical value, y. This allows for the representation of length and breadth within a grid coordinate system. Think of horizontal coordinates made up of components such as North and West, latitude and longitude, or the horizontal coordinate system of a standard computer screen represented by (x, y). This system is illustrated as a Cartesian coordinate system in Figure 2-3.

Cartesian coordinates are expressed in ordered pairs. Each element of the coordinate pair is the distance measured across a flat plane from the point of origin. The origin is the intersection point of the x and y axis. Any point to the left of the origin on the x plane is negative and similarly on the y-axis, any point south of the origin is negative. The distance is measured along the line parallel with one axis that extends to the other axis. If the measurement is parallel with the x-axis, it is called the x-coordinate. If it is parallel with the y-axis, it is called the y-coordinate.

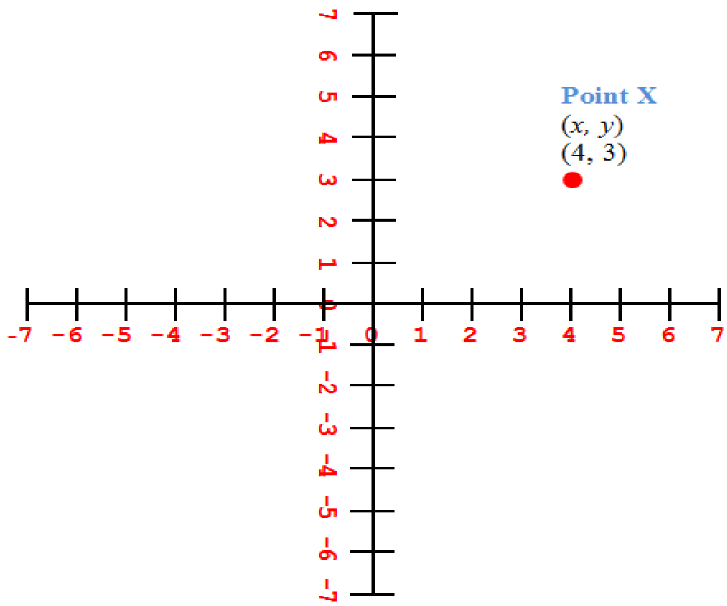


Figure 2-3: Cartesian coordinate system

Figure 2-3 shows two axes perpendicular to each other labelled as x and y. Point x can be represented anywhere along a two-dimensional plane, using both *x* and *y* as values within this space. These are the fundamentals of any coordinate system. This can be taken one step further however where a position on a third dimension can be described.

In a global coordinate system this height is represented as a value by the height above sea level. In an indoor system this could be the x, y coordinate values on a particular floor. A complete interpretation of an objects position in a particular space can therefore be concisely described within a three-dimensional plane using a vector of three-dimensional Cartesian coordinate values. More importantly, if these principles are held, then the rules of Euclidean geometry also hold true. The distance between two coordinate points can therefore be accurately measured using coordinate geometry, meaning the errors of a position estimated via a positioning system can be accurately gauged against its true position (Van Sickle, 2010).

2.3 Positioning

A position is a precise value and positioning is determining the precise position of oneself or an object (Kirson, 1992); (Sharp and Yu, 2018). Cartesian coordinate values allow for the precise description of a position. Positioning is the process of evaluating these coordinate values for an object by utilizing key measurements that are functions of the coordinates. Traditional measurements, used to evaluate a position are range, differences achieved in range estimates, azimuth and angles of both arrival and transmission. An Azimuth is the horizontal angle of a bearing, clockwise from a standard direction, such as North (Barrett and Yonge, 1958).

With the advances in sensor technologies in Smart Phones, more positioning measurements can be exploited to assist with localisation. These sensors offer measurements such as velocity and acceleration. Accelerometers measure linear acceleration of movement (Nikbakht *et al.*, 2005; Liu *et al.*, 2010) and gyroscopes measure the speed of rotational angle (Mischie, 2012; Tang and Li, 2015). Magnetometers provide an orientation in relation to the Earth's magnetic field to ascertain direction using the earth’s magnetic field (Chen, 2012). On-board barometric sensors measure atmospheric pressure which can be used to derive altitude (Zaliva and Franchetti, 2014; Bolanakis *et al.*, 2015; Wicaksono *et al.*, 2015). Pedometers can be used to estimate the number of steps taken (Tenmoku *et al.*, 2003; Oshin and Poslad, 2013; Sai *et al.*, 2016). Some sensors provide directional querying, which can determine what a phone is pointing at. Although this is not explicit positioning information, it can be very useful and provides a type of Location Based Service (LBS).

Sensors not specifically designed to provide positioning information such as microphones and cameras can also provide ‘*opportunistic*’ positioning measurements that can be exploited to help estimate position (Dammann *et al.*, 2012; Yang *et al.*, 2014). Received Signal Strength (RSS), proximity, time and angles of transmission and reception can be derived from Wi-Fi, Bluetooth and Global System for Mobile Communications (GSM) sensors.

2.4 Positioning Measurements

Modern mobile devices offer a multitude of measurements that can be used for positioning purposes. Signals transmitted by radio-based chips such as Wi-Fi, Bluetooth and GSM can create positioning measurements. A pedometer can also measure the number of steps taken which can be used as input for a Pedestrian Dead Reckoning (PDR) positioning system. PDR systems use speed of travel, elapsed time and heading, as a method to estimate a position (Chen and Guinness, 2014).

Inertial sensors are widely used with positioning and navigational systems (Chen *et al.*, 2016). These sensors get their name from the fact that they are based on inertia, which references Newton's first two laws of physics. The first, being that an object at rest, tends to stay at rest and secondly an object in motion stays in motion. To overcome inertia, a force must be applied such as resistance which will slow or stop something already in motion. Inertial Sensors on a mobile phone measure motion via an accelerometer and measure rotation through a gyroscope. They can therefore measure these forces to ascertain orientation and velocity.

Inertial Navigation Systems (INS) have been used to provide navigational assistance (Miller and Wagner, 1957). Implementations are found in airplanes, ships, missile guidance systems and submarines. Magnetometers are built-in sensors found in most modern mobile phones and these sensors are most commonly used as digital compasses allowing them to detect their position relative to the earth. A magnetometer provides a heading which is a degree of orientation relative to magnetic North (Grosz *et al.*, 2016).

Mobile phones have a variety of on-board wireless communications sensors. Generally, these employ some sort of radio frequency signals on mobile networks, Wireless Local Area Networks (WLAN's) or Bluetooth Personal Area Networks (PANs). Typically, the signals transmitted between devices within these networks were not initially envisaged to provide positioning information. They do however, inherit many characteristics that are spatially correlated, such as RSS, allowing the measuring of such, to derive range or range difference. This offers the opportunity to use these radio signals as positioning measurements. As these signals were not originally intended for this use, they are commonly referred to as ‘Signals of Opportunity’ (Chen, 2012). These measurements be they opportunistic, or designed specifically for measurement or positioning purpose, are derived using some of the different positioning technologies currently available.

2.5 Positioning Technologies

Many technologies have been employed to assist with positioning for both indoor and outdoor environments. The range capability of a technology, its energy efficiency, precision, implementation costs, availability in mobile devices, and complexity are all characteristics that need to be evaluated when deciding on deployment. The following section describes some of the technologies in use in IPSs whilst evaluating their implementation in a cooperative solution.

2.5.1 Wi-Fi (IEEE 802.11)

Wi-Fi based positioning systems exploit the Radio Frequency (RF) transmissions that are used during wireless network communications from WAPs to mobile devices to help position (Sharp and Yu, 2018). Wi-Fi is defined by the IEEE 802.11 standard and uses RF transmissions in both the 2.4 GHz and (less frequently used) 5 GHz band (IEEE, 2016). With the proliferation of smartphone devices, tablet form factor and the more recent widespread adoption of Wearable Devices, mobile users are now habitually attached to Wi-Fi enabled devices. This allows designers of IPSs to interrogate these devices, to ascertain the location of these assets, or by association, the position of the users. It also provides the ability for designers to incorporate all the preinstalled components of a Wi-Fi infrastructure into an IPS, offering a cost-effective solution. Considering Wi-Fi networks are now somewhat ubiquitous in our everyday lives, offering connectivity in our offices, shops, towns and homes, the capacity to locate indoors using Wi-Fi could also be ubiquitous. As this technology is so pervasive, it lends itself well to a cooperative positioning methodology allowing most off the shelf mobile devices to cooperatively assist in locating other mobile devices.

APs are strategically installed throughout a buildings infrastructure to provide mobile network coverage. Time, Angle or Signal Strength based techniques can be used to estimate the position of Wi-Fi enabled mobile devices relative to these APs. Time based systems use the time it takes a signal to travel to and\or from wireless devices to estimate range (Yang and Shao, 2015). Angle based systems use the signal angle to triangulate a position (Yang and Shao, 2015). Signal strength-based systems use the attenuation of a signals strength to estimate range (Zhuang *et al.*, 2016). Generally, Wi-Fi location systems are implemented using the RSS fingerprinting method, which uses pre-recorded RSS readings obtained during a sampling phase to ascertain the position of a device based on its current RSS readings (Zhuang *et al.*, 2015). This approach was first advocated by the Microsoft Research Labs Radio Detection And Ranging (RADAR) project (Bahl and Padmanabhan, 2000). There are however, some environmental factors that can cause problems with this process such as the IEEE 802.11 specification adopting a radio frequency of 2.4 GHz, which is also the resonant frequency of water (Rowe et al., 2007). Hence an environment with a high Relative Humidity (RH) level, tends to absorb more power from the radio signal than during lower RH levels. Since the average human male body is made up of 60% water, radio signals travelling around an empty hall will have a higher RSS value than one during a busy period. A college campus during the academic year, will provide different RSS values than outside the academic year, when no students are around the halls or rooms (Yang et al., 2009).

Another environmental factor that can have an impact on positioning is the actual indoor infrastructure. Doors, for example, by their very nature will open and close, ensuring that during the fingerprinting process it can be difficult to predict which door will be open or closed at any one time. It is also difficult to know the presence of furniture or items (filing cabinets, bags, suites of furniture, tables, or chairs) when the online estimation phase is attempting to locate a device at a later instance (Shih *et al.*, 2010). These environmental factors can affect the radio signal propagation from the APs to the target mobile devices. This can result in changes in the RSS and can incur location determination errors. This is because the existing Wi-Fi based location systems constructs and maintains only one database signature of RSS readings, and this database signature is configured by the environmental condition at the time of site survey. When the environmental condition changes later, this static database image will no longer reflect the expected RSS values seen in that environment, at that time.

2.5.2 Infrared (IR)

Infrared (IR) radiation is electromagnetic radiation with a wavelength that is longer than that of visible light. IR light cannot penetrate most objects in a typical room so it can be used to provide room level accuracy as a transmitted signal can only be *'sensed'* inside that room (Xie *et al.,* 2016). One of the earliest Infrared based IPSs, was the Active Badge System (Want and Hopper, 1992) which positioned by sensing an Infrared signal, in an office environment. IR signals cannot penetrate walls, and do not travel far so they generally operate at room level. An IR system uses tags worn or mounted on the user\object to be located and receivers to locate the tags. Tags periodically emit signals and when the receiver (e.g. ceiling or wall mounted) detects that signal, it can record *'sensing'* that tag in that particular room\hall. Sub-room level accuracy can be achieved using multiple receivers although quite a lot of receivers are required given the limited range, which can increase costs.

IR positioning systems do not suffer from interference from other RF devices because IR uses light waves. However, some household devices such as TV\DVD remote controls, Plasma TVs and even direct sunlight can interfere with signals (Xiao *et al.,* 2011). There are also IR windows on both receivers and tags which need to remain free from dirt or obstruction to prevent them impeding the transmission and receiving of signals. If the main requirements for a positioning system is the need for room level accuracy and a cheap implementation then IR can be a perfect solution. The main advantage of using an IR positioning system is that they are small, lightweight and easy to implement. There are also some security and privacy issues with IR positioning systems (Gu *et al.,* 2009). Due to the limited availability in modern mobile devices coupled with the limited range and need for LoS, IR is not a commonly deployed positioning technology (Casas *et al.,* 2007).

2.5.3 Radio Frequency Identification (RFID)

A Radio Frequency Identification (RFID) positioning system consists of a reader and a tag. When a tag can *'sense'* a reader or vice versa, the positioning of either can be derived based on the transmit range of the tag (Huang *et al.,* 2015). RFID as a technology has been around for quite some time, beginning as an identification system in World War II. RFID is still used as an identification system today, although its main use is in asset tracking, supply chain management and life-cycle management applications. Nonetheless, there are and have been notable location-based solutions built around this technology (Siddiqui, 2004; Becker *et al.,* 2008; Sanpechuda and Kovavisaruch, 2008).

An RFID tag is a simple device made up of an antenna and a small amount of memory, making them one of the cheapest components in any positioning system. Tags can generally be described as passive or active, although semi-passive tags are also available. Active tags have their own radio transmitter and battery power allowing them to initiate communication and have a greater range over passive tags. However, the advantages provided by the battery can be negated by its need for maintenance and its duration can effectively rule it out as a solution in some circumstances. Passive tags need to be woken or interrogated by a reader to initiate communication and have a shorter range than active tags, typically under 1 metre. Semi-passive tags offer similar capabilities to passive tags, whilst also having a battery allowing other environmental conditional monitoring, and a greater read range. Some believe that a hybrid solution to RFID localisation is preferable as RFID on its own cannot provide the '*optimum solution'* (Siddiqui, 2004; Sanpechuda and Kovavisaruch, 2008).

Becker et al (2008) propose an 'inside-out' RFID localisation solution, whereby the reader is tracked, and the tags are the reference points, which can be read up to 6 metres apart. They demonstrate the possibility of localising and tracking a mobile reader in an aircraft cabin. The goal of their application is to allow automated maintenance support for aircraft technicians by tracking their position and providing location aware information to them at discrete locations throughout the aircraft. Each read merely provides '*detected'* or '*not detected'* information. The position is estimated based on the position where the reader is capable of reading all currently detected tags.

Some RFID solutions are developed where centimetre level accuracy does not form any part of a requirements analysis. Support systems for emergency responders are an example of this. The important consideration here is which room in the building the missing fire-fighter last entered. "*Lost Inside*" has been identified as a primary cause of traumatic injuries to fire-fighters, by the US National Fire Protection Association (NFPA) (Fahy, 2002).

The Flipside RFID system (Guerrieri *et al.*, 2006) uses an RFID implementation to correct PDR drift. Here RFID tags are placed within a building and once a reader reads a tag at a known location, their PDR estimated position can be recalibrated given this new information relative to the tag. LocAtioN iDentification based on dynamic Active Rfid (LANDMARC) (Ni *et al.*, 2003) is designed to investigate RFID technology as a localisation solution to locate objects accurately and cost-effectively.

The accuracy achieved with an RFID solution can be very precise, due primarily to the limited read range of the components used. Once a reader can read a tag (or a tag a reader), the object to be located can be placed within the read range of the tag and reader (< 1 metre) with passive tags (Ruiz *et al.*, 2012). This is before any filtering or location algorithms are employed. Furthermore, the read times in RFID are exceptionally fast as low as 100 milliseconds in some implementations. This can make RFID a perfect solution in situations where devices being tracked converge or funnel into smaller narrower areas.

2.5.4 Ultrasound

Ultrasound based positioning systems typically use a transmitter (speaker) and a receiver (microphone) to measure the time it takes a sound to propagate to estimate range and thereby derive a position (Ma *et al.,* 2018). The highest frequency of sound that a human ear can detect is approximately 20,000 Hz, which is defined as the end of the sonic range and the beginning of the ultrasonic range. Ultrasound is acoustic energy that is beyond the range of human hearing. Locating using Ultrasound works similarly to the concept of locating using RADAR, and **SO**und **N**avigation **A**nd **R**anging (SONAR). SONAR and RADAR were however, primarily used to merely detect the existence or presence of an object, be it a school of fish, an airplane, a ship or submarine. Bats, dolphins and whales use SONAR (echolocation) to navigate.

Systems using Ultrasound to locate in the indoor arena generally use beacons (tags) and receivers to provide a more accurate means of pinpointing the exact location of objects. The beacons transmit a high frequency pulse which is picked up by the receivers, the receivers are simple microphones. Because the pulses travel at a known speed – speed of sound (343.2 metres per second), the distance to\from the transmitting\receiving devices can be determined using Time of Arrival (ToA) methods. Ultrasonic waves cannot penetrate walls and are generally used for room level location, because the transmitted pulses from the tags in a room are picked up (heard) only by the microphone (receiver) in that room. The receivers can be tuned for direction, providing sub-room level accuracy and this can be further honed by installing multiple receivers.

The most popular examples in literature of successful utilisation of Ultrasound as an indoor location system are the Active Bat System (Want and Hopper, 1992) and the Cricket System (Priyantha *et al.,* 2000). The Active Bat System uses multiple receivers in the ceiling and could locate Bats (beacons) with 9cm accuracy, 95% of the time (Hightower and Borriello, 2001). The Cricket implementation works in the opposite way to Active Bat, by placing the transmitters in the ceiling and the receivers on the mobile device. The transmitters broadcast their position, which is *'heard'* by the mobile receivers, which then calculate their position based on this received location information. Fewer receivers are required for Cricket, making it a cheaper alternative to Active Bat, but it cannot match the accuracy of

Active Bat. (Filonenko *et al.*, 2010) investigated implementing an Ultrasound IPS, using mobile phone speakers and microphones to emit and receive ultrasound. Borriello et al. (2005) showed it is possible to transmit and receive Ultrasonic waves via mobile phones using **W**ireless **A**coustic **L**ocation with **R**oom Level Resolution using **U**ltra**S**ound (WALRUS). One notable disadvantage of Ultrasound positioning, is the fact that interference cannot be heard by the human ear, making it difficult to troubleshoot interference issues.

2.5.5 Ultra-Wideband

The presence of multipath signals is one of the major contributors to errors when using RF positioning systems (Chen and Guinness, 2014). Ultra-Wideband (UWB) offers a method to overcome these errors by being able to distinguish between one incoming signal and a second arriving a little while afterwards (Di Benedetto, 2006; Jimenez and Seco, 2016). Furthermore, considering the number of wireless devices in use today and considering current and predicted adoption rates, the ability of wireless technologies to coexist in the same environment is a fundamental requirement. UWB offers a glimpse of a solution to this problem (Cassioli *et al.,* 2005).

Ultra-Wideband was adopted by IEEE in the IEEE 802.15.4 Wireless Personal Area Network standard, for precise localisation, and low data rate and short-range transmissions. Ultra-Wideband positioning works similar to other localisation technologies, using tags and receivers in transmissions, that can be utilised to calculate a time, distance or angle of transmission to determine position. Wymeersch et al. (2009) employ Ultra-Wideband in their **S**um-**P**roduct **A**lgorithm over a **W**ireless **N**etwork (SPAWN) algorithm to prove that *"Cooperation among nodes has the potential to dramatically improve localisation performance"*. One of the primary benefits of Ultra-Wideband, is its ability to engineer high data throughputs due to the short duration of the pulses. This leaves it well positioned for short distance data intensive applications, such as High Definition Camera\Camcorder data transfer, wireless printing, or portable media players.

In recent years' attempts have been made to address some of the limitations of UBW, as a solution to the indoor positioning problem. The IEEE 802.15 committee released the 802.15.4-2011 standard, which was recently further revised to 802.15.4-2015 (IEEE, 2016). This allowed the range between 2 Ultra-Wideband devices be measured with a greater deal of precision, using the time that it takes a radio wave to travel between the 2 devices. Using this approach, provides much more accurate range estimations than RSS. Furthermore, because UWB typically operates at sub 1GHz or between 3.2 and 4.8GHz or 5.2 and 10.5GHz, the radio waves are impacted less in the presence of noise, in the busy 5.0GHz channel, where Bluetooth and Wi-Fi operate.

Ubisense, has been providing UWB positioning solutions since 2002. Examples of UWB providers include Ubisense, TimeDomain and Zebra. Decawave, offer development kits for UWB positioning. French mobile phone manufacturing company BeSpoon, recently began incorporating miniature IR-UWB (Impulse Radio - UWB) chips in their SpoonPhone. This proves that the technology can coexist alongside currently installed technologies on a modern smartphone.

A recent study of the performance of Decawave and Bespoon (Jimenez and Seco, 2016) found that they could offer range level accuracy of < 5.5cm and 11cm respectively in LoS conditions. Decawave advocates a coverage area of 300m while BeSpoon describe ranges of up to 880m, which would put this technology far beyond the current capacity of both Bluetooth and Wi-Fi. Most of the higher accuracy levels offered by Decawave, can be described by the incorporation of an antenna optimised for better signal reception. The smaller scale BeSpoon implementation cannot afford the luxury of such a large antenna in the confined space of a smartphone.

2.5.6 Bluetooth

Bluetooth can be used to position by estimating the range or angles between devices or using fingerprints of RF signals pre-recorded in an off-line stage to then use to position in real-time (Hossain *et al.*, 2013), Bluetooth was designed by phone manufacturer Ericsson in 1994 to replace the then ageing RS-232 (EIA, 1969) and Infrared interfaces for connecting peripheral devices. It is a proprietary, open, wireless standard for data exchange over short distances ~10m, creating small area networks called Personal Area Networks (PANs). It operates at the same 2.4GHz frequency as Wi-Fi and is specified in the IEEE 802.15.1 standard. A PAN is made up of smaller clusters of Bluetooth enabled devices, up to eight connected devices make up a Piconet and 2 or more Piconets form a Scatternet.

The overriding benefit of using Bluetooth for indoor positioning is its availability in nearly every mobile device in use today. Bluetooth has been historically linked to battery consumption, with smartphone users sometimes disabling it. In June 2010, the Bluetooth Special Interest Group (SIG), completed the core specification for Bluetooth 4.0. Although earlier versions of Bluetooth have been utilised for localisation and indeed cooperative localisation (Kloch *et al.*, 2011a) the introduction of fourth generation Bluetooth solves some of the problems relating to battery consumption and range. Bluetooth Smart Ready or Bluetooth Low Energy (BLe) is an improvement over its predecessors in its limited consumption of battery power and its massively increased coverage ~200m.

Kloch et al. (2011b) investigate effects in collaborative indoor localisation as an example of self-organising in ubiquitous sensing systems using Bluetooth to correct PDR drift. They analyse the collaborative approach as a solution to the indoor localisation problem and found that when using PDR in isolation the variance grows bigger as people are walking. The position estimation becomes less accurate the further people being tracked travel. When two people both using PDR estimates come close together (close enough to be read by a Bluetooth device), their single position estimates can be used together (because how far apart they are, can be calculated) to provide a more accurate position estimation.

2.5.7 Optical - Camera\Vision

RF based positioning systems suffer from multipath errors and Electro-Magnetic (EM) interference (Chen and Guinness, 2014). Indoor lighting such as fluorescent or Light Emitting Diodes (LEDs) do not suffer from such issues but can still offer a means to position by being able to distinguish one light over another and thereby position a device relative to a light source that it can see (Zhang *et al.*, 2014).

Most modern-day mobile devices, such as phones, tablets or laptops come bundled with at least one on-board camera. Researchers have investigated innovative techniques using these cameras to help position, especially in the indoor environment.

In (Nakazato *et al.*, 2004) a system was developed that uses a camera to derive position from georeferenced visual markers which act as frames of reference for wearable computer systems. Hijikata et al. (2009) uses the unique pulses of LED to differentiate one LED from another and using their preordained position as landmarks or a reference frame to ascertain position. LEDs can be programmed to emit specific pulses of light which can be used to differentiate one LED light from another. Each light within a building is assigned a unique pulse signature which identifies that light from all other lights within the building. A scene analysis, similar to that carried out with RSS fingerprinting is recorded to map the location of each of the LED lights with their corresponding light emitting pulses. Therefore, as a user navigates the building the camera on their mobile device can *'see'* the different signatures as they pass under the LED lights. The signature can then be used to provide the position of that particular light and thereby locate the user of the mobile device that is under that light.

A fundamental barrier to implementation when using cameras to position is the requirement that the camera *'see'* the environment it is attempting to position in. This means that the mobile device must not be concealed in a handbag, backpack or pocket, which is where most mobile devices are stored when a user is on the move. One of the benefits of using other positioning technologies is the pervasiveness of their implementations. Applications that require location as a context can achieve this without user intervention. Accuracy levels can be high with some Camera\Vision implementations, especially the LED version. The need to have the camera or mobile device in the hand so that it can see the lights, can rule out certain applications, especially cooperative implementations as people typically carry their phones in concealed locations.

2.6 Fingerprinting

A location within an environment can be represented by a set of RF signal patterns called a fingerprint (Kaemarungsi and Krishnamurthy, 2004; Wigren, 2007; Hossain *et al.*, 2013; Leca *et al.,* 2017). This fingerprint is captured as part of a scene analysis, where readings are recorded, typically into a fingerprint database at pre-specified locations. This is also referred to as the Offline Training Stage, when implementing a fingerprinting based solution. This is where a human operator carries out a site survey by sampling RF readings.

The most common implementation of this is in an indoor environment where the RSS from the WAPs located around the building are analysed. These samples are then loaded into a database which stores the RSS readings of APs at different preordained sampled points. Then, during the online estimation phase, a mobile device's location is determined in real time by looking up sampled points on the database with the closest RSS values to those currently seen on the mobile device.

The Ekahau (Ekahau, 2016) and Polestar (Pole Star, 2016) systems are examples of IPSs that employ this method. In addition to RF readings being recorded from WLAN's, Bluetooth and RFID fingerprints can also be recorded, to allow for this method of positioning to be implemented in these networks. Furthermore, fingerprinting is not just used in the indoor arena but radio maps of cellular fingerprints can also be recorded in the outdoor environment to help position devices (Wigren, 2007; Ibrahim and Youssef, 2010).

2.7 Sensor Fusion

Sensor fusion can combine different technologies and techniques to create a superior multi-modal system compared to a singular one (Weyn, 2011). (Zaliva and Franchetti, 2014) fused sensor data from GPS and Barometric chips to obtain a more accurate altitude reading. Micro-Electro-Mechanical Systems (MEMS) sensors in mobile devices can be used to '*know'* when to change a screen orientation or to count the number of steps a user has made during a given day. Along with providing this functionality, these sensors can be used in an opportunistic fashion to assist with positioning.

When used in isolation, positioning accuracies using these technologies have been typically poor. However, there has been some noteworthy successes when using the positioning estimates of different sensors and aggregating their results to provide a combined position estimate. (Kloch *et al.,* 2011a) used BLe sensors to correct PDR drift which occurred when only using motion sensors. PDR is the process of estimating a current position, with reference to a previously known position and altering that position based on estimated speeds over an intervening timeframe (Chen and Guinness, 2014).

2.8 Wireless Sensor Networks (WSN)

The concept of cooperation among wireless devices is not a new phenomenon. In a Wireless Sensor Network (WSN), devices (nodes) collaborate when deployed in an Ad Hoc infrastructure (Bouhdid *et al.,* 2017). Nodes generally consist of a processor, memory, an RF transceiver, a power source and a sensor, to gather the required sensory data. The nodes, sometimes 100s even 1000s, collaborate, to establish a mesh network for communication, sensory, control, and actuation purposes. WSN's are used in Environmental, Industry, Health, Military, Transportation, and Home to monitor sensory data. When the data to be collected, or the devices collecting the data, are mobile in a WSN, location can be a key ingredient which helps derive a more comprehensive understanding of the context of the collated data. This has led to a wealth of research in the area of positioning in WSN.

Bearing in mind the collaborative nature of the network infrastructure itself and the devices within it, considerable research into the area of cooperative positioning has arisen. The Cortina project (Giorgetti *et al.,* 2011; Zheng *et al.,* 2011) is a distributed Real-Time Location System (RTLS) designed to track assets or people moving indoors. Using wall-plugged wireless sensors that self-configure, self-heal and self-calibrate, Cortina is a cooperative positioning system, that reduces maintenance and deployment costs. People or assets are allocated tags that are localised using RSS measurements from nearby reference nodes. In a novel technique, the Cortina System estimates floor levels based on barometric readings from on-board sensors, against readings on the wall mounted reference devices on each floor.

Table 2-1 provides a summary of these positioning technologies, showing their relevant accuracies, where they are mostly implemented, their expensive and their complexities. It also provides information on each technology's theoretical transmission range.

Wi-Fi based positioning is typically used in the indoor arena, although outdoor versions do exist (Jinghua *et al.*, 2014; Leca *et al.*, 2017). Implementation complexity and costs are relatively low considering most of a wireless networks existing infrastructure can be used.

Positioning Technology	Accuracy Meters	Range Meters	Cost	Complexity	Domain
Wi-Fi	<1	1 – 200	Low\Medium	Low	Indoor/Outdoor
Infrared	<0.5	1 – 5	Low\Medium	Low	Indoor
RFID	<0.5	1 – 10	Low	Low	Indoor
Ultrasound	<1	2 – 10	Medium	Low	Indoor
Ultra-Wideband	<0.1	1 – 80	Medium	Low	Indoor
Bluetooth	<10	1 – 200	Low	Low	Indoor/Outdoor
Optical	<1	1 – 10	High	High	Indoor

Table 2-1: Positioning Technologies Comparison Table

The range of a Wi-Fi positioning system is constrained by the bounds of the technology itself which is in the area of 200 meters (IEEE, 2016) in a Line of Sight (LoS) environment. Accuracy levels under 1 metre have been achieved (Yang and Shao, 2015; Chen *et al.*, 2016). Hauschildt and Kirchhof (2010) developed an Infrared positioning system that uses sensors in the corner of rooms that measure the angles from sources, giving accuracy levels under 5-metres. The associated costs of Infrared systems are relatively low, but they have a low coverage area and are normally used within rooms due to LoS requirements. Ruiz *et al.* (2012) implemented a low cost IPS using foot mounted passive RFID tags to locate pedestrians to within 5-metres. Sonitor (2018) is a commercial ultrasonic positioning system that uses ultrasound to position providing room level accuracy albeit with a limited range of less than 18 metres. Sato et al. (2011) achieved sub decimetre accuracy levels with their Extended Phase Accordance Method (EPAM) range measurement technique.

Bluetooth implementations are typically low cost and easily implemented due to their availability in modern day smart phones. Kranz et al. (2010) demonstrated an RSS fingerprinting method which achieved accuracy levels of up to 5-metres using Bluetooth. Camera based systems can be somewhat inexpensive to implement due to the availability of high definition cameras on most modern mobile devices. Specialist systems such as the LED system developed by (Hijikata *et al.*, 2009) can be expensive implementations due to specialist LED hardware and the complexities of their implementations.

2.9 Ranging Techniques

The location of a receiving device, relative to a transmitting device, can be measured by estimating signal metrics based on the physical waveforms transmitted during communication (Liu *et al.*, 2010). These range measurements can be then used as input for a positioning algorithm, to further derive the position of a device. Establishing range measurements between mobile devices can be achieved using several different techniques.

These techniques are not necessarily trivial in their implementation, multipath effects where signals travel different paths from transmitter to receiver (Chen and Guinness, 2014) are challenging. Reflection and refraction where signals bounce off obstacles (Guvenc and Chong, 2009) along with other environmental factors (Rowe *et al.*, 2007; Yang *et al.*, 2009) pose unique challenges when measuring a radio signal.

There are numerous ranging techniques that can be employed to gauge the distance between two devices, to establish a range. Ranging techniques calculate distance or range, usually in terms of centimetres or metres. Each of the techniques discussed next, have their inherent flaws and cannot be guaranteed to provide accurate range estimates in all environments and circumstances. It would be considered common practice today, to use a combination of these techniques in a hybrid solution, in most situations where a more accurate ranging estimate is required (Siddiqui, 2004; Yassin and Rachid, 2015; Atyabi and Nefti-Meziani, 2016).

2.9.1 Received Signal Strength (RSS)

One of the most popular ranging techniques used in indoor positioning RSS is a measurement of the voltage that exists in a transmitted radio signal, which is an indication of the power being received by an antenna (Farid *et al.,* 2013). A common misnomer within wireless telecommunications nomenclature is that the terms Received Signal Strength (RSS) and Received Signal Strength Indicator (RSSI) can be exchanged without impact (Konings *et al.,* 2017). There is no unit of measurement for RSSI. RSSI is unit-less and is always a positive value, which is the RSS represented on a positive scale. RSS on the other hand has a unit, typically dBm, dB or wattage and represents the real value of the signal strength and are typically represented using negative values. A dBm is a measurement in decibels that describes a radio signal relative to 1 Milliwatt (1 thousandth of a Watt). A decibel is a unit of intensity. RSSI provides a way to scale these negative values, to make them easier to understand and interpret. This came about with the proliferation of mobile phones and mobile broadband, providing manufacturers with a more simplified value, to explain this phenomenon to their customers. So, if the maximum RSS value was 0 dBm and the minimum was -100 dBm, these can be mapped so that 0 dBm represents 100 RSSI and -100 dBm is scaled to 0 RSS (Konings *et al.,* 2017).

When a signal first leaves a transmitting device, the power of the signal drops or attenuates. This is true of both wired and wireless transmissions. As a radio signal propagates through the air some of its power is absorbed and the signal loses a specific amount of its strength. Therefore, the higher the RSS value (or least negative in some devices), the stronger the signal. Knowing the amount of signal loss over a given distance, provides a method to calculate the distance from a transmitting device, given an RSS.

At its most basic level, this allows for the *'coarse'* positioning or as referred to in other literature, *'presence-based localisation'*, *'presence detection'* (Mrazovac *et al.,* 2011) or *'proximity localisation'* (Qiang and Kaplan, 2010) of a device relative to the transmitting device. This can be illustrated by the

RSS calculated distance being the radius of a circle and the *'searching'* device being at the centre of that circle. The estimated position of the Lost Device is anywhere on the circumference of that circle.

In an IEEE 802.11 network, if the locations of WAPs are already known, then the location of Mobile Devices traversing the network can be located relative to them, albeit only to the circumference of the radius of the calculated distance. Range measurements can be used in conjunction with a positioning algorithm, to further derive the precise location of a device.

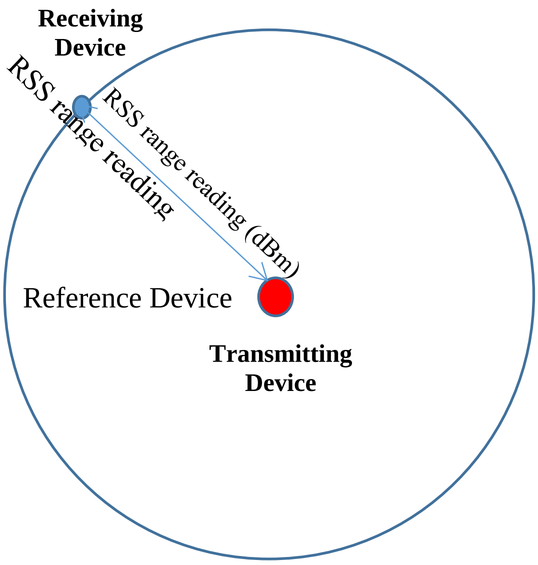


Figure 2-4: Presence Based Localisation

Figure 2-4 illustrates the coarse positioning of a mobile device, when only one reference device is present, or within range of the mobile device. The receiving device can obtain the RSS reading during initial communication with the transmitting device. The receiving device can then estimate its distance relative to the transmitting device based on the RSS value. With a single range measurement however, the position can only be estimated as being somewhere on the circumference of a circle, the centre of which is the transmitting device and the radius being the RSS range reading measurement. Further range estimates to other reference devices are required to provide a more granular position fix.

2.9.2 Proximity

Proximity-based positioning is a technique of sensing when one is within the '*vicinity*' of an entity that has been associated with a location (Chen and Guinness, 2014). It is a qualitative measure, in that the definition of '*vicinity*' is usually ambiguous. However, sometimes knowing precisely where in an area a mobile device resides is not a requirement. Rather, understanding that it is simply in that area can be sufficient information for an application to deliver a LBS.

A shopper moving around a shopping centre could be *'sensed'* when they come within a given range of a specific shop and then be supplied with notifications of a promotion within that shop. Proximity-based positioning is not new. GSM and General Packet Radio Service (GPRS) mobile phone networks, have used Cell-ID based positioning for some time (Yilin, 2002) to assist with such services as smooth or soft handover routines. As the phone user moves between cells within the cellular based mobile network, devices can *'sense'* the Cell-ID of the cell they are currently connected to. Then, if they move within the vicinity of another cell, the handoff can be predicted as being to that cell and initial handoff procedures can begin to ensure the smooth transition between cells.

This Cell-ID based localisation strategy is one of the simplest proximity-based positioning techniques. A mobile device attaches to a cell tower once it moves into its coverage area, the location of each cell tower is already known. Therefore, the mobile device can be located to within the coverage area of the RF transmitter of that cell tower. The precision of this technique falls within the transmitting capacity of each cell tower, this can be anything from 1 Kilometre up to 35 Kilometres (Rahnema, 1993).

This strategy has also been employed in the indoor arena, with implementations via Bluetooth, Wi-Fi and RFID. Positioning in this environment is not too different from the GSM approach with the only notable difference being that the mobile device can have a priori knowledge of the location of each of the APs on the network. This allows the device to position itself in the network, once it *'sees'* the MAC address (enters the RF transmission range) of the AP.

The range or yield of implementations using these technologies, is limited to the transmission capacity of the technology itself. This can seem to have negative connotations at first glance, but because their transmission capacity is lower, the corresponding accuracy of this technique with these technologies, is also low. When locating a device using proximity-based positioning with either Bluetooth or Wi-Fi the error bounds is directly linked to the transmission range of the technology. If a Bluetooth or Wi-Fi device can be '*sensed'* by a reference device, then it must reside within 200 metres of that device.

One interesting implementation of Bluetooth as a proximity-based positioning technique, is where the Bluetooth beacons are configured to lower transmission ranges, thereby upping the accuracy of the solution. SITA, an IT solutions company for the airline industry implemented a Bluetooth 4.0 BLE solution in Miami Airport (SITA, 2016). The solution uses over 500 Bluvision sensor beacons and Bluetooth to Wi-Fi gateways (BluFis) installed throughout the airport, to position passengers and help them navigate throughout the terminal. They claimed accuracy levels of greater than 1 metre. The Bluetooth beacons can be configured to transmit at lower ranges within the airport, offering greater accuracy at these points. RFID implementations are also restricted by their limited transmission capacity. Depending on the RFID technology used, this can be a little as inches or up to a maximum of a few metres. Again, although this may seem limiting, it can be used to provide information about a mobile device entering a given area. RFID tags can be placed on doors to provide room level accuracy, or at choke points to *'sense'* when a mobile device passes that point.

2.9.3 Time of Arrival (ToA)

For a signal with a known speed, determining the propagation time can indicate the distance between the transmitting device and the receiving device (Liu *et al.,* 2010). Using timing information to ascertain position is a concept that has been widely used by navigators for many years. From a conceptual perspective, consider having a clock and someone else also having a perfectly remote in sync clock. If there was a video link of the other clock and the time difference between the two clocks could be viewed, then the time lag is a representation of the time it took the video transmission to travel. If the video travelled at the speed of light, then the distance or range between the two clocks can be calculated.

Time of Arrival (ToA) is a method used to obtain a range estimate, ToA is the time it takes for a signal to travel from the transmitting device to the receiving device (Liu *et al.*, 2010). ToA is calculated using the time of transmission plus the delay that is introduced when propagating the signal. The speed of a signal travelling through the air is approximately 10^6 times the speed of sound. As a general rule of thumb, radio frequency broadcasts at a speed of 1 foot per nanosecond (Patwari *et al.*, 2005). The distance between the transmitting device and the receiving device can therefore be calculated using the known speed of propagation and the time it took for the frame to be received as follows:

$$R = time \times speed. \qquad (1)$$

where *R*, is the distance between the receiving device and the transmitting device and is derived from *time*, which is the time spent by the frame travelling across the medium, multiplied by *speed* which is the propagation speed of the signal. An outline of the ToA method and how it is determined in an Ultra-Wideband network, is provided in (Guvenc and Chong, 2009).

One obvious drawback of the ToA method, is the fact that the clocks on the transmitting and receiving devices must be perfectly synchronised (Chen and Guinness, 2014). Considering the signal travels at speeds nearing the speed of light, a small discrepancy in clocks can have a dramatic impact on the estimated position.

Managing and maintaining this precise synchronisation of clocks, in a cooperative paradigm would be somewhat troublesome given the heterogeneity of the devices involved. Patwari et al (2005), also highlight the further issue of the time delays in the transmitter and receiver hardware and software that add to the measured distance. Although the insignificant delays are generally understood, discrepancy in hardware specification and response times can be another source of ToA inconsistency (Patwari *et al.,* 2005). Again here, the heterogeneous nature of a cooperative localisation scheme, with a disparate assortment of hardware providing the cooperation, would introduce hardware and software attenuation that could prove difficult to account for, given the precision requirements involved.

2.9.4 Time Difference of Arrival (TDoA)

Time Difference of Arrival (TDoA), attempts to overcome the synchronising of time posed with the ToA method. It does this only at the receiving device however, as the synchronising errors are the same for both signals. The transmitting devices still need to be synchronised so that their clock offsets can be known.

$$\frac{R1}{c1} - \frac{R2}{c2} = ToA_1 - ToA_2 \qquad (2)$$

This can be relatively simple to achieve in a network of base stations or fixed sensors, it would be more difficult, if not impossible to do this with cooperating mobile devices. It is not too dissimilar to the ToA method. In fact, it uses 2 ToA measurements as input. It employs 2 signals received from 2 different transmitting devices. The difference in time between these signals, is used to determine the position of the transmitting device.

In (2), *c* symbolizes the speed of 2 different signals, typically the speed of light in free space. ToA_1 *and* ToA_2 represent the transmission time of the different signals propagating from the transmitting devices to the receiving device, and *R1* and *R2* are the range or distance between the 2 devices. TDoA effectively is the difference between ToA_1 and ToA_2. This concept is illustrated in Figure 2-5.

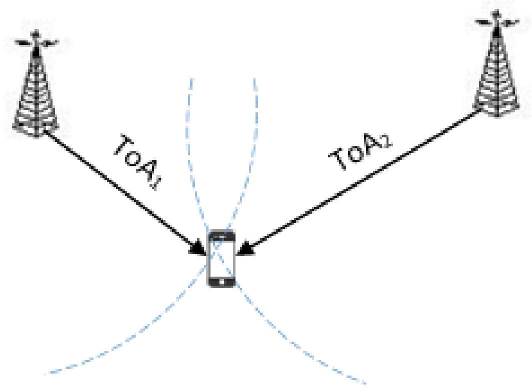


Figure 2-5: TDoA Concept

Takabayashi et al. (2008) proposed an algorithm using TDoA calculations to estimate the position of a device for target tracking and argue that TDoA is a suitable ranging method to use where the number of sensors is limited. The barriers to implementation, involve the heterogeneity of devices in a cooperative localisation solution which were outlined previously in the ToA method.

2.9.5 Round Trip Time (RTT)

Round Trip Time (RTT) range estimation was designed to resolve the clock synchronisation issues of ToA and TDoA techniques. The RTT of a signal is calculated as follows:

$$R = \frac{(t_{RT} - \Delta) \times speed}{2} \qquad (3)$$

where t_{RT}, is the time required for a signal to travel from the transmitting device, via the receiving device and back to the original transmitting device again. Δt, is the delay introduced by the receiving device before the signal is forwarded on, and *speed* is the speed of the transmitted signal. Only one device records the time taken to transmit the signal and the arrival time of the signal, thereby resolving the issue of synchronising two clocks. RTT offers a robust solution to the synchronisation issue in other range estimation techniques. This leaves it well situated to operate in a cooperative localisation solution.

2.9.6 Angle of Arrival (AoA)

With the Angle of Arrival (AoA) or also known as the Direction of Arrival (DoA) ranging method, an array of antennas or directional antennas, are used by the receiving devices to calculate the angle from which the signal was transmitted (Belloni *et al.*, 2009). The position of the lost device, (Mobile Device X in Figure 2-6) is estimated by determining the intersection of two or more propagation paths of the transmitted signal. These are illustrated as Mobile Device A and Mobile Device B.

The principle benefit of AoA is the fact that unlike ToA and TDoA methods, no computational load is placed on the receiving and\or transmitting devices, to maintain clock synchronisation. AoA range estimation techniques have been extensively used (Niculescu and Badri, 2003; Hui *et al.*, 2007; Gezici, 2008).

The single biggest disadvantage of the AoA method, is that a small error in the angle measured, can lead to a catastrophic error, in the positioning estimation of the device to be located. This error rate is exponentially related to the distance between the transmitting and receiving devices. Furthermore, AoA based ranging techniques, are vulnerable to multipath signalling errors and most implementations require LoS between sending and receiving devices. Antenna arrays and directional antennas, although becoming more prevalent in smart phones, are not components that are typically found in everyday mobile devices. This increases the cost for any implementation and renders it redundant for cooperative localisation.

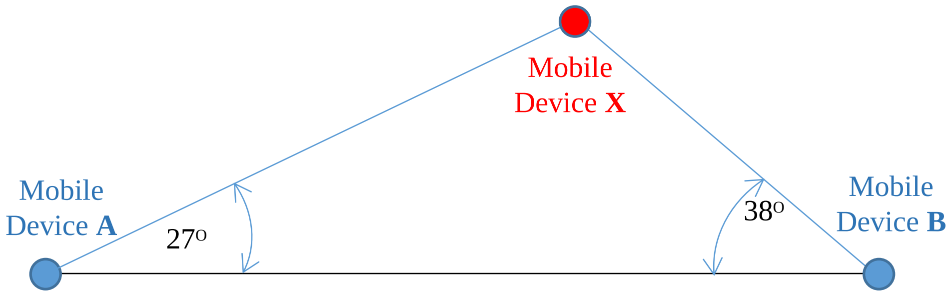


Figure 2-6: Angle of Arrival (AoA)

2.9.7 Pedestrian Dead Reckoning (PDR)

Dead Reckoning is the process of estimating a current position, with reference to a previously known position. It can be as simple as measuring the number of paces that a mobile user has taken in a given direction since they initially began to move. Implementing PDR as a solution incorporates the use of speed of travel, elapsed time and heading, to estimate a position (Chen and Guinness, 2014). Early navigators used a range of techniques to negotiate unfamiliar environments using dead reckoning, employing the sun, moon, stars, wind, tidal drifts, waves and swells as reference points to do so.

Consider the situation, where someone is providing directions to navigate to a destination based on a focal point that is visible. If the destination lies 200 yards West or to the left of a church that can be seen along the journey then as an initial course is set, the church spire can be used as guide or frame of reference. This can work perfectly while the church spire is within sight, but problems occur when the spire can no longer be seen. In this case, a heading can be maintained in the direction the church is perceived to be in but because this frame of reference cannot be seen, it is inevitable that a certain amount of 'drift' occurs. The further an object travels without the aid of a reference point, the more susceptible it is to drift even further off course. When moved to a position where the church spire can again be seen, the drift can be corrected, and a course reset, to a new more accurate heading.

As humans walk, our bodies generate cyclical movement patterns which occur as a result of moving our legs. Analysis of these movement patterns provides an estimate of how many steps have been taken. Analysis, also known as gait analysis can be evaluated via fused data from Inertial Measurement Unit (IMU) sensors on a smartphone.

Modern day positioning systems use PDR as positioning aids, typically in a hybrid framework, to augment other technologies. Kloch et al. (2011a) implemented a PDR positioning solution and found that when using PDR in isolation, the variance grows bigger as people are walking. They use Bluetooth LE to measure the distances between mobile users (frames of reference), in a cooperative fashion and use these distances to correct drift. When travelling in a car and entering a tunnel (when out of range of any satellites), most GPS devices use a dead reckoning algorithm based on the previous trajectory, along with the average speed of travel, to *'guestimate'* a position within the tunnel, correcting any errors when the car eventually exits. Modern day implementations of PDR use sensors such as accelerometers, gyroscopes, magnetometers and barometric altimeters on mobile devices to detect movement and\or orientation to help derive position.

2.9.8 Azimuth

A measurement that can be used to help ascertain position when moving is bearing, heading or azimuth. An azimuth is typically measured in degrees and denoted by the alpha 'α' symbol. It defines a straight line of the horizontal angular distance of a point, in a clockwise direction, from the xy plane of the local geodetic coordinate system (Chen and Guinness, 2014).

Geodetic North (true North) is typically used as a fixed reference plane, so East would have an azimuth of 90^0, while South would have an azimuth of 180^0. A Magnetometer is one of many sensors in a mobile phone that can be used to calculate an azimuth, as a measurement to estimate position. The magnetometer in a mobile device can detect the earth's Magnetic North, albeit with the understanding that Magnetic North is not the same as True North. Magnetic declination is the difference between True North and Magnetic North and can be mapped onto a mobile device's representation of North, to accurately reflect True or Geodetic North. In fact, magnetic declination can differ based on the position of the earth and needs to be updated at periodic intervals (Caruso, 1997).

Because magnetic fields can be interfered with by basically any ferrous material, this can have a dramatic effect on measurements obtained in the indoor environment. Here, any metal objects, such as furniture, or even a buildings infrastructure, can have a detrimental effect on measurements obtained (Mohri ,1984; Kendell and Lemaire, 2017). Gyroscopes are sensors that also come as standard equipment in modern mobile devices and can assist in achieving an azimuth. More particularly they can assist with the exact orientation of the device (Jie *et al.,* 2002; Johnson *et al.,* 2010; Ju *et al.,* 2014). Gyroscopes can provide the orientation of the device by measuring the pitch, roll and yaw of a device.

Augmented Reality (AR) applications typically require both the position of a device, as well as its orientation, to accurately depict what the user is seeing, relative to where they are at and the orientation of the device that is augmenting the world they are viewing. Understanding in which direction a visitor is facing in a gallery could define that they are looking at a vertical column of three paintings. Understanding the tilt of the mobile device could provide specific information relating to each painting in turn as the device pans down through them. Yaw is a measurement which is the value of the rotation against the Z axis. Roll is a measurement that is the value of the rotation against the X axis and Pitch is a measurement that is the value of the rotation relative to the Y axis. Each of these measurements, are measured in degrees of rotation and are analogous to the Pitch, Roll and Yaw of an aeroplane. It allows for the measurement of the position and orientation of a mobile device, through its centre of gravity, in a 3D space.

2.9.9 Altitude

A sensor that is included in the newest smartphones offers a novel manner to measure Altitude. A barometer is a device that is normally associated with Meteorologists estimating weather conditions. A rising air pressure reading generally forecasting good weather. However, the measurement that a barometer uses to forecast weather, can also be used to estimate altitude. A barometer measures atmospheric pressure, the weight or force of the earth's atmosphere which can vary at different heights. It is measured in Pascals and 1 Pascal is roughly around 14.696 pounds per square inch.

The average air pressure at sea level is 101.325 kPa. By measuring barometric pressure readings on a mobile device, the current height above sea level or altitude of the device can be gauged. There has been several attempts to solve the challenge of obtaining floor level accuracy in the indoor environment (Bai *et al.*, 2013; Moder *et al.*, 2014; Jeon *et al.*, 2015). It is a challenge that remains unsolved. The atmospheric pressure readings captured by a barometer, can therefore be used to help estimate position, especially within the indoor environment.

2.10 Position Estimation Algorithms

A position estimation algorithm uses ranging measurements as input, to help predict with as much accuracy as possible, a location. Two key components typically make up the estimation of the position of a Lost Device. First, range finding techniques as discussed in the previous section, are used to estimate the distance from the transmitting device(s) to the receiving device(s). This is calculated using a range measurement, for example the length of time it takes a signal to propagate the distance from the transmitter to the receiver (ToA).

The second component, the position estimation technique, uses range measurements with an estimation algorithm (mathematical formulae), to calculate the position of the Lost Device. An estimated position can fall into one of two categories, relative or absolute. A relative position is one that is expressed relative to another known frame of reference. For example, the position within the context of neighbouring devices, or the local environment. This could be the mobile devices position relative to an office\room door or a position on an *xy* plane relative to a given floor within a building. With absolute positioning, the position of the mobile device can be expressed relative to a geocentric coordinate system, providing an *x, y* and *z* position. In this situation the position achieved via the IPS would be mapped to global latitude, longitude and altitude coordinate values (Chen and Guinness, 2014). The following sections detail three such position estimation algorithms.

2.10.1 Triangulation

Scientist, Engineers and Navigators, have been using triangles to measure distance for some time. Triangulation is a geometric calculation, used to find a position based on angles to it from a priori positions, at either end of a line of known measurement. To explain this using a cooperative paradigm, consider a distant un-localised mobile device (Device X), which is within range of two other mobile devices Mobile Device A and B illustrated in Figure 2-7. Mobile Devices A and B have already been localised, using the in-house IPS and are separated by a known distance (length 'L'). The base angles from A and B to mobile device X, can be calculated using AoA measurements determined using AoA techniques. The location of the mobile device can then be derived from the intersection point of two lines, drawn at their respective angles from Mobile Devices A and B.

This could be further extended to provide a 3D position estimation, using the known point of a third Mobile Device C and the distances from it, to the other Mobile Devices (Mobile Device A and Mobile Device B), along with the AoA from it to the mobile device. This 3rd plane, could be used to calculate floor level within a building, and provide a specific geodetic *x,y,z* coordinate value within an IPS.

Triangulation uses the AoA estimation technique which provides an estimate of an angle in degrees.

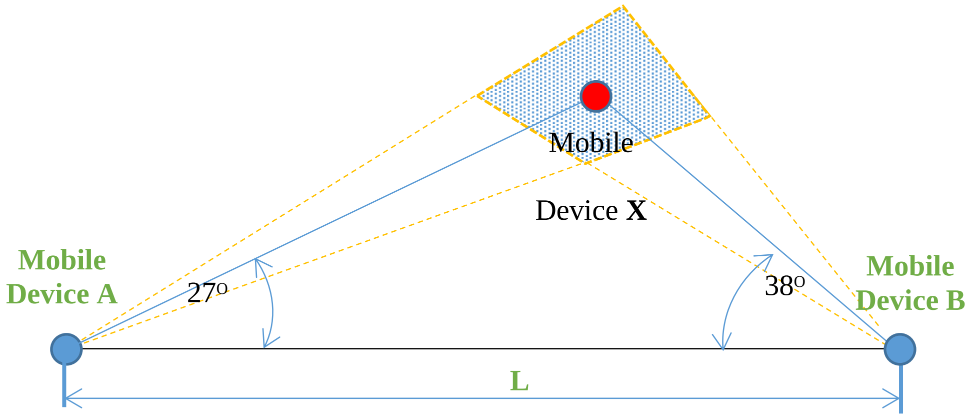


Figure 2-7: Calculating intersection for positioning

This technique, as described earlier provides an estimation of the angle from a reference frame, like all estimates it comes with a certain degree of accuracy. This level of accuracy is illustrated in Figure 2-7, in the shaded area as the error space with this solution.

2.10.2 Trilateration

Trilateration is a key component of the GPS position estimation technique. It is a process that can estimate the position of a mobile device, given the positions of at least three other objects and the distance from those objects to the mobile device. We can illustrate this using a cooperative localisation example. Take the basic scenario depicted in Figure 2-8(a) where the circle depicts the distance from Mobile Device X, to Mobile Device A. This distance would have been derived, using one of the ranging techniques - RSS, TDOA or RTT. All that can be known about the whereabouts of Mobile Device X is that it resides somewhere on the circumference of the circle that is constructed using the radius of the estimated range between Mobile Device X and Mobile Device A.

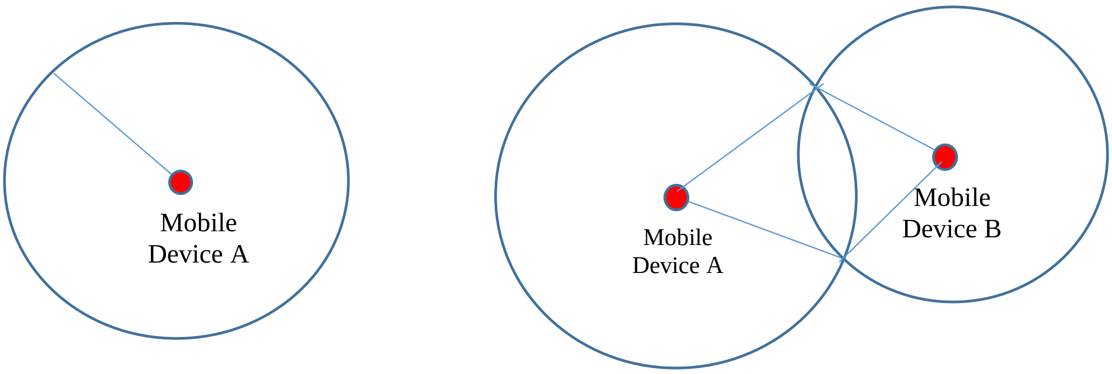


Figure 2-8: (a) Distance from A *(b) second mobile added*

A Second Mobile Device B will allow the position of X to be narrowed further, as can be seen in Figure 2-8(b). Now the range to X has been calculated relative to Mobile Device B. Therefore, considering X must be on the circumference of two circles, created from radii defined by the range estimate from Mobile Devices A and B to Mobile Device X, there are only 2 possible positions where X might be, at the intersections of these two circles.

To calculate the exact position of X, a third Mobile Device, Device C is required. When the distance from C to X is calculated, the distances from X to A and B are already known. It can then be determined that X, can only be at one specific position, to match those three particular distance estimations from Mobile Device's A, B and C – the intersections of the three circles. This can be seen in Figure 2-9.

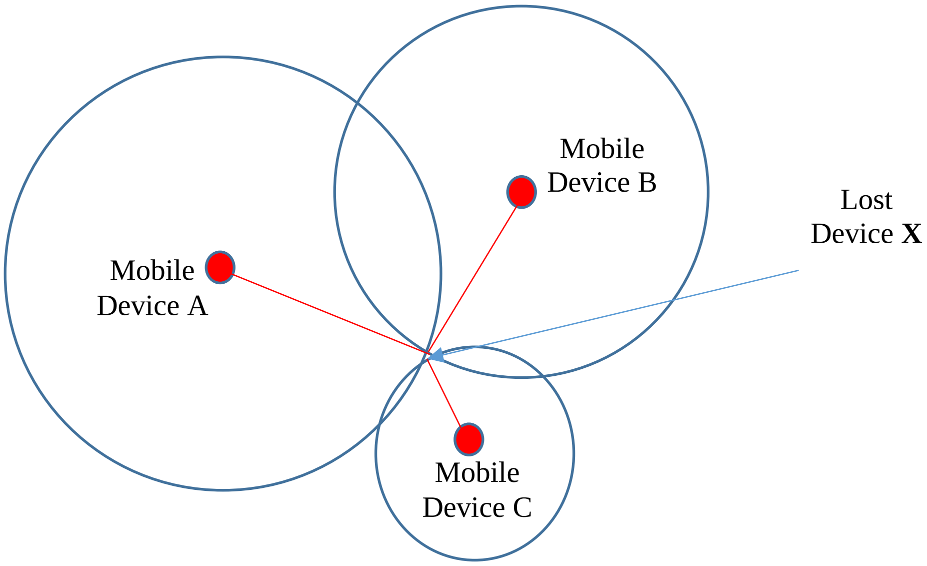


Figure 2-9: Trilateration example

Typically, using a standard IPS, a range-based position estimation algorithm requires multiple fixed reference devices that are within range of the *'lost'* device to localise. Given these algorithmic prerequisites, when there are not enough reference devices within range, a position fix cannot be established. Any number of the environmental obstacles that affect indoor positioning could cause this to happen. Here, a positioning solution can be implemented, to allow mobile devices act as reference devices, providing the required parameters for the algorithm. This illustrates how a positioning solution could be used to extend the range of an IPS, when it finds itself in these common scenarios.

2.11 Sources of Positioning Error

How RF waves behave as they travel through the atmosphere is known as radio propagation. Akin to any waveform travelling across a given media, radio waves are affected by different phenomena such as reflection, refraction, absorption, diffraction, polarisation and scattering. Each of these phenomena can have a detrimental effect on positioning errors when using the signals as measurements to estimate the range or direction of a signal.

Positioning errors in the indoor environment caused by these phenomena are non-trivial (Catedra *et al.,* 1998; Parsons, 2000; Akyildiz *et al.,* 2002; Rappaport, 2002; Rowe *et al.,* 2007; Yang *et al.,* 2009). Radio waves operating at different frequencies propagate in different ways, understanding the effects of radio propagation is fundamental when designing an IPS that will use measurement of transmitted signals as they are received by a device.

2.11.1 Reflection

When light (waves) hit a reflective object such as a mirror, the light is reflected off at an angle relative to the angle at which it struck the object. The same is true for radio waves. When an RF signal encounters a solid object, the signal either gets reflected, absorbed or both (Bashore, 2000).

When using any ranging techniques, reflection of a signal off walls, ceilings, floors or furniture can have a dramatic effect on the measurement achieved. If a positioning system were using RSS as shown in Figure 2-10, the RSS received would be dramatically different to what the true RSS should be. Here, Device B is using the RSS received from the transmission from Device A, to estimate the distance between the two devices.

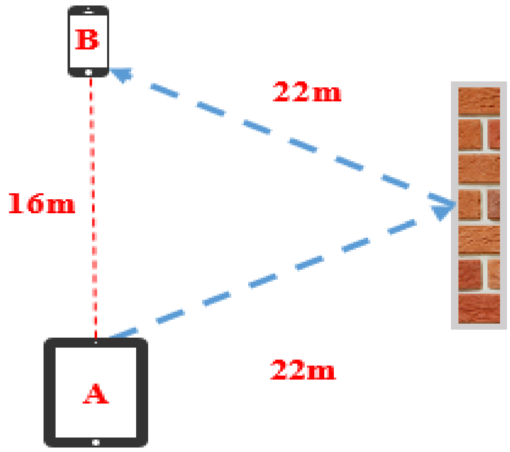


Figure 2-10: Reflection

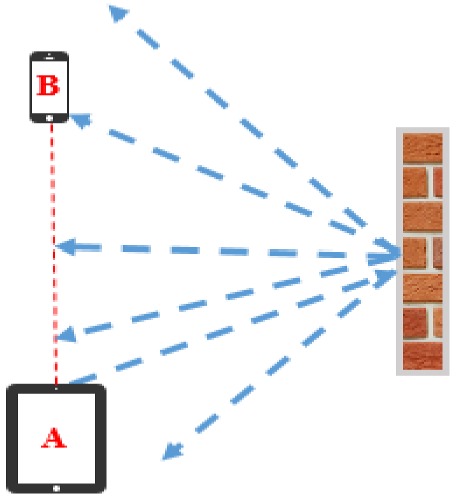


Figure 2-11: Scattering

The RSS value that should be received and should reflect the actual distance of 16 metres, between the two devices however the RSS that Device B is receiving is the signal strength measurement that has reflected off the wall. This results in a larger (more negative) RSS reading because the signal has bounced off the wall and effectively travelled 44-metres instead.

2.11.2 Scattering

Scattering, or scatter is defined as an RF signal reflecting in multiple directions when encountering an uneven surface (Coleman and Westcott, 2015). It is similar to reflection in that the signal bounces off an object or objects which can have a dramatic effect on errors when used to measure range, angle of arrival or time of flight. The effect of a scattered radio signal can be seen in Figure 2-11.

2.11.3 Refraction

To understand refraction, we can observe how light travels through glass or water when looking at an object in water. For instance, this could be a fishing rod dipped into a pond so that the part of the rod immersed in water can appear bent or skewed. This process is known as refraction and can affect radio waves in the same way it affects light waves. Refraction is the bending of an RF signal as it passes through a medium with a different density, thereby causing the direction of the wave to change (Coleman and Westcott, 2015).

As signals travel from transmitting satellites, refraction can occur as the signal enters the earth's atmosphere. In the indoor arena when a signal has to travel though an object, refraction can affect its measurement, be it time, range or angle based, as can be seen in Figure 2-12.

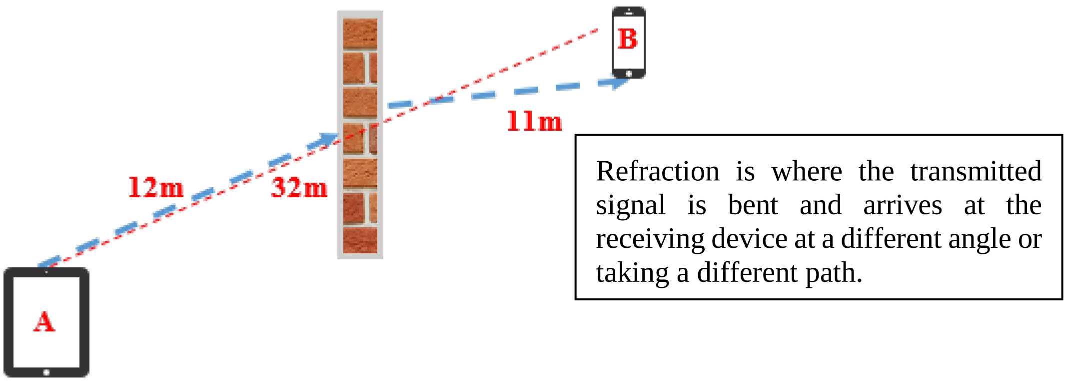


Figure 2-12: Refraction

When a signal is travelling through an object such as a wall, as in Figure 2-12, the signal is also affected by attenuation which can be a cause of large errors in Non-Line of Sight (NLoS) environments where LoS is a requirement (Guvenc and Chong, 2009). Attenuation is the reduction in signal strength, as a signal travels from a transmitting device, through the atmosphere to a receiving device. Therefore, when an RF signal travels through an object of which there are many in the indoor environment, its positioning measurement is affected by both the attenuated signal and the refraction on that signal, making NLoS positioning in the indoor arena a challenge which has not been adequately resolved.

2.11.4 Absorption – Path Loss

Attenuation is a factor of the absorption characteristics of the object or material that a radio signal is passing through. Signal attenuation which is measured in decibels (dB), can be evaluated using (4) where f is the transmission frequency expressed in MHz, d is the distance expressed in feet and n is the path loss exponent in dB:

$$\text{Path loss (approx)} = -38 + 20 * \log_{10}(f) + 10 * n * \log_{10}(d) \qquad (4)$$

f = transmission frequency (MHz)

d = distance (feet)

n = path loss exponent (dBs)

In a LoS environment the path loss exponent (n) is 2, when the signal is travelling through the air, but in NLoS environments, like most of an indoor environment, the path loss exponent is typically set to ($2.4 < n < 4$). This is because the different materials that a signal has to pass through in an indoor environment differ dramatically in the way that they absorb the energy from a radio signal. For example, a wall might cause 3-4 dBs of attenuation, whereas the same signal travelling through a shelf or bookcase might cause 1-2 dBs. By correctly modelling the environment the Path Loss equation can be used to estimate the distance (d) between a transmitting device and a receiving device.

2.11.5 Diffraction

Diffraction can occur on any waveform, such as light, sound, water and electromagnetic waves, such as radio waves. A rainbow occurring, because of light diffracting at different angles, to provide the colours is an example of diffraction in nature. A hologram is another example of light diffracting. When a radio signal encounters an obstacle or boundary, such as a corner in a hallway, it bends or diffracts around the corner, essentially filling in the shadow (McCune, 2010). This is similar to how a wave comes in to a harbour when the water waves spread out after they diffract through the harbour mouth. With particular reference to radio waves propagating in the indoor environment, this can have an effect on range estimates, time and angle measurements, received from a transmitted signal.

2.12 Performance Metrics

There are many ways to measure the effectiveness of a positioning system, such as precision, accuracy, complexity, robustness, cost and scalability (Hui *et al.,* 2007). Each of these metrics, offer a valuable insight, when assessing one technology over another within a specific environment. Performance metrics can also be used to set baselines to gauge a systems effectiveness during its lifetime.

2.12.1 Accuracy

One of the most important performance metrics when positioning is accuracy, especially when considering the impact on user experience. Accuracy is the closeness of agreement between a measured quantity value and a true quantity value of a measured (Balazs, 2008).

Very poor accuracy can dictate the range of suitable application for a particular solution. The accuracy of a given position estimate is a function of the average Euclidean distance, between the estimated position and its actual position. This is also known as the mean error or the positioning error. Accuracy is relative however, as some systems only need a coarse estimate such as determining the vicinity of a user within a region. Others require a finer, more precise level of accuracy.

Quite often a balance needs to be reached with accuracy and other performance metrics, such as complexity and cost, depending on the solution to be implemented**.**

2.12.2 Precision

The JCGM define measurement precision as a means to define measurement repeatability, intermediate measurement precision, and measurement reproducibility (Balazs, 2008). The precision of a positioning system is a measurement of how often a system is accurate, which is usually referenced as a percentage, to within a given distance. Precision can offer a probability of a technology or system being accurate, to within a certain bound of error.

A common way to represent this probability, when measuring the precision of a system is to use Cumulative Distribution Functions (CDFs) to equate the precision of one system over another. If a system can locate a device 970 times out of 1000 during tests, to within 3 metres of its true position, it can be said that that system has a location precision of 97% within 3 metres (CDF is 0.97 for a distance error of 3 metres).

2.12.3 Complexity

Understanding the complexity of an algorithm used to locate in a positioning system can be an important factor when considering whether to implement a centralised or decentralised model. A complex algorithm that takes a long time to estimate a position could indicate the need to locate it on a centralised server. This server could have the required resources, both hardware and software to achieve an optimum response time. Complexity can be difficult to quantify on any system. Time can be a good indicator of the complexity of an algorithm (Basili, 1980). The time it takes an algorithm to obtain a position fix can be a reasonable estimate of its complexity.

2.12.4 Robustness

Non-line-of-sight (NLoS) are radio transmissions through paths that are partially obstructed. This is typically as a result of a physical object in the innermost Fresnel zone. Radio signals depend to different degrees on LoS between a receiver & transmitter (Li *et al.*, 2015). Obstacles such as buildings, cars, trees and mountains can reflect, absorb or scramble the radio frequencies. Ultimately, they limit the use of certain types of radio transmissions. The lower the power level, the less likely is the chance of receiving a transmission successfully.

The robustness of a system is the capacity of that system to withstand a situation, where it does not receive adequate data to locate a device. A system for example might perform better than another system in a harsher radio environment, when using radio signals if this environment precluded accessing of an adequate radio signal due to NLoS by using mitigating techniques.

For example, an RSS based system that failed over to use PDR techniques when an adequate number ranging signals were not available, would offer a level of robustness above a system that would not be able to locate in those conditions. Robustness could also mean the durability of a systems infrastructure such as a system needing to locate in an environment that was subject to severely high or low temperatures. The capacity of such a system to return a location over a system that could not locate would define its robustness. These can be important factors when deciding which technology or system to use as a solution to the indoor positioning problem.

2.12.5 Scalability & Cost

Scalability is the capacity of a system to grow, with reference to the area covered by the IPS, or its ability to accommodate larger volume of devices or traffic, at a later stage (Farid *et al.*, 2013). Implications for scalability can relate to the wireless channel becoming congested, or an increase in the computational load on a device resolving a position estimation.

The total cost of a positioning system can be evaluated in many ways incorporating many associated factors, such as time costs (for installation) or capital costs for hardware and maintenance to keep the system functioning (Mautz, 2012). Cost can have mitigating factors, such as time, space, energy consumption and weight that need to be considered, when evaluating the performance of one solution over another. The time cost of a solution, is the time it costs to install, test and maintain a system. A solution using radio fingerprinting, for example, takes time to build and populate a database with radio signatures. This also requires time to be updated regularly during the lifetime of the system. If a system used tags that a user was required to carry around with them, then the weight and size of the tags, are important factors. If a device or tag is in an environment that does not have access to a power supply, then energy costs and consumption are important factors that need to be considered here.

2.13 Filtering Techniques for Location Estimation

Positioning of mobile devices within the indoor environment is fraught with difficulties and although ranging estimation techniques and positioning algorithms can alleviate some of those issues, they do not completely resolve them. Radio signals are notoriously inconsistent in the indoor arena, due to the reflection of the signal off objects or the refraction of the signal around corners – known as multipath. A signal can take multiple paths from a transmitting device, to a receiving device.

When gauging the range between two devices, the direct path is the only path that can be used to accurately estimate distance. All other signals that have taken alternative routes to the receiving device, bouncing or refracting off the many obstacles in the indoor environment, introduce errors. Environmental conditions can also have a bearing on a signal. For example, the number of people in the vicinity (Yang *et al.*, 2009) or air humidity conditions (Rowe *et al.*, 2007). Considering these variables create a randomness of the position estimation. Filtering techniques can be integrated into a location-based system, to refine estimations by filtering out estimation errors and improving the accuracy of positioning estimates.

2.13.1 Bayes Filters

Bayesian filtering is the most commonly implemented filtering technique used in localisation solutions and is used to estimate the chances of something happening, when provided with the likelihood of something else occurring. When related to cooperative localisation, Bayesian filters allow the measurement of the probability that the estimated position of a device is accurate. Considering the propensity for errors in any IPS, it is a fundamental aspect of any solution that the uncertainty in a given measurement must first be quantified. This can relate specifically to censoring of information from given devices, which is detailed in the following section.

The *'truth'* of a devices position can therefore be evaluated before an estimate of another devices' position relative to it are calculated. Considering the nomadic nature of mobile reference devices in cooperative localisation, the ability to minimise the propagation of estimation errors is a key ingredient to the development of a cooperative localisation algorithm. Howard et al. (2003) describe a cooperative method for relative localization of mobile robot teams, using Bayesian formalism with a particle filter implementation.

2.13.2 Kalman Filters

Kalman filters are one of the most popular types of Bayesian filter and one of the simpler to implement, requiring little processing power to execute. This is an important factor in any implementation, particularly a distributed architecture where the computation would be carried out on resource limited mobile devices. In (Zhang and Leonard, 2008) a cooperative Kalman filter for cooperative exploration uses a set of measurements monitored over a given period. These measurements contain some white noise (random variations), along with some additional imprecisions and produce estimations of unknown variables, which are found to be more accurate than estimates calculated using only one measurement. Kalman filters overcome these inaccuracies using Bayesian interference and estimating a joint probability distribution between the variables.

The Kalman filter is a specific application of Bayesian interference, which uses the Bayes Theorem. Bayes theorem is used in statistical analysis to describe the probability of an event happening based on prior knowledge of conditions relating to that event (Grossmann *et al.*, 2007). In a real-world example, the Bayes theorem could be used to measure temperature from somewhere that a thermometer could not be placed by monitoring its surrounding conditions.

The Kalman Filter is a recursive algorithm and it is considered computationally efficient as it only needs to store the previous state of the system to estimate the current system state. The original Kalman Filter modelled linear systems and observed statistical noise within these systems. It was primarily designed to be used in navigation and guidance systems (Welch and Bishop, 2006). It was used in the Apollo space program to reduce statistical noise, sensor noise and other inaccuracies within their navigation and guidance systems.

National Aeronautics and Space Administration (NASA) and the Ames Research Centre (ARC) worked together to extend the Kalman Filter for specific on-board Moon trajectory estimation calculations and since then many different versions of the extended Kalman filter have been developed (Grewal and Andrews, 2010; St-Pierre and Gingras, 2014; Deng *et al.*, 2015; Moore and Stouch, 2016).

Kalman Filters use a measurement model and a process model, in the form of matrices, to process the linear quadratic estimations. The measurement model consists of the system variables that are observed and measured over time, along with the measurement noise covariance matrix. The process model consists of a state transition matrix, a control input matrix, a process noise covariance matrix, an error covariance matrix and the system state.

Kalman Filters estimate the current state of the system using two main steps, predict and correct. The current state of the system is '*predicted'* based on the previous state of the system, which is stored in memory. Once the prediction has been processed and saved, the system variables must be measured. The system measurements are assumed to have noise and errors. As time passes and as the filter is given more data, the error covariance will converge on zero. In effect, the longer the filter is running on a set of data, the more it *'learns'* in terms of cancelling out statistical noise. This process of predicting and correcting can be repeated indefinitely depending on the size of the system and the number of variables involved.

2.13.3 Maximum Likelihood Estimation (MLE)

Maximum Likelihood Estimation (MLE), is a statistical technique used to address the issue of measurement ambiguity in localisation (Chen and Guinness, 2014). Given most range-based position estimation techniques require at least three reference devices during position estimation, the MLE method can be considered. It uses *n* reference devices to calculate the Lost Devices position (generally $n \geq 3$). Tian et al. (2009) use MLE to estimate the coordinates of *'lost'* devices for an Indoor WSN location-based system and an outdoor Global Navigation Satellite System (GNSS) location-based system respectively.

2.13.4 Least Squares Estimation

Least Squares is a statistical method used to solve mathematical equations that are otherwise unsolvable. The least squares method does not attempt to solve the unsolvable mathematical equations or functions, instead it estimates the MLE. The least squares method was developed cumulatively during the eighteenth century by astronomers and mathematicians. The primary motivation for developing this method came from the need to navigate around the globe more accurately and the need to calculate the orbits and positions of celestial bodies more accurately (Nievergelt, 2001).

The least squares method is a popular approach for determining regression equations from other mathematical functions. Instead of solving equations precisely, it estimates the best solution by minimizing the '*sum of the squares'* created by the mathematical functions. The least squares method can be applied to linear regression equations and with some added complexity, to non-linear regression equations. The least squares approach can be used in conjunction with "error-in-variables models" to account for known errors in the measurement model being used. The error-in-variables models are particularly useful for determining nonlinear least squares solutions where there are no alternative solutions available for the given data.

Implementing the least squares error-in-variables method for trilateration or triangulation will usually provide a more robust and less skewered measurement (Fantuzzi *et al.,* 2002; Ren *et al.*, 2015), despite measurement errors and other sources of statistical noise that may normally taint the data.

The examples detailed next examine both linear and non-linear applications of the least squares methods. A linear problem will be presented first, explaining the least squares method. The linear example will be followed by a non-linear example which closely models a real-world application of the least squares method. The use of an error-in-variable measurement model is demonstrated in the non-linear example to illustrate how the least squares method can benefit by using error-in-variable models.

Consider three lines as illustrated in Figure 2-13 where we want to find the intersecting point of all three lines. However, the intersection point we are trying to find does not exist because there is no place that all three lines intersect. This is a common problem in mathematics and it is considered more desirable to find a solution that is as close as possible, or an approximation, rather than getting no solution whatsoever.

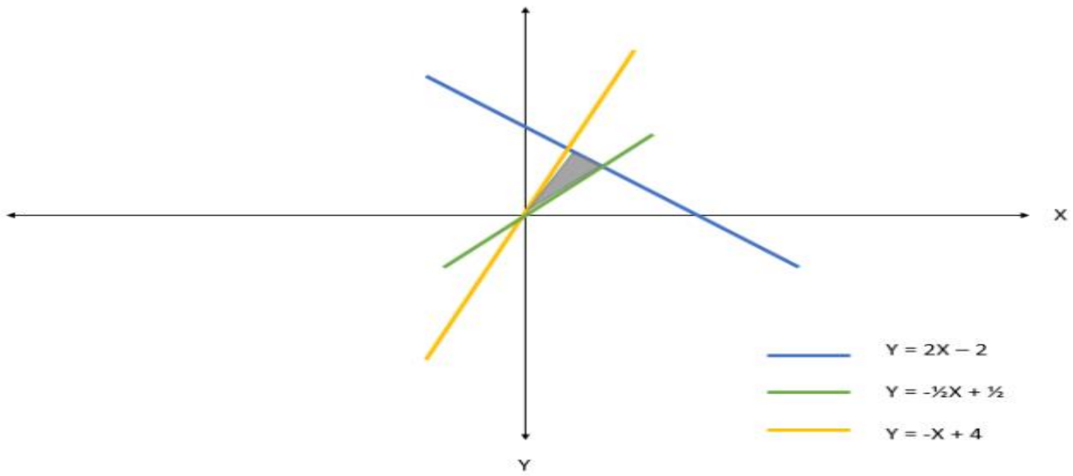


Figure 2-13: Linear regression equations represented graphically

The least squares method can be applied to these linear equations to find the '*closest'* possible solution to the problem. The solution will be the closest, in terms of distance, to the hypothetical intersecting point, even though the point itself does not exist. The least squares solution intersection point is guaranteed to lie within the shaded area between the three lines.

A similar method can be applied to non-linear regression equations i.e. curves or circles. When trilateration is used to position an object, three fixed points are used as reference points. The distance from each reference point to the object is measured or estimated and an imaginary circle or arc with a radius equal to the distance is drawn on the Cartesian plane. The intersecting point of at least three circles is needed to position a '*lost'* object, and if one of the measurements from the reference points is incorrect then the intersecting point will not exist as shown in Figure 2-14.

The least squares method can be used to find the '*maximum-likelihood'* solution to this problem. The least squares method is quite effective when applied to the non-linear problem as it will always return a definitive position for the lost object whereas using trilateration alone may not always yield an objects position.

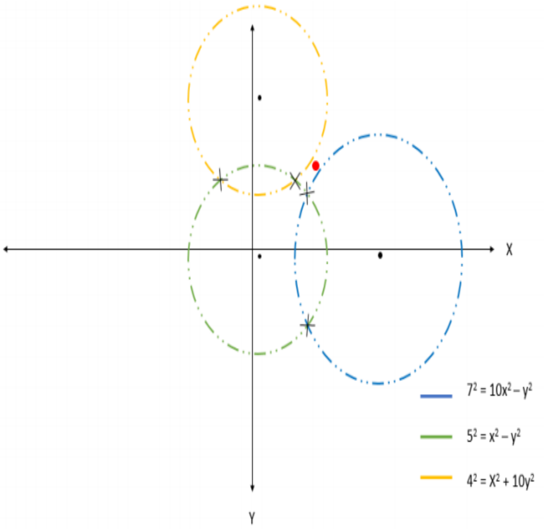


Figure 2-14: Non-linear regression equations represented graphically

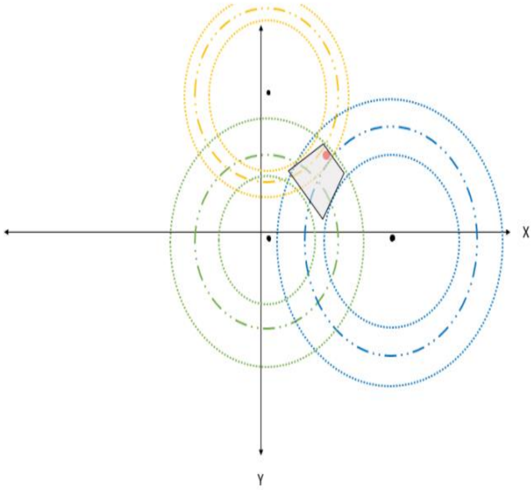


Figure 2-15: Error-in-variables model showing shaded "maximum-likelihood" area

The least squares method can be built upon to provide a more robust estimation of an objects position using error-in-variables measurement models. Let us assume that the error bounds of the reference points that are used for measuring the distance to the lost object are known, for example, plus or minus 1 metre. These known errors can be incorporated into the measurement model to widen the area *'sensed'* by the reference points. This is commonly known as an '*error-in-variables'* measurement model. This model will draw two imaginary circles for each reference point as illustrated in Figure 2-15.

The first (smaller) circle will have a radius equal to the measured distance minus the lower error limit and the second (bigger) circle will have a radius equal to the distance plus the upper error limit. The error-in-variables measurement model provides a '*maximum-likelihood*' area that the least squares method can be applied on to give an estimation of the actual position. When this model is applied to the least squares method, the estimation position of the object tends to be even closer to the actual position of the object than without using this model (Zhou, 2009).

2.13.5 Quantifying Error Bounds

When testing the efficiency of a positioning technique or algorithm, some method must exist to quantify the extent of errors that exists within the position estimate. Understanding this allows us to measure the effectiveness of one filtering technique over another. The Cramér Rao Bound (CRB) is one technique that can be used to evaluate this. It provides a lower bound on the variance achievable by any unbiased location estimator (Scholtz,1968).

In a simulated testing environment such as MatLab, Mobile Devices assisting the estimation of a Lost Device could be configured to have incorrect positioning information themselves and the results of the position estimates on a Lost Device could be quantified. It could be used as a baseline by designers of positioning algorithms that use RSS, ToA or AoA ranging techniques.

When testing an algorithm using a simulated environment, once the derived lower bound or baseline is nearly achieved, then benefits of continued tweaking of the algorithm are negligible. Given the lower bounds of the derived Cramér Rao, specific characteristics of localisation techniques can be assessed. For example, the behaviour of a cooperative localisation strategy in predefined scenarios can be evaluated relative to the deviations from the bounds.

2.14 Global Positioning System (GPS)

GPS is providing a global solution to outdoor positioning, although research is still on-going to further hone its precision and coverage (Hall *et al.,* 1996; Postorino *et al.*, 2006; Matta, 2000). Some of the current limitations of GPS coverage include the indoor arena. The attenuation of GPS signals as they propagate (Bossler *et al.,* 2010) from satellite to earth inhibit their capacity to penetrate buildings and building materials. This rule GPS negligible as an indoor positioning solution. Given that people spend most of their time in indoor situations, designers of IPSs have had to look at different ways to locate users in these GPS denied environments. This has inspired localisation research into using techniques such as sound (Priyantha *et al.,* 2000; Borriello *et al.,* 2005; Filonenko *et al.,* 2010), camera vision

(Comaniciu *et al.,* 2003) light (Want and Hopper, 1992; Scopigno *et al.,* 2015) radio waves (Bahl and Padmanabhan, 2000; Ekahau, 2016), inertial sensors (Rantakokko *et al.,* 2011) and barometers (Jacobson *et al.,* 2003).

There are however, some limitations to localisation technologies, these are somewhat insignificant in the outdoor arena. Natural obstacles such as trees, mountains and cavernous regions, can cause obstructions that rule certain technologies redundant in such terrains. Other man-made phenomena, such as the urban canyon effect (Spangenberg *et al.*, 2008; Xie and Petovello, 2015) can obscure access to signals which are fundamental to localising. An urban canyon, is an area where high rise buildings border roads on either side, mimicking a canyon-esc landscape. Skyscrapers in large metropolitan areas, can cloud large street areas and roads, inhibiting clear lines of sight to the skies above. Fortunately, these obstacles are few, in the grand scale of things and have not had a significant impact on the implementation of a positioning solution, outdoors.

2.15 Indoor Positioning Systems (IPS)

Spatially aware applications such as facilities management, risk management and the movement of people, have more recently been making inroads in the indoor arena. The need to accurately locate objects or persons in these spatially complex settings, is fundamental to the legitimacy of the information delivered by these applications. The development of accurate and robust positioning systems that will provide these precise positioning fixes of humans and objects in the indoor world, is therefore paramount to this requirement.

A study of 285 subjects uncovered that they spent over 80% of their time indoors during weekend days and over 85% on work days (Odeh and Hussein, 2016). A study conducted in Copenhagen found that people on average spent more than 90% of their day indoors. Indoor environments included the subjects' homes and workplaces but while the subjects were away from home, they were found to be more likely to be still inside in buildings, rather than outdoors (Bekö *et al.,* 2015).

The need for an indoor solution, considering the time expended by people in the indoor environment, is obvious. There are quite a few IPSs on the market with each of them espousing a more accurate, cheaper, efficient solution. Many of them use a wide variety of technological solutions implemented using a range of positioning techniques. We outline some of the more popular solutions available.

2.15.1 Ekahau

The Finnish Company Ekahau (2016) is a market leader in Wi-Fi positioning systems. Their proprietary Java based system contains three parts: (1) The Ekahau Positioning Engine (EPE), (2) the Ekahau Site Survey (ESS) and (3) the Ekahau tags. The EPE communicates with the mobile device's Wi-Fi chip and retrieves the RSS information and compares it to that gathered during site calibration, by the ESS. The EPE is a positioning server that provides the location coordinates (x, y, and floor) of the mobile terminal, or Wi-Fi tag. Ekahau are one of the pioneering companies in IPS and are one of the leading developers in Wi-Fi tools making enterprise level site survey tools.

2.15.2 Pole Star

Pole Star are a French company with offices in Paris, France and Los Altos, California and global headquarters in Toulouse. NAO Campus, the Pole Star IPS, uses a hybrid of technologies, Wi-Fi, GPS, BLE and Motion Sensors (MEMS) to track mobile devices on both the Android and iPhone platforms.

Some examples of indoor location services include delivering safety related information or other relevant information on public events like music concerts or sports events (Aloudat *et al.,* 2014). These applications are assisted in their development, with advances in mapping technologies such as Google Indoor Maps (Aly and Bouguet, 2012; Zheng *et al.,* 2012). Typical LBS applications include helping users navigate to the correct shop in a shopping centre or the correct room in a building. Modern-day Inventory Management requires the ability to quickly detect the location of products within a warehouse (Zhang *et al.,* 2014). The ability to push location-aware advertisements, invoicing or searching, provide a significant commercial worth (Hu *et al.,* 2015). Applications to help navigate a passenger at a train or bus station or airport to the correct platform, bus stop or departure gate can add significant value to the perceived intelligence of an application. The positioning provider can also assimilate important information when providing these services, through resource tracking (Teizer, 2015), fleet management (Lee *et al.*, 2014) and user statistics (Piwek *et al.*, 2016).

2.16 Indoor Positioning Challenges and Opportunities

Although a lot of the technologies and concepts used in the outdoor arena can be incorporated into an indoor solution, the indoor environment introduces significant challenges when locating devices. Some of the reasons for this are:

- The reflecting and refracting of signals from the obstacles that constitute the indoor space can result in serious multipath effects.
- The indoor infrastructure and day-to-day obstacles, combined with the need for horizontal connections make for very few LoS situations.
- The indoor infrastructure also affects the attenuation of signals and causes the diffraction of signals.
- Moving furniture, opening and closing doors/windows can result in spatiotemporal fluctuations.
- Due to the smaller spaces within an indoor environment, there is a greater need for accuracy.

There are however considerable benefits available when positioning within an indoor environment:

- There is a smaller coverage area in a building.
- Weather changes have a lesser impact, as do humidity changes, compared to the outdoors.
- Walls, corridors & rooms offer fixed geometric constraints, allowing a position estimate, to locate within those constraints.
- Most indoor environments provide seamless access to power supplies and data networks, along with walls and ceilings, to mount devices on.

- The smaller environment, typically means mobile devices are moving at a slower pace, making them easier to locate and/or update.

All these elements should be considered when attempting to design an indoor solution and the challenges are sometimes magnified when attempting to do this using a cooperative methodology.

2.17 Summary

This chapter focused on the need to estimate one's position in today's mobile computing environment. It began by introducing the concept of positioning and the techniques used with these technologies by man to navigate. This narrative continues describing the many technological advancements and tipping points that have occurred over the years in positioning, delivering the near global coverage that exists today. The limitations of this global coverage in the indoor environment was presented along with the obvious requirement for it. The different technologies and algorithms used to position were critiqued, along with some novel methods to enhance the accuracy levels with these. An overview of how to evaluate an IPS was described, as well as an insight into some of the sources of positioning errors when positioning indoors. The chapter concluded with an overview of some IPSs and mobile applications that use them.

3 Cooperative Positioning

Chapter 2 offered an insight into the concept of positioning, covering aspects of positioning in both the outdoor and indoor arenas. This chapter begins to narrow the emphasis further, covering the cooperative positioning paradigm. It begins by describing some of the different devices that can be used in a cooperative system. Some common issues with positioning coverage are highlighted, whilst explaining some problems with the authenticity of positioning information from cooperative devices. The chapter concludes by describing some scenarios where a cooperative positioning can locate in key situations.

3.1 Cooperative Devices

The indoor location problem has been present for many years and has motivated a considerable amount of research into discovering a solution. Cooperative solutions provide a significant contribution to this research. Cooperation among devices to self-locate requires one key prerequisite - there must be an adequate number of devices willing to assist in locating a Lost Device. The proliferation of tablet devices and Smartphones, fully-loaded with a myriad of on-board sensors, somewhat addresses this need. The advent of the Internet of Things (IoTs) however, providing access to 100's of billions of devices (Kortuem *et al.*, 2010) offers an even more fertile community of wirelessly connected smart objects in a connectivity ecosystem.

The pace of innovation of wearable computing coupled with falling costs, mirrored in the consumer interest in Smart Watches, offers no sense of a drop-off in access to these collaborative devices. Indeed, the requirement for nomadic wearable devices to be locatable, further exacerbates the requirement for an expansive solution to accurately locate in all areas of an indoor environment. Devices such as these, were typically not designed with wireless network functionality to merely assist in locating other devices. Re-harnessing this technology, albeit a great reuse of an existing technology, does however, highlight a secondary issue. The question is whether these network connected devices can realistically be expected to disconnect from that network and to connect in a Peer to Peer network, so that they can cooperatively assist in locating Lost Devices. Wi-Fi Direct offers the ability to be in both Ad-Hoc Mode and Infrastructure Mode simultaneously (Alliance, 2010). Bluetooth LE allows the Wi-Fi chip to remain connected to the network whilst transmitting. Therefore, using cooperative positioning to extend the range of an IPS using Wi-Fi Direct and Bluetooth LE capable devices allows users to remain connected to their network, whilst cooperatively assisting in locating other devices they can *'sense'*.

The more devices used that can exploit position information, the more LBSs and applications have a fundamental reliance on the accuracy and coverage of this positioning information. Examples of these include navigation and path finding applications, image geotagging, friend finder apps, location-based advertising and marketing.

3.2 Indoor Positioning Coverage

Generally, IPS implementations can be grouped as either exogenous or endogenous, depending on the available infrastructure that can be employed to establish location information. An exogenous infrastructure implementation is typically designed from the ground up as an IPS system. An endogenous solution however consists of infrastructure that has not been installed primarily for positioning.

Currently, one of the most popular techniques to locate devices in the indoor environment is to utilise the preinstalled wireless infrastructure, which is used to provide network access for mobile devices. Typically, good system implementations are those that achieve an appropriate balance between requirements, technological advances and costs. Whilst utilising an existing infrastructure such as this offers many noble qualities, not least the reduced costs in procuring equipment to implement a solution, it does introduce some challenges. The decision process behind the strategic positioning of such equipment to provide mobile network coverage, does not fulfil the requirements of an IPS to locate devices. Therefore, it is inevitable that blind spots should exist where devices that need to be located cannot be *'sensed'*, by an adequate proportion of the Wi-Fi infrastructure. When determining the location of Wi-Fi equipment such as WAPs, the typical focus of network designers was to provide the highest available throughput to the largest congregations of wireless network users, at key areas within the building. The ability to locate devices within that environment was not necessarily to the fore in their decision process, leaving gaping holes in terms of coverage in some of the IPSs currently in-place. This, coupled with some of the architectural barriers to the positioning of WAPs within a building's infrastructure, would suggest a solution to this issue is not something that is achievable in the short term.

To measure the extent of this coverage issue, a walk-through site survey of the Wi-Fi infrastructure in the main building on the campus at Letterkenny Institute of Technology (LyIT) was completed during the Spring of 2015, using the Ekahau Site Survey (ESS) (Ekahau, 2016) and Wi-Fi Planner. This allowed the network to be analysed for both connectivity and performance, highlighting issues of location blind spots within the college campus. The Ekahau Site Survey 8.0 (ESS 8.0) system was applied to perform a Throughput Site Survey (TSS). The TSS measures throughput, as well as jitter and packet loss, to evaluate the performance of a wireless network at given locations. The site survey assimilates information from the network infrastructure at a given area, describing how the network performs in that particular section of the building. ESS typically functions by assisting with the design of new Wi-Fi networks, as well as troubleshooting issues with existing Wi-Fi implementations. It uses different measurements to evaluate various aspects of the Wi-Fi networks infrastructure and generates maps that illustrate its performance. It also measures Wi-Fi range alongside Data Transfer Rates, Level of Interference\Noise, Signal Strength, Signal to Noise Ratio, Strongest Access Points and Ping Round Trip Time. These can then be analysed to evaluate the suitability of a certain area of a building, to provide a given level of service for a specified technology. For example, tests can be implemented and evaluated to highlight Wi-Fi blackspots or areas with low coverage or high levels of contention. The system generates a heat map of the surveyed area to illustrate coverage issues.

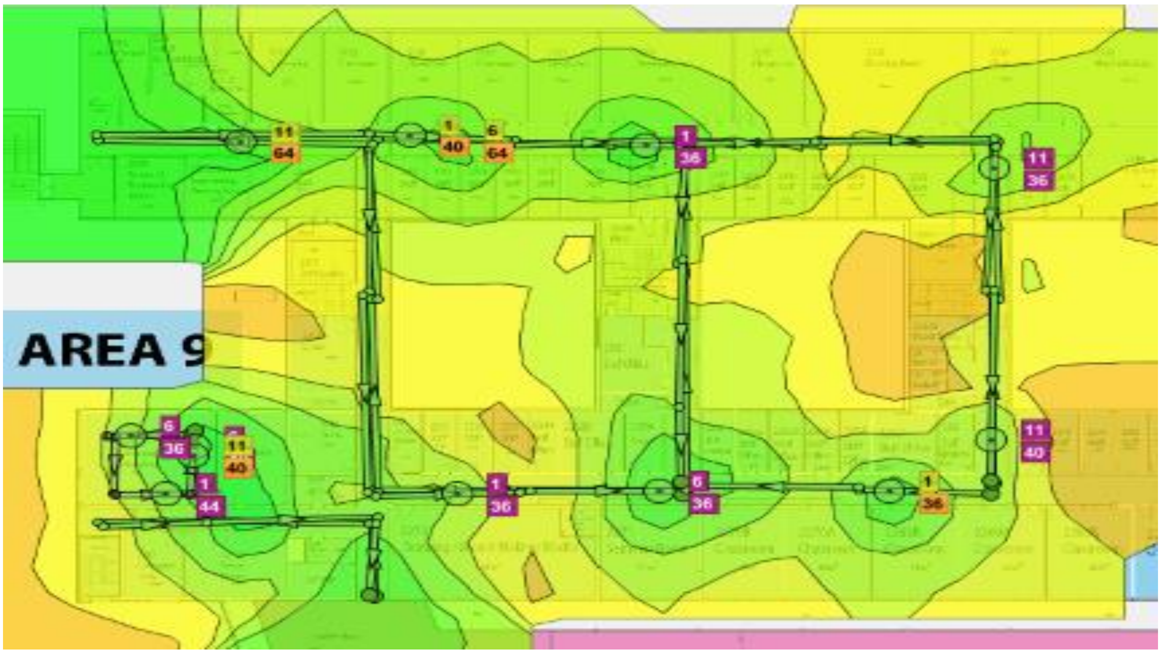


Figure 3-1: Infrastructures capacity to provide Wi-Fi Connectivity

An interesting facet of the ESS application, is its ability to configure the output and to measure the Wi-Fi connectivity capacity of a given area within a predefined infrastructure. Simultaneously, it can measure the capacity of that same area's infrastructure to position devices within that surveyed section. Therefore, the capacity of a currently installed infrastructure can clearly be identified in any area within a building, to effectively locate a mobile device. Figure 3-1 displays the sample area, which was the second floor of the West Wing of LyIT Letterkenny Campus. It illustrates the infrastructure's capacity to provide optimal connectivity to mobile devices within a Wi-Fi network.

The areas highlighted in green in Figure 3-1 illustrate the areas that offer the best connectivity for Wi-Fi. It uses Wi-Fi range, Data Transfer Rates, Level of Interference\Noise, Signal Strength, Signal to Noise Ratio, Strongest Access Points and Ping Round Trip Time as inputs. The stronger orange colours highlight areas that would provide the worst coverage in that section of the building.

Figure 3-2: Infrastructures capacity to locate

Figure 3-2 is a heat map of the same area within the building, with precisely the same infrastructure. However, the ESS is this time measuring the infrastructures capacity to locate devices within this area. Green areas on the map signify areas where there is adequate infrastructure to accurately locate devices. The darker areas highlight zones where the current infrastructure does not have the capacity to accurately locate. As can be appreciated, large areas on the map cannot be utilised to adequately locate devices in this section of the building. The difficulties that can be encountered when attempting to implement an IPS by means of an endogenous infrastructure, are graphically depicted in these images. Whilst utilising an existing infrastructure such as this offers many benefits, such as the reduced costs in procuring equipment to implement an IPS solution, the problems are obvious. Moreover, it emphasises the hypothesis of this research and the necessity for a solution to extend coverage into un-locatable areas of a network.

Cooperative devices within a cooperative system, positioned at the edges of these green areas, would already be located with the current IPS. Where these cooperative devices could access (or 'see *into'*) these black areas on the map in Figure 3-2, they could assist in locating devices within that area, this results in the extension of the reach of the IPS beyond its regular capacity.

3.3 Device Censoring in Cooperative Positioning

One of the most obvious difficulties with implementing a system that utilises information from other devices, is validating the authenticity, or measuring the *'truth'*, of that received information. If a device that is being used to position '*thinks'* that its real position is 2 metres from where it is, then its estimate of another position relative to it, is going to be out by at least 2 metres. This is especially relevant in cooperative localisation. In a standard IPS, the reference devices are generally fixed, and their positions are derived using some sort of fixed measurements making them very accurate. For example, a WAP could be positioned by physically measuring its distance from other *'known'* reference frames within the building, its distance along a wall or height above a door. With cooperative localisation however, the reference devices are located by the IPS, which may have introduced errors. If this estimated position of a mobile device is used to obtain the location of other devices within their range, it can propagate its accumulated errors in the estimation of the position of the Lost Device. Moreover, employing mobile devices, which as their name would imply are nomadic in nature, the position they last received from the IPS may be old.

When implementing cooperative positioning in dense networks, reference devices can accumulate positioning information from multiple devices. Node censoring schemes have been investigated by Wymeersch et al. (2009) where they consider different censoring schemes, based on the calculated Cramér Rao Bound (CRB). The CRB provides a lower bound on the variance achievable by any unbiased location estimator (Scholtz, 1968). They propose a method to estimate both transmit and receive censoring. This method provides a dual purpose, in that it can prevent the transmission of incorrect range estimations, which in turn can avert the miscalculation of a devices position. Furthermore, because the reliability of the estimate is calculated before transmission, it also prevents the communications overhead of that incorrect measurement being broadcast.

Consider the example in Figure 3-3 the Lost Device X can be '*sensed'* by 5 different devices each of which can cooperate to position it. The position of each of these cooperating devices was estimated by a positioning system which introduced a certain amount of errors into each position estimate. Mobile Device A has a positioning error of 0.5-metres, see Table 3-1, which is illustrated by the red circle in Figure 3-3. Because Mobile Device A is being used as a reference frame, its estimated position is also used to help position X. Therefore, the positioning error of Mobile Device A is added to the cooperatively estimated range between it and Lost Device X. Mobile Device E has a positioning error of 5.5-metres, which could add in a range estimate error of 5.5-metres between it and Lost Device X, Range E-X in Figure 3-3.

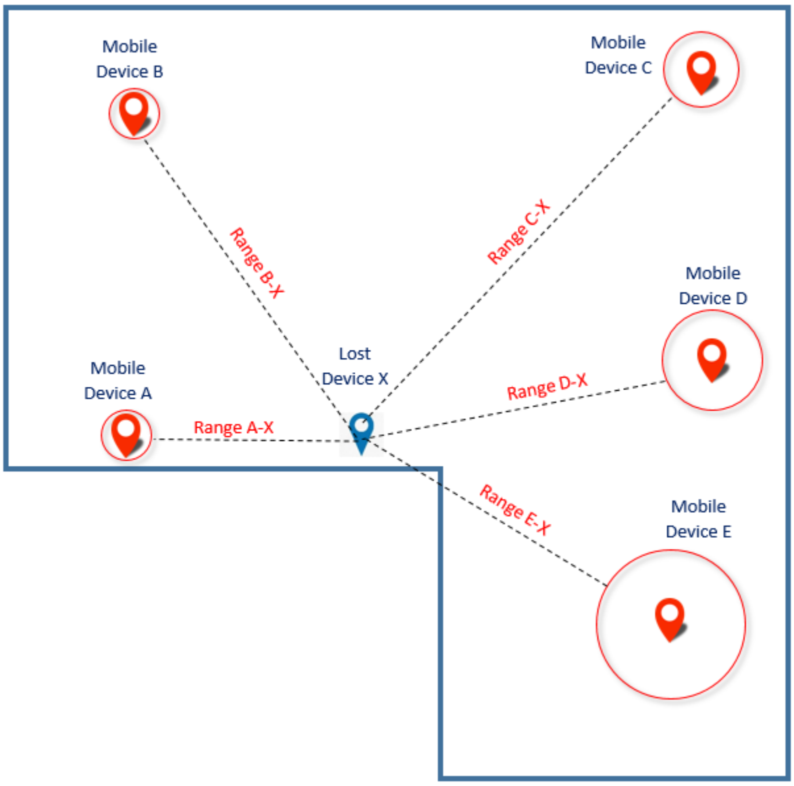


Figure 3-3: Device Censoring

If this error rate is known, as in (Wymeersch *et al.*, 2009) and can be measured using the CRB, then the devices with a more accurate position estimate or lower CRB can be used to position Lost Device X, thereby minimising the propagation of previously accrued positioning errors. In the scenario depicted in Figure 3-3 this could mean disregarding the information from Mobile Devices D and E and only using Mobile Devices A, B and C to cooperatively position Lost Device X.

Mobile Device	Positioning Error
Device A	0.5 m
Device B	0.5 m
Device C	0.75 m
Device D	2.25m
Device E	5.5m

Table 3-1: Propagation of Range Errors

Implementing a device censoring scheme can also preserve bandwidth and prevent positioning latency, whilst alleviating any computational overhead on the receiving device to estimate reliability. Hadzic and Rodriguez (2011) also advocate the reduction of error propagation in cooperative localisation. They propose a distributed reference device selection strategy, based on utility functions, specifically for Multilateration based position estimation algorithms. They suggest an algorithm for the discarding of unreliable links and analyse the Cramér Rao Lower Bound (CRLB) of positioning errors. The ability to calculate the truth about a reference device's known position is important to the success of any cooperative positioning system.

3.4 Cooperative Positioning Scenarios

To describe the use of cooperative positioning in operation, consider the following scenario - 'Bob' is sitting at the far end of the airport lounge, reading his newspaper on his tablet and is considering ordering food. He has availed of the free Wi-Fi offered at the airport and can view online that his flight is due to leave on time. Bob has been to this airport before but is unfamiliar with the time it should take to get to his specific departure gate for this flight, or in which zone he must go to pass security. The airport's IPS could assist with this, but he only has visibility of one WAP. This fact is illustrated in Figure 3-4, where Bob can be seen connected to WAP 4.

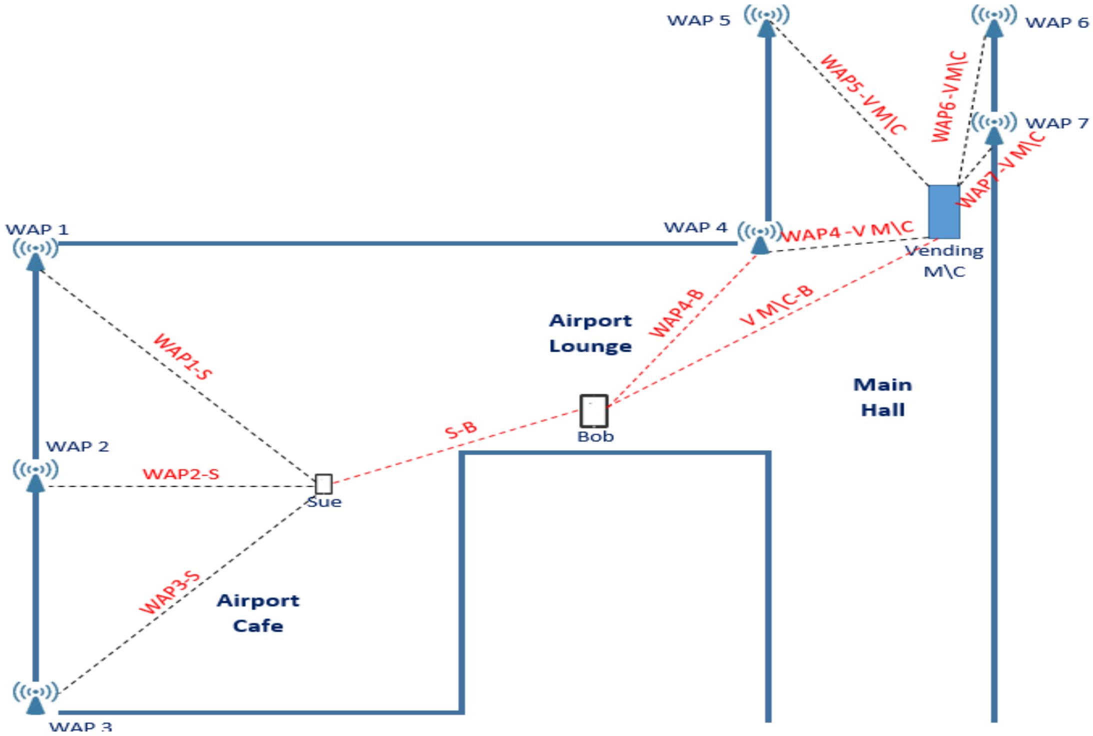


Figure 3-4: Bob's Airport Scenario

This provides a robust network connection; however, it is incapable of positioning Bob within the airport. Sue is in the airport café, some 45-metres (S-B) to the West of Bob. Sue's phone can be '*sensed'* by three different WAPs (WAPs 1, 2 and 3) within the airport's network and can be located to within two metres of her current position, via the in-house IPS. Sue's phone can also '*sense'* Bob's tablet. The drinks vending machine in the main hall is 25-metres to the North of Bob, the right-hand top corner of Figure 3-4. Due to its location in the main hall, it has access to four WAPs (WAPs 4, 5, 6 and 7) that are utilised in the airport's IPS. This smart device also has a wireless Network Interface Card (NIC), allowing it to connect to the airport inventory system, providing minute-by-minute updates on its current stock levels.

However, more importantly, it is positioned within the networks IPS. The 25-metre distance (V m\c-B) to Bob's tablet is a simple hop, well within its read range. In a normal scenario, Bob would be beyond the range of the airport's IPS, but because a properly designed cooperative positioning solution can utilise the known positions of Sue's phone, the drinks vending machine and WAP 4, Bob can be positioned. The Cooperative Positioning solution acquires these devices that know their position and estimates range distances from Bob's Lost Device, to them. These range estimates are then placed into a positioning algorithm, to position Bob within the airport. The cooperative positioning system provides a position estimate relative to the devices locating it, which can then be mapped onto a global overview of the airport IPS. Bob can now see that he is 15 minutes from the departure gate. He is advised to go via the security area just behind the lounge. Bob orders the duck, all is good.

There are other specific scenarios that a cooperative positioning system can explicitly assist in the location of devices when the Lost Device is beyond the range of the in-situ IPS or the IPS does not have enough positioning infrastructure. Some examples of these situations are presented here.

3.4.1 Scenario 1: Not enough fixed reference points to accurately position

In a standard IPS, a specified amount of fixed reference devices that know their location, are generally required to accurately locate *'lost'* devices, depending on the positioning technique used. If the situation exists, whereby not enough devices can '*sense'* the Lost Device, a mobile device could be used to act as a form of proxy reference device, to assist in the positioning of the Lost Device. In this scenario, a cooperating device that is implementing the cooperative positioning system application, would relay information to the Lost Device.

Figure 3-5 illustrates this scenario. Lost Device X is in the stairwell of the building, Fixed Reference Devices N and O can '*sense'* Lost Device X. If these reference devices were only to provide wireless network coverage, then Lost Device X would have ample connectivity to the network to do so. Positioning using these signals of opportunity can be troublesome when enough devices are not available. This hypothetical IPS uses trilateration to position; therefore, Fixed Reference Devices N and O do not provide enough information for the trilateration algorithm to obtain a position fix for Lost Device X. Mobile Device A is within view of three fixed reference devices (M, N &O) and can therefore be positioned accurately with the IPS. Mobile Device A can '*sense'* Lost Device X, via the transmission range of it's on board Wi-Fi chip. Mobile Device A can therefore provide the range information between itself and Lost Device X. Lost Device X can then use it along with the ranging information from Fixed Reference Devices N and O, to allow it to obtain a trilateration fix via a cooperative positioning system.

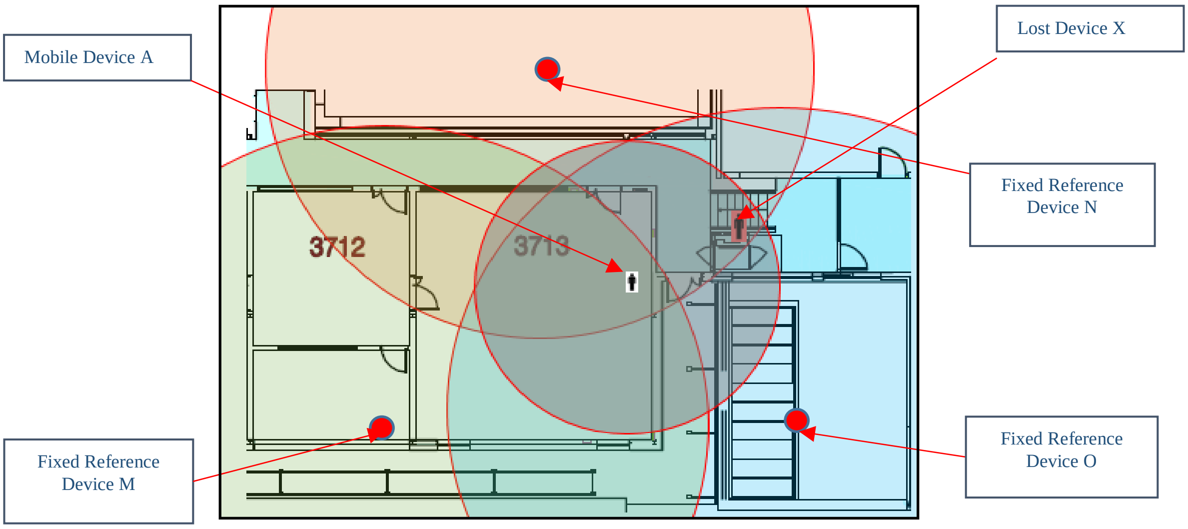


Figure 3-5: Scenario 1 Not enough fixed reference points

3.4.2 Scenario 2: Lost Device outside the building beyond the range of the IPS

In an endogenous IPS, the infrastructure used to position was not originally intended to do so as a primary function. The wireless network infrastructure is exploited in a somewhat opportunistic fashion, to position. Since the infrastructure was not designed primarily for that purpose, situations often arise that limit the capacity to position in given situations. Network designers would not have been concerned with providing wireless access to the network such as to someone on the outside of a building. Indeed, they may even have deliberately done so as a security precaution. On the other hand, it may be important for a location-based application or service to know that someone or some object is close to the building, in a business's carpark, smoking area, or some other area just outside the building. In this scenario, mobile devices at the outer extremities of a building's IPS, that have already been located, can be used to locate devices outside the network/building, offering the capacity to extend up to 200 metres into those areas.

A properly designed cooperative positioning system could utilise mobile reference devices to determine the position of a specific Lost Device. In doing so, it can extend the locating distances of an IPS by exploiting the existing mobile infrastructure, without the need for any further hardware. Figure 3-6 illustrates a building with an IPS strategically designed to cover as much of the 'L' shaped building as possible, given the range limitations of the devices used within it. The location of devices can be determined while they are within range of the APs, which make up the IPS positioning infrastructure so almost any device within the building can be located. The rectangle shaped balcony area, at the top of the map, is the one area of the building that is not covered by an AP. This is illustrated in it being the one area that is not concealed by the large circles, which denote the coverage areas of the IPS. Therefore, mobile device X which is out on the balcony cannot be positioned using the in-house IPS. Mobile device X will be referred to as the Lost Device, as it cannot obtain a positioning fix at this stage. Mobile device A and B are located at the outer reaches of the IPS and have already been localised. Mobile device A and B will therefore be referred to as reference device A and B.

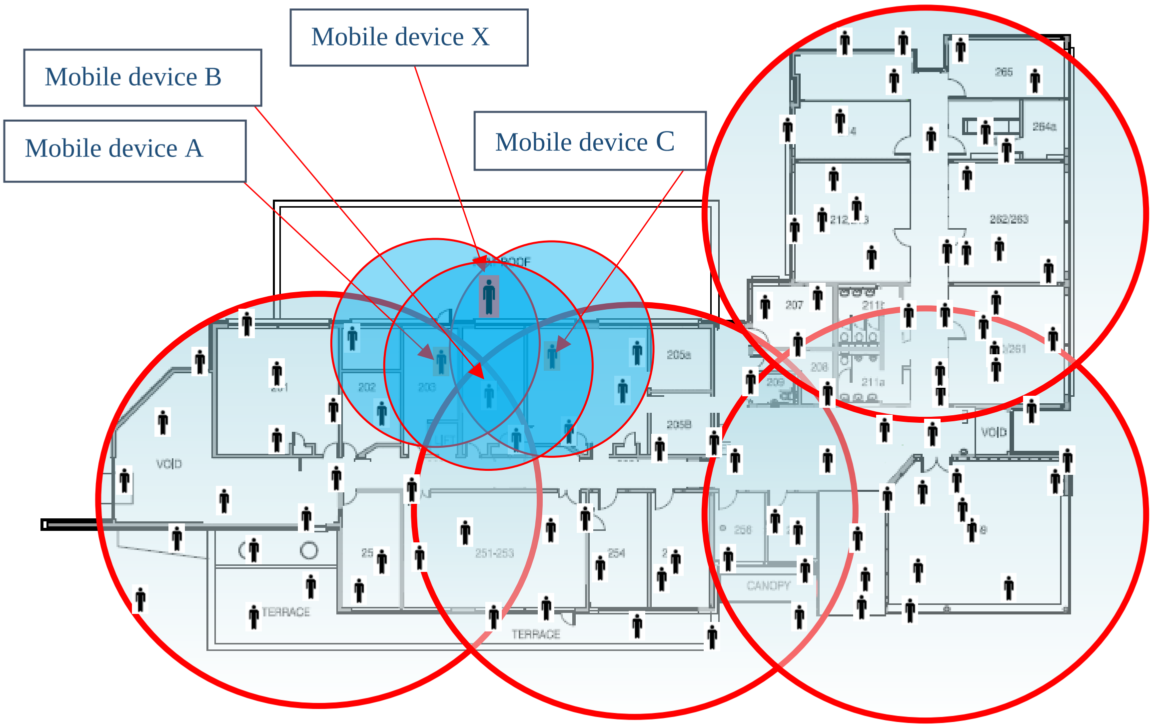


Figure 3-6: Building with WAPs showing coverage

The wireless network cards on reference devices A and B also have a range of signal and the Lost Device lies within that range. A coarse position fix can be estimated as the intersection of the two overlapping coverage ranges of the mobile devices A and B. A more granular location estimation of mobile device X can be achieved by incorporating a third mobile device, mobile device C to allow trilateration to achieve the intersection point of all three circles.

3.4.3 Scenario 3: Indoors, but beyond the range of the IPS

As illustrated earlier, positioning in an indoor environment as opposed to the outdoor environment is particularly challenging due to several fundamental factors.

- Errors are exacerbated due to multipath and NLoS conditions.
- Signals to and from satellites 22,000 km in space have almost a clear view of everything on the earth's surface.
- There is a high concentration of people moving within the environment that affect radio signals.
- A signal from a transmitting device to a receiving device in the indoor environment is mostly horizontal in its trajectory. It therefore has a higher propensity to propagate through people before accessing the mobile device. Both Wi-Fi and Bluetooth transmit within a radio frequency of 2.4 GHz, which is also the resonant frequency of water. As humans are almost 80% water, this can influence ranging estimates obtained via signal propagation (Rowe et al., 2007).
- There is a higher concentration of obstacles that impact on signal attenuation. The many walls, doors, ceilings, pillars and furniture that make up an indoor environment are not conducive to the accurate gauging of range using radio signals, modifying the propagation channel.
- There is a greater demand for precision, accuracy and yield in the indoor environment.

Given the aforementioned difficulties, blind spots can emerge within a building, created by obstacles that affect the propagation channel of radio signals, as described in the tests carried out in Section 3.2. Mobile devices within rooms, halls and offices, in the general vicinity of these blind spots, that have access to the wireless network and by default are a part of an IPS, can extend the range of the IPS into the blind spot, using a cooperative positioning system.

3.5 Summary

This chapter outlined the methodology of cooperative positioning, focusing on how a collaboration of resources could be utilised to provide a solution to the range issue present in indoor positioning. The chapter began by presenting this concept of cooperation or collaboration within the realms of computing per se, providing examples of cooperative devices. The problem of positioning coverage was also presented, describing specific experiments that were carried out which highlighted the coverage issues within the Wi-Fi network at LyIT.

This further illustrated the problems when employing an endogenous solution, which is one of the most popular solutions being adopted today. Some issues relating to the selection of mobile devices to assist in a cooperative positioning solution were also covered. The chapter concludes by providing specific scenarios where a cooperative positioning system could best provide a solution to the range issue in IPSs. These scenarios are further explored in Chapter 5, where they are replicated in live testbed environments. This allows the cooperative positioning system that provides a solution in these scenarios to be appropriately appraised.

4 CAPTURE Model & Implementation

In Chapter 3, an insight into the methodology of cooperative positioning was provided, outlining scenarios where this approach could be used to solve the range issue in indoor positioning. This chapter describes how this methodology was modelled and implemented within the CAPTURE framework. Mobile devices that could be utilised within this cooperative methodology are described here, along with some issues regarding the heterogeneity of mobile devices used to evaluate range. Live testbed environments were used throughout the implementation of CAPTURE, to best evaluate any future real-world implementation. A description of these are provided here also. These live testbeds were furthermore used to best emulate some of the scenarios where CAPTURE could be utilised most. The chapter begins by reinforcing the rationale of the CAPTURE system using the original hypothesis and research questions to do so. The CAPTURE algorithm used to position lost devices is also described.

The utilisation of devices to assist in a cooperative methodology with the location of unknown devices has been heavily researched in both the indoor and outdoor arenas (Patwari *et al.,* 2005; Shen *et al.,* 2010; Win *et al.,* 2011). This research has spanned all the technologies and techniques used to locate within these realms. The primary objective of this research has however, been focused on using this collaborative methodology to solve the problem of location accuracy.

Further honing of positioning accuracies to millimetre levels are primarily the focus of specialist systems. Autonomous devices in the indoor arena may, for example, require more accuracy to be able to navigate around obstacles that they cannot *'sense'*. People, on the other hand can be advised of their position and assisted with their navigation, but still retain their own *'on-board'* sensors that can be used to correct position estimates or directional advice offered by a navigation system or App. An App telling a user to turn right into a wall, where a door exists two feet beyond, can pose a problem for a robot, but can be swiftly corrected by a human. The combination of this cooperative methodology, applied to solving the problem of coverage in IPSs using off the shelf mobile devices, is not found in the literature, making our approach a unique contribution to research in this field. CAPTURE also has the built-in capacity to provide a pop-up, ad-hoc positioning system that could be used in emergency situations when parts of the existing positioning infrastructure have been damaged or where none exists.

The hypothesis of this thesis is that mobile devices at the extremities of an IPS, which have themselves already been located, can subsequently cooperate in the determination of the position of devices beyond the range of that IPS. This hypothesis leads to the following questions:

1 Can mobile devices be used to accurately measure range between devices?
2 What range can these mobile devices reach, i.e. how far can they possibly extend a system, and can these range estimates be used to then position devices?
3 Can a framework be designed to allow any device within an in-situ IPS, to cooperatively assist in the locating of other devices, effectively extending the range of the IPS?

4.1 Heterogeneity of Devices when Cooperating

Mobile devices used for cooperative positioning, are typically heterogeneous in nature, even when considering devices of exact or similar make and model. The heterogeneity exists, because of the diverse range of radios, antennas, and firmware on-board devices. This can lead to a divergence in range estimates between devices used to position, especially when capturing RF signals. For example, RSS estimates recorded on different devices, could vary at the same location. Lui et al. (2011) have shown that path loss readings when recorded with different devices can be inaccurate and recommend calibrating for each individual device. Considering the promiscuous nature of cooperating devices and the exploitation of the variety of devices available in the IoT world to help with cooperative positioning solutions, the challenge is evident. For a more detailed analysis of the effect of device diversity on RF signals, we refer further to the study of Park et al. (2011). Evaluating the divergent range estimates that can be introduced with different mobile devices, can help address the questions posed in the first and second research questions (RQ1 and RQ2).

2. What range can these mobile devices reach, i.e. how far can they possibly extend a system and can these range estimates be used to then position devices?

Device heterogeneity is a challenge for cooperative positioning implementations and the effects of this were evaluated in the tests on CAPTURE and are documented in Table 4-1.

Device	Wi-Fi Error	Bluetooth Error
HTC Desire Eye	1.05 m	5.01 m
HTC Desire 510	-2.07 m	1.66 m
Samsung Galaxy S4 Mini	7.62 m	4.35 m
Sony Xperia E5	0.22 m	-2.04 m
Motorola Moto G5	7.49 m	7.64 m
Samsung Galaxy Pocket Neo	7.54 m	0.42 m
Samsung Galaxy Mini	2.83 m	2.68 m
Apple iPhone 6	7.25 m	-1.52 m

Table 4-1: Device Heterogeneity

For this experiment all the devices used were mobile phones. Each of the phones were placed 5-metres away from the mobile device. RSS readings were recorded and used to evaluate a range estimate. These experiments were carried out on both the Bluetooth and Wi-Fi chips on each phone. The problem with the accuracy of range estimates is obvious, considering the array of ranging errors that were found during these tests. The Samsung Galaxy S4 Mini for example, was out by an error of 7.62 metres when tested with Wi-Fi and 4.35-metres with Bluetooth. During all further positioning tests with CAPTURE, beyond these specific heterogeneity tests, CAPTURE was calibrated to achieve an initial meter read. This meter read was then used as input to the CAPTURE ranging algorithm which helped overcome some of the issues with device heterogeneity.

4.2 CAPTURE Algorithm

CAPTURE was designed using a cooperative methodology, Figure 4-1 illustrates the overall conceptual view of the CAPTURE model. The positioning algorithm illustrated as a yellow box in the middle of the diagram was designed using this model. The reference devices on the left-hand side of the diagram provide the necessary (x, y) coordinate information of the three (or more) cooperating devices for the positioning algorithm. These are the mobile reference devices.

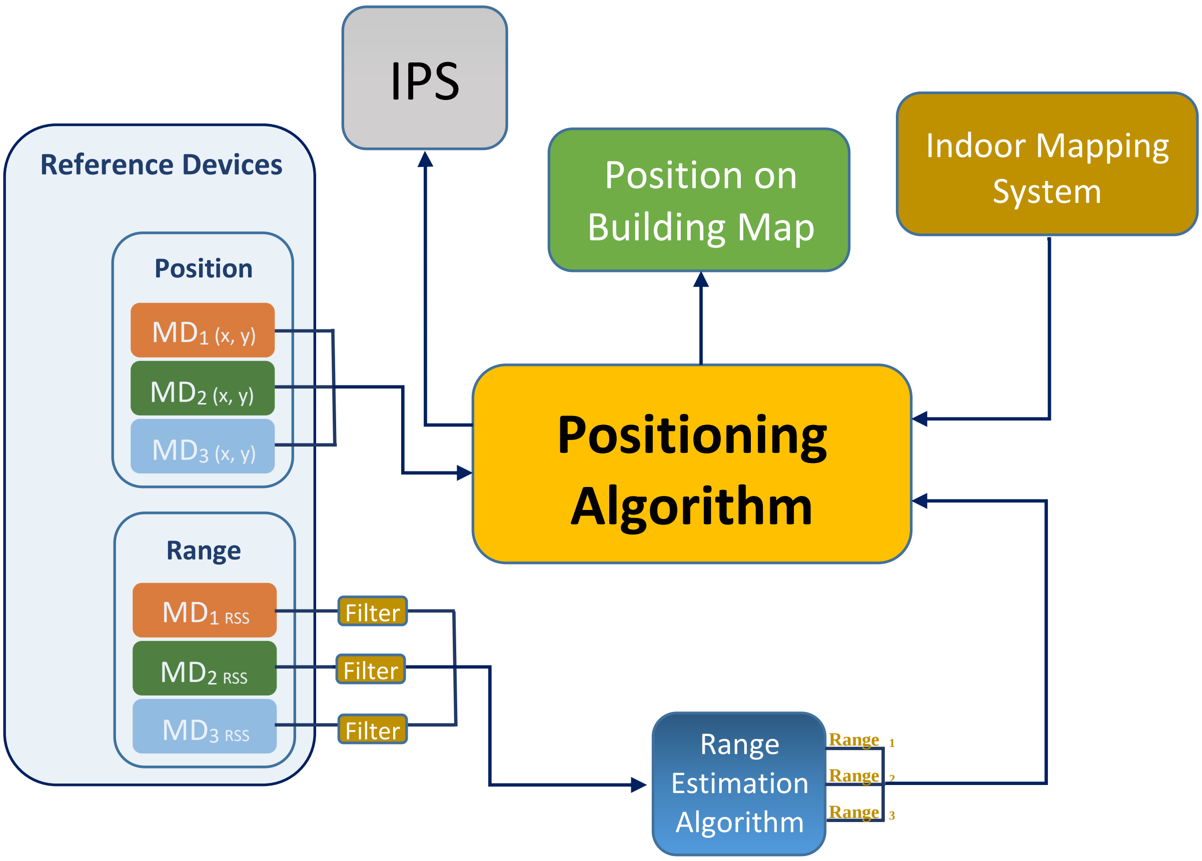


Figure 4-1: CAPTURE Conceptual Model

The signal strength recorded between these devices and the Lost Device ($MD_{1\ RSS}$, $MD_{2\ RSS}$ and $MD_{3\ RSS}$) are filtered before being evaluated in the range estimation algorithm. This filter removes any noise from the recorded signal strengths, smoothing the input to achieve a final signal strength value between each transmitting and receiving pair. The pseudocode for this filter can be seen in Appendix 1.3. The range estimation algorithm produces three (or more) range estimates which are used as input for the positioning algorithm. The range estimation algorithm is based on the path loss model and is further described in the pseudocode section in Appendix 1.3. The positioning algorithm, which is illustrated in Figure 4-2 takes the position (x, y) of each reference device.

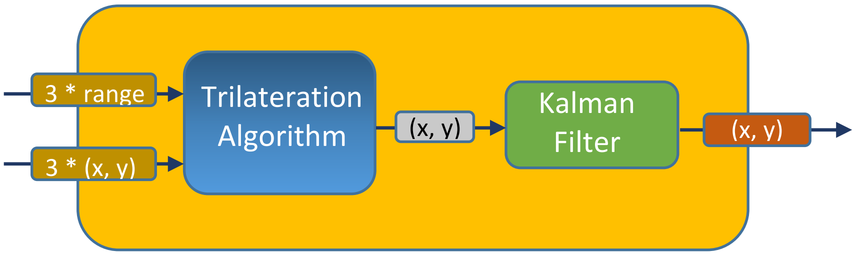


Figure 4-2: Positioning Algorithm

Each reference device supplies its position, obtained via the in-house IPS. These coordinate values are combined with the previously evaluated range estimate between each reference device and the Lost Device and used as input for the positioning algorithm. The trilateration function of the positioning algorithm then produces an x, y Cartesian coordinate position as output. This x, y output is then used as input for the Kalman filter function, before producing a final position fix of the Lost Device.

The specific Kalman filter implementation pseudocode is provided in Appendix 1.2. Using this final fix, a map of the corresponding area is then requested from the indoor mapping system, the (x, y) position of the Lost Device is then rendered (as a blue dot) onto the map, illustrating the position of the Lost Device to the user. The position of the Lost Device can also be relayed to the in-house IPS if required for tracking purposes.

4.3 CAPTURE Model

CAPTURE was initially designed to measure the capacity of two mobile devices to evaluate range. The only variable when attempting to position using trilateration is range. Defining how best to accurately evaluate range between mobile devices, was an important factor to consider before setting out to attempt to position thereafter. One way to measure range between two mobile devices is to use the strength of the radio signal as a means to then derive range. As a signal propagates through the air, it attenuates a rate that is inversely proportional to the square of the distance travelled which makes it a challenge to estimate range effectively using this method.

CAPTURE uses the `WifiManager` class in the Android class Library to retrieve the RSS values between two phones. The `WifiManager` API provides the main method for managing and configuring all aspects of Wi-Fi connectivity on an Android phone. CAPTURE then records these RSS values into a database. It records 20 RSS values per second, CAPTURE then aggregates these values to record an overall average value. These averages are then used in combination with a filter to remove any outliers. This filter is described in Appendix 1.3. Outliers can be caused by signal multipath effects described in Section 2.10 and can have a dramatic effect on range estimation, if not handled appropriately.

The database to record these RSS values was hosted locally on the mobile device itself. SQLite comes bundled on the Android OS and is an open source database that manages the data in text files on the device. Android provides APIs to access and manipulate data on the local database.

4.3.1 Range Estimation using Path Loss Model

The range estimation algorithm takes the newly aggregate RSS value and estimates range using the path loss model described in the following equation:

$$RSS = -(10n\,Log10\,(d) + A) \qquad (5)$$

where:

n: Path Loss Exponent

d: Distance from transmitting device

A: RSS at 1 metre distance

The path loss exponent can vary from 1.5 to 4, where 1.5 represents a LoS environment.

An RSS reading at 1 metre was established as -43.6316 dBm, after a survey of over 500 readings at various positions within the Sports hall testbed. This large sample of readings were recorded quickly at each location. During experiments it was noted that further readings had little to no effect on the calculated aggregated value. If a Wi-Fi signal is not available to help cooperate, CAPTURE will attempt to use the devices Bluetooth signal to position. It employs the same propagation model implemented with Wi-Fi to calculate range, recording the RSS of the Bluetooth signal transmitted between the devices. CAPTURE records the RSS between the two cooperating devices, taking five RSS readings every second. It then takes these twenty-five readings every five seconds and runs them through a simple filter to remove any outliers. This filter is described in the pseudocode section in Appendix 1.3. The average RSS reading is then used to ascertain range via the path loss model algorithm illustrated in (5).

When in Bluetooth mode, CAPTURE uses the same algorithm as Wi-Fi mode, apart from the number of recordings per second. Bluetooth connections have to be established between two devices before RSS readings can be parsed. This takes some time to set up and tear down these connections. The Bluetooth 1 metre range used as input for the path loss model was also different, registering at -66.82dBm, the path loss exponent was maintained at 1.5.

The testbed for these experiments when using Bluetooth mode were the hallways of the main campus at LyIT. Using the data received from two separate technologies via two distinct sensors allowed for the evaluation of a fusion of sensor data. Both technologies could be evaluated both in isolation and combined to better understand the benefits or drawbacks of each approach.

4.3.2 Positioning using Centroid and Trilateration Models

Another aspect of CAPTURE was an attempt to broaden the definition of mobile devices that could be utilised within its cooperative paradigm. This allowed us to investigate the capacity to use other devices, especially devices that could be categorised under the IoT umbrella. The capacity to incorporate such devices helped somewhat address the problem of having an adequate number of devices at any one time to assist in the cooperative positioning of other devices. Using Wi-Fi and\or Bluetooth RSS measurements merely allowed for the estimates of range between devices. To obtain a more detailed position fix, these range estimates had to be used with a positioning algorithm.

To properly measure the positioning capabilities of CAPTURE the main canteen area in LyIT was used. The canteen provided an optimal environment to position on a 2D plane, unlike the hallways that were used to evaluate the ranging capabilities of CAPTURE up to this stage. The canteen area was also the first NLoS testing environment used with CAPTURE. Initially a Centroid positioning algorithm was incorporated to evaluate a coarse position fix. This allowed for the addressing of the issues set out in: RQ3 "*Can a framework be designed to allow any device within an in-situ IPS, to cooperatively assist in the locating of other devices, effectively extending the range of the IPS?"*

Centroid Positioning is where devices position themselves to the centroid of their proximate reference points (Bulusu *et al.*, 2000; Blumenthal *et al.*, 2007). These centroids are generated by overlapping circles that can be created using the range estimations between the cooperating devices and the Lost Device as the radii of these circles. Clusters of cooperating devices would generate centroids and the position of the Lost Device could be estimated as the centre of these centroids.

The accuracy of such a positioning methodology is dependent on the accuracy of the range estimates, which in turn is dependent on the technology and range estimation technique used. One factor that could dramatically affect when positioning using centroids is the number of devices used to create the centroid. Two devices can sometimes result in a large centroid which would translate to a large positioning error. However, with the introduction of further devices, the size of the centroid could be reduced, having a direct correlation to the positioning error. Figure 4-3 illustrates the concept of positioning using centroids.

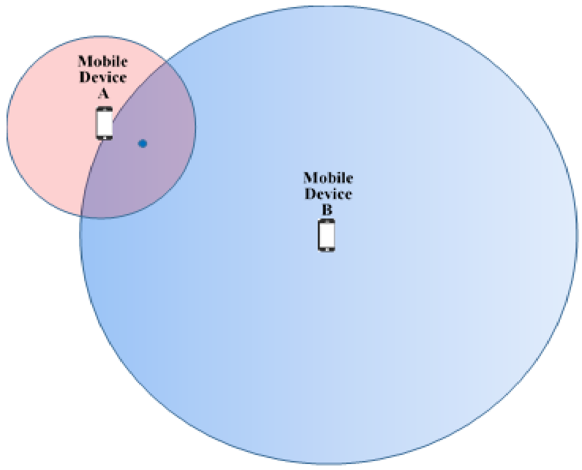


Figure 4-3: Centroid Positioning

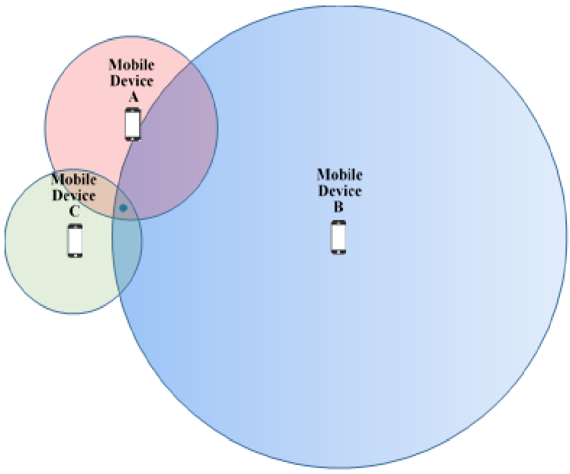


Figure 4-4: Centroid positioning with 3 devices

The red circle, of which Mobile Device A is at its centre, has a radius of the range estimate between it and the Lost Device. The blue circle, which has Mobile Device B at its centre has a radius of the range estimate between it and the Lost Device. The overlapping centroid area depicts the vicinity of the position of the Lost Device. By calculating the centre of the centroid, a coarse positioning estimate of the Lost Device can be determined. The introduction of a third device, Mobile Device C, along with its green circle illustrated in Figure 4-4, has a dramatic effect on the size of the centroid. The centre of this new centroid more accurately depicts the true position of the Lost Device. The addition of more reference devices could further enhance the positioning accuracy of this method.

Using this methodology of positioning using centroids, an implementation of CAPTURE was designed to utilise the known position of multiple reference devices and their respective range estimates to a Lost Device, to thereby determine the position of the Lost Device. The advancement of this methodology was further fuelled by the literature during this period which describes an IoTs that would deliver a plethora of devices to assist in cooperative positioning.

This provided a space to evaluate the implementation of the trilateration algorithm within CAPTURE. Trilateration positions using the intersecting points of circles whose radii are the range between two devices and requires the intersection points of three circles to do so. CAPTURE must therefore have visibility of at least three devices to allow it to position on a 2D plane because only with three devices can one single intersection point be defined. Each of the cooperating devices send their (x, y) coordinate information to the Lost Device.

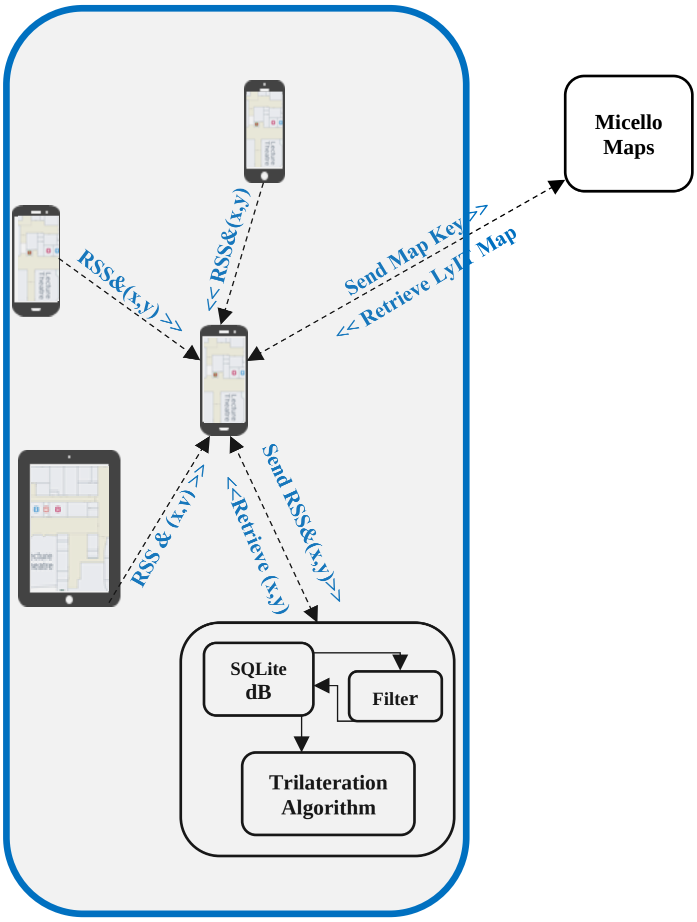


Figure 4-5: CAPTURE Model

The Lost Device takes each of the RSS values and filters them to remove any outliers before estimating the range between itself and the cooperating Device. It then takes these three parameters (range, x, y) and inputs them into the trilateration algorithm which then returns a position estimate. CAPTURE also incorporates a mapping system, which takes the estimated position of the Lost Device and displays its position as a blue dot on to a map of the LyIT building. It does this by sending an API key to Micello maps which then returns a HTML map of the campus

Micello is an indoor map guidance application for android and iOS platforms. It provides indoor maps and navigation data for places like shopping centres, airports, university campuses, hospitals, business venues, and conference centres. It uses electronic maps to convert floor plan images into interactive maps (Micello, 2018). The x, y coordinate position of the Lost Device is passed to a JavaScript function in the html map, which takes a blue dot .png file and renders it onto the map at that particular position.

4.4 CAPTURE Implementation

Implementations of CAPTURE were used to evaluate the feasibility, functionality and accuracy of CAPTURE, the results of which are detailed in Chapter 5. This also allowed CAPTURE to prove the overall thesis hypothesis and answer the resulting research questions. The initial implementation of CAPTURE used IEEE 802.11 signals to estimate range between mobile devices. These range estimates were originally used to gauge the accuracy levels of measuring distance between two devices using RSS measurements. This was implemented and tested in an experimental testbed in a Sports Hall which provided a 40m diagonal testing range providing LoS measurements for all tests. When implementing CAPTURE here, all users vacated the hall. This provided an optimal environment to use as a benchmark for future tests on future versions.

All the mobile devices used in the experiments were given a name (BSSID). CAPTURE then reads the RSS from all available reference points, i.e. all devices it can *'sense'*, but it filters out only the test phones used in the implementation. This is achieved via a lookup table mapping the MAC address of the mobile device to the mobile device name. This allows the use of only a specified mobile device or a group of mobile devices during any given implementation.

CAPTURE estimates range between two transmitting devices by using a path loss equation, described in (5). The recorded RSS readings are used as input for this algorithm along with a pre-recorded RSS reading at 1 metre and a path loss exponent to calibrate for the environment.

A good equation modelling the environment in which experiments are to be deployed is essential to ensure the accuracy of position estimates. After initial pre-tests were evaluated, a path loss exponent of 1.5 was determined for the sports hall test environment. To obtain the pre-recorded RSS reading at 1 metre, 500 readings were recorded at various locations throughout the hall, as can be seen in Figure 4-6 these readings are documented in Appendix 2.2. The readings were smoothed with a filter to remove any outliers before an average was calculated.

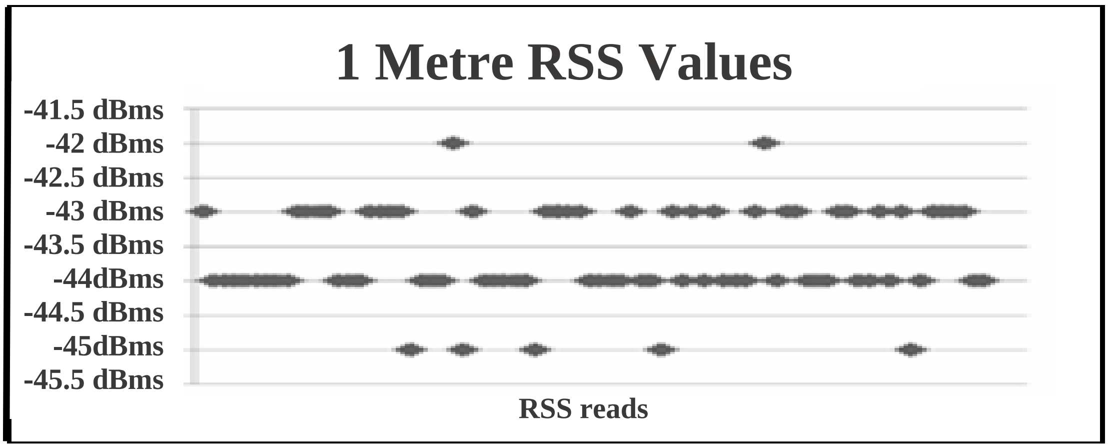


Figure 4-6: 1 Meter RSS readings

The final established RSS reading at 1 metre was evaluated as -43.6316 dBm. Figure 4-6 illustrates the spread of these 500 recorded readings taken in the hall. The 1 metre read of -43.6316 dBm and path loss exponent of 1.5 were then used in the path loss algorithm to calculate a range when given a RSS reading.

4.4.1 Future Cooperating Infrastructure

CAPTURE's methodology is to use mobile devices, as reference devices, to help in the positioning of Lost Devices. All the evidence at this stage advocated using as many devices as possible to help negate positioning errors. Furthermore, the forecasted availability of billions of these devices, from television sets, electric kettles, wireless sound systems, to any of the other myriad of devices said to make up the IoTs would ensure a never-ending source of such reference devices. Adopting this framework however, mandates that the CAPTURE system has no control over the core components that make up its positioning infrastructure. The autonomist nature of such components, along with their heterogeneity regarding their individual core components throws up quite a few issues when designing and implementing such a system. To mitigate for this, a set of experiments were carried out to measure the effect of such heterogeneity, the results of which can be seen in Table 4-1. Furthermore, experiments were carried out on a variety of IoT indoor devices, to see if they could be used in CAPTURE's cooperative methodology to measure range. Some of these devices are mobile to a certain extent, in that they are not permanently fixed to a structure. However, like TVs and satellite TV boxes, they could be classified as semi-fixed reference devices. Other devices such as Fitbits and Smartwatches are much more mobile in their utility.

Sensor	Device	Positioning Error (metres)
Bluetooth	Sound Bar Speaker	3.62 m
	Fitbit	2.56 m
	Smart Watch	3.29 m
	Docking Station Dongle	2.72 m
	Sky Box	-1.48 m
Wi-Fi	Smart TV	1.66 m
	PlayStation Portable	1.82 m
	GoPro	3.16 m

Table 4-2: Indoor Cooperative IoT Devices

Table 4-2 illustrates the results achieved during these tests and does show, albeit with limited accuracy, that these devices can indeed be used to measure range. The devices were placed 4 metres away from the device estimating the range. No prior calibration took place, which could explain the large error bounds. Either way, this experiment does prove that these devices that make up the IoT can be used to cooperatively position devices within their range.

The second research question, (RQ2) *"What range can these mobile devices reach, i.e. how far can they extend a system, and can these range estimates be used to then position devices?"* allows us to investigate the overall yield of any future CAPTURE implementation to examine how far CAPTURE can reach beyond the limits of an in-situ IPS. The theoretical bounds of Bluetooth and Wi-Fi is circa 200m as highlighted. Although in an indoor scenario, the many obstacles that radio signals must travel through attenuate to such a degree, as to make even 50% of these theoretical bounds unobtainable. During the implementation of CAPTURE, an evaluation of the true range that CAPTURE could extend into was completed. These tests attempted to address RQ1, by evaluating the distance that two devices could be *'sensed'* by each other. One test was carried out in a LoS environment to evaluate the best-case scenario for CAPTURE. Further tests involved obstacles that had varying orders of magnitude of range that could be achieved between each of the devices.

4.4.2 NLoS Implementations

Up to this stage of development, CAPTURE had been developed and tested, primarily in LoS scenarios. This provided the capacity to create a sterile testing environment, which in turn offered a benchmark to evaluate later implementations against. Obviously, such situations do not replicate well in real-world scenarios. It was therefore decided that this and any future implementations had to consider NLoS scenarios. This would allow these implementations to better reflect the real-world scenarios that CAPTURE would most likely encounter. Fundamental to this was a set of preliminary experiments to quantify the effect typical indoor obstacles had on the ranging errors of CAPTURE. Advances in accuracy levels with UWB in the indoor environment at this time (Jimenez and Seco, 2016), also warranted its evaluation as a positioning technology.

An example of some of the preliminary ranging experiments carried out with CAPTURE in UWB mode can be seen here[1]. These experiments measured the effect each of these different obstacles listed in Table 4-3, had on the range estimates that were evaluated on each of the different ranging technologies. Plasterboard had a small impact on signals, affecting the Wi-Fi signal the most by 1.17 metres, although in the earlier LoS experiments the Wi-Fi reading was also reading under 5-metres. The glass partitions obviously had one of the smallest impacts on range estimates, although the Bluetooth reading was out by nearly 4.5-metres.

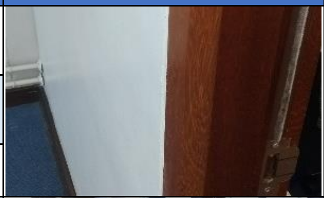
Material Obstacle	Sensor	Ranging Error	Image	Description
Plasterboard	Wi-Fi	3.83m		Studded wall partition with two sheets of plasterboard. Wall is 4” wide.
	Bluetooth	4.33m		
	UWB	5.12m		
Glass	Wi-Fi	5.10m		There are many glass doors and partitions throughout the campus. Glass is 8mm thick.
	Bluetooth	9.33m		
	UWB	5.50m		
Steel Mesh	Wi-Fi	6.20m		This steel mesh design is located throughout the college acting as partitions in stairways etc. The steel is 4mm.
	Bluetooth	7.71m		
	UWB	5.37m		
Concrete Breeze Block	Wi-Fi	19.84m		Most of the campus walls are concrete breeze blocks. The blocks are 6” wide on their edge.
	Bluetooth	12.21m		
	UWB	5.78m		
Reinforced Concrete Wall	Wi-Fi	53.41m		The reinforced concrete walls are 9” thick with reinforced steel (rebar) inset.
	Bluetooth	36.61m		
	UWB	5.74m		
Fire Door	Wi-Fi	15.46m		All doors within the campus are fire doors, they are 4” wide wooden doors with a double fireproof inset.
	Bluetooth	31.74m		
	UWB	5.47m		

Table 4-3: Impact of Building Obstacles

[1] https://captureips.com/videos/UWB_Tests.mov

Steel mesh because of the holes in it, also impacted only marginally on readings. The concrete breeze blocks dramatically altered the range estimates for both Wi-Fi and Bluetooth and the reinforced concrete wall had an even greater impact on these. This is most likely due to the density of the concrete and the steel reinforcement within it. The fire door had a large impact on Bluetooth although Wi-Fi was badly affected also. One of the most notable aspects of this test was the limited impact that all of these obstacles had on UWB. The average error for UWB was 0.49 metres over all tests.

4.4.3 In-House IPS Integration

Research question 3 (RQ3) addresses the capacity for CAPTURE to extend the range of an in-situ IPS. To accomplish this, CAPTURE had to integrate with an IPS. The methodology was to design a type of CAPTURE plug-in that would be generic in design, allowing it to offer additional range to any IPS, by simply plugging-in to it. The Pole Star IPS system which is installed in LyIT Campus was the IPS used to evaluate this concept. During the summer of 2014 a Pole Star IPS was installed on two floors of the LyIT Campus, using Bluetooth 4.0 LE Beacons, illustrated in Figure 4-7, to locate mobile devices within those regions. These beacons are compatible with all Bluetooth Smart 4.0 devices and provide over five years of battery lifetime.

Figure 4-7: Bluetooth 4.0 LE Beacon

Figure 4-8: BLE Beacon Placement

The beacons were positioned at ceiling level with 10-metre intervals, along the hallways of the building, as can be seen in Figure 4-8. The beacons are 20mm * 45mm * 60mm and weigh 60 grams, with batteries (25 grams without). They typically offer a LoS range of 100m+, for both the indoor and outdoor environments, but promote a 25m indoor variable yield. Over 400 beacons were strategically placed throughout the Campus. Figure 4-9 illustrates the positioning of these on the second floor of the main campus building.

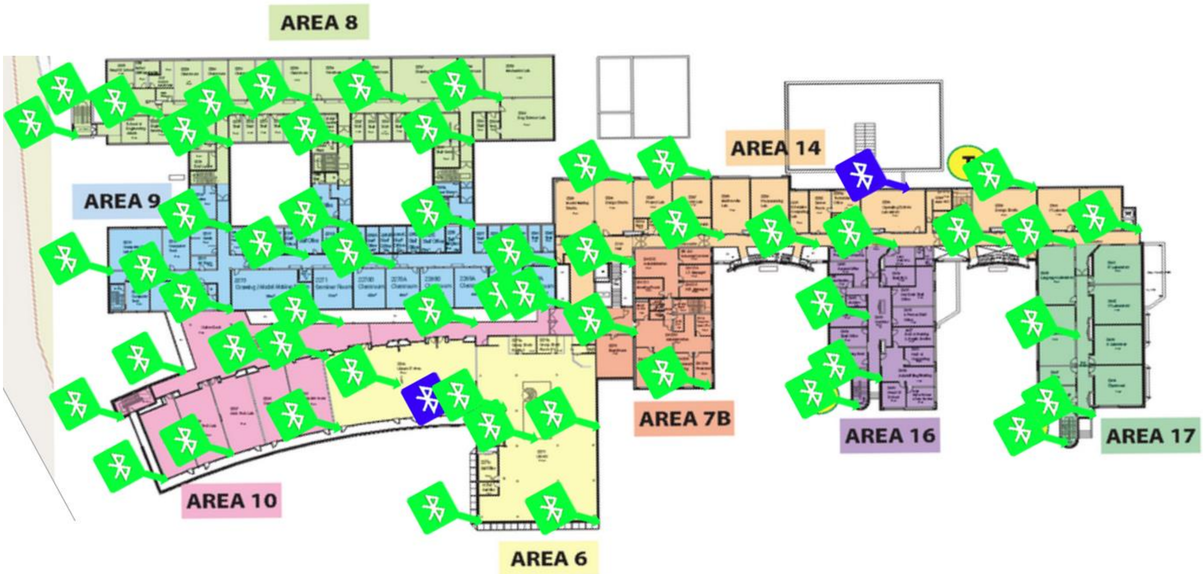


Figure 4-9: LyIT Polestar Beacon Positioning

Once the beacons were in place, fingerprinting, or a scene analysis was carried out to record the signature of specific RSS readings from these beacons at known locations. This database of fingerprints\signatures is then used to derive the position of a mobile device as it moves around the Campus. Students use the LyIT IPS for project work and tests are carried out regularly on the accuracy of the system. The most recent study found its accuracy to be within 2.27m for 97% of position fixes and under 3.4m for 85% of position fixes.

4.4.4 Position Mapping Component

CAPTURE can be integrated with an in-house IPS to provide location information to other information systems within an organisation, but the primary application of this component is to provide a visual representation of a user's position relative to where they are in a building. CAPTURE uses Micello Maps to provide this functionality. Micello provide the capacity for organisations to incorporate coordinate information into navigation content and indoor maps. Pole Star partner with Micello to deliver mapping solutions for their NAO Campus positioning system. Figure 4-10 shows an interactive html map of the LyIT campus created using Micello maps.

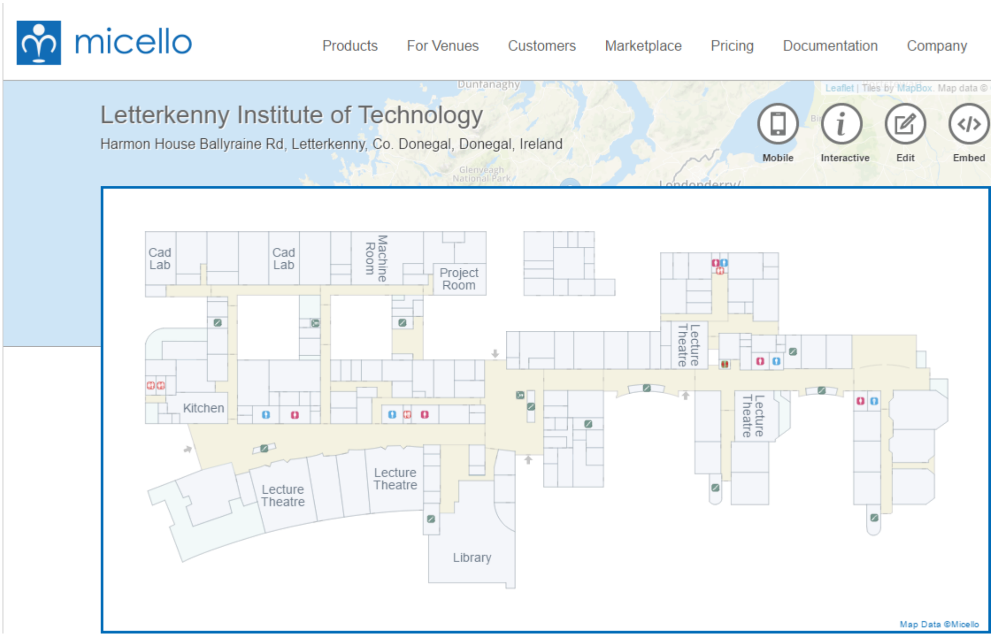


Figure 4-10: LyIT Campus Maps

The LyIT specific maps are accessed via the LyIT project API key. The blue dot of the estimated position is then placed on the map using the x and y coordinate values that are passed into the `show_gps_position()` function on the micellomap.js JavaScript file, to illustrate a real world position.

4.5 Summary

In this chapter the CAPTURE model and subsequent implementation of that model were presented along with an introduction to the live testbeds where CAPTURE implementations were tested. The chapter opened by detailing some of the many devices that could make up a CAPTURE solution using a cooperative paradigm, before emphasising some issues already noted in literature surrounding device divergence. It then broke down the CAPTURE cooperative algorithm used to position, producing conceptual diagrams to describe its specific implementation. The different technologies used to implement CAPTURE are also defined here, highlighting their utility within the overall system. The chapter closes with an insight into how an implementation of CAPTURE was integrated into an in-house IPS. Chapter 4 also provided an insight as to how the CAPTURE model attempts to address the research questions set out in the original hypothesis.

5 Evaluation

Chapter 4 described the CAPTURE model, which helped shape the underlying framework for an implementation. It outlined the technical components and infrastructure used to design and implement CAPTURE that was then used to develop a proof of concept. This chapter now deals with how to use these implementations to validate this concept. Proving the concept, or hypothesis of extending range with CAPTURE was realised via controlled experiments. These experiments and their results are described and evaluated here. The chapter begins by describing some of the equipment used in the experiments, before outlining the results of some of the preliminary experiments. The different testbeds that were used to evaluate CAPTURE are described. The results of the experiments are presented and a description as to how these results meet the thesis hypothesis and underlying research questions is given. Results of tests on battery consumption when devices collaborate are presented.

The hypothesis of this thesis is that mobile devices, at the extremities of an IPS, which have themselves been located, can in turn assist in the determination of the position of devices beyond the range of that IPS. This hypothesis leads to the following research questions:

1. Can mobile devices be used to accurately measure range between devices?

2. What range can these mobile devices reach, i.e. how far can they possibly extend a system, and can these range estimates be used to then position devices?

3. Can a framework be designed to allow any device within an in-situ IPS, to cooperatively assist in the locating of other devices, effectively extending the range of the IPS?

The results obtained from the experiments carried out in this chapter provide concrete evidence that address these research questions.

5.1 Measuring Equipment

During all the tests, measurements were recorded between reference and Lost Devices to plot their true or actual positions and the relative distances therein. This allowed for controlled experiments to be carried out on estimated positions or distances. Any results that were recorded during these experiments could then be compared against the controlled results. A Trumeter professional road distance measuring wheel was used to record all controlled samples. The measuring wheel provides a digital reading of the distance travelled by the wheel. The wheel measures 1 metre in circumference, provides metre and centimetre readings and advertises an accuracy level of +\- 1%.

Trilateration techniques used to determine position can calculate a precise position when given precise data as input. The coordinates of the mobile reference devices and the estimated range between them and the Lost Device are not exact and are the only variables in the equation used to determine the coordinate position of the Lost Device. Since it is already known that the range measurements are not precise, the best approximate coordinate position of the Lost Device needs to be found. Understanding the error bounds of the systems provides the capacity to adequately address these approximations.

5.2 Experimental Testbeds

Testing and evaluation of CAPTURE was carried out in five distinct phases. The first phase of experiments was carried out in the Sports hall, with second tests carried out in the corridors of the main building of the Letterkenny campus. The main canteen area in the Letterkenny campus was used as the third testbed with the Library building providing the fourth testbed. For the final test case implementation of CAPTURE, tests were carried out in the Library. Each of these testing environments where CAPTURE was evaluated, address one or more of the research questions that emanate from the original hypothesis of this work.

5.2.1 Experimental Testbed 1 – Sports Hall

The Sports Hall was used as the initial testing environment because it offered the ability to implement the required experiments in an environment with limited interference. The hall provides wide LoS views to and from devices, with no interference from people moving around in the test area. A map indicating the dimensions of the Sports Hall can be seen in Figure 5-1. The red outlined box indicates the area where the tests were carried out. The sports hall is 959 m^2 in size, offering a maximum testing range of 40m in the diagonal. The primary objective of this testbed and the purpose of these initial tests were an attempt to address the issues posed in Research Question 1 (RQ1) and Research Question 2 (RQ2).

1. Can mobile devices be used to accurately measure range between devices?
2. What range can these mobile devices reach, i.e. how far can they possibly extend a system and can these range estimates be used to then position devices?

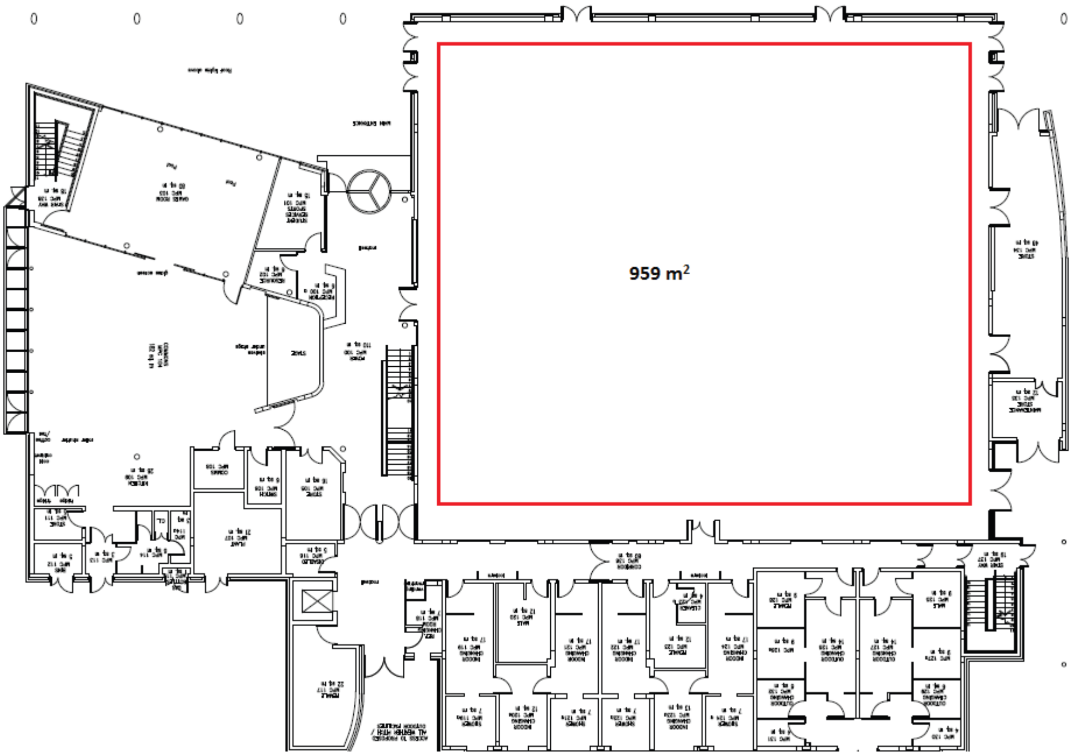


Figure 5-1: Sports Hall

All phones used during the implementation were the same make and model allowing for any issues with varied RSS reads with different antenna types to be ruled out. Some of these issues have been described in the following literature (Lisheng *et al.*, 2011). Lisheng et al., go so far as to describe the distortion being as much as 11.2 dBm out with different antenna types over a 25-metre read range. During the experiments all phones were place at a distance of 80cm above floor level, to mimic as close to a real-world example of a user holding them in their hands as they moved. The phones were placed on identical platforms during the experiments to negate the impact of Hand-Grip body-loss effect which can also impact ranging measurements (Rosa et al., 2011). (Kaemarungsi and Krishnamurthy, 2004) show that device orientation can also introduce errors when calculating signal range estimates, so all phones had the same orientation when used in these tests.

Further experiments were then carried out to measure the accuracy of both the RSS values received and the resulting range estimations determined by the algorithm. Table 5-1 illustrates the results of tests used to capture the RSS values between two phones at 5-metre increments, diagonally across the hall. It highlights the RSS value beginning at -57.26 dBm for the 5-metre range. A sample set of 500 readings were recorded per 5-metre section, an average was then taken from this set. The standard deviation was also documented to illustrate any fluctuations in the received values, the deviation was typically low during the Wi-Fi tests.

Distance	5m	10m	15m	20m	25m	30m	35m	40m
Average RSS	-57.26 (dBm)	-61.57 (dBm)	-69.53 (dBm)	-67.57 (dBm)	-68.38 (dBm)	-70.75 (dBm)	-71.85 (dBm)	-73.68 (dBm)
Std. Dev	0.50m	0.40m	0.85m	0.48m	0.69m	0.98m	0.68m	0.79m
Estimated Range	4.51m	8.27m	25.31m	19.22m	21.54m	30.06m	35.10m	35.38m

Table 5-1: CAPTURE Wi-Fi Range Estimates

The average was then used as input for the path loss algorithm described in Section 2.11.4 to derive a range estimate based on the RSS values received. As mentioned before, RSS values do not provide a linear representation of measurement, and therefore some of the increments do not initially seem like they could assist in finding a distance at a given measurement. One notable issue with the recorded RSS values was the reading taken at the 15-metre distance.

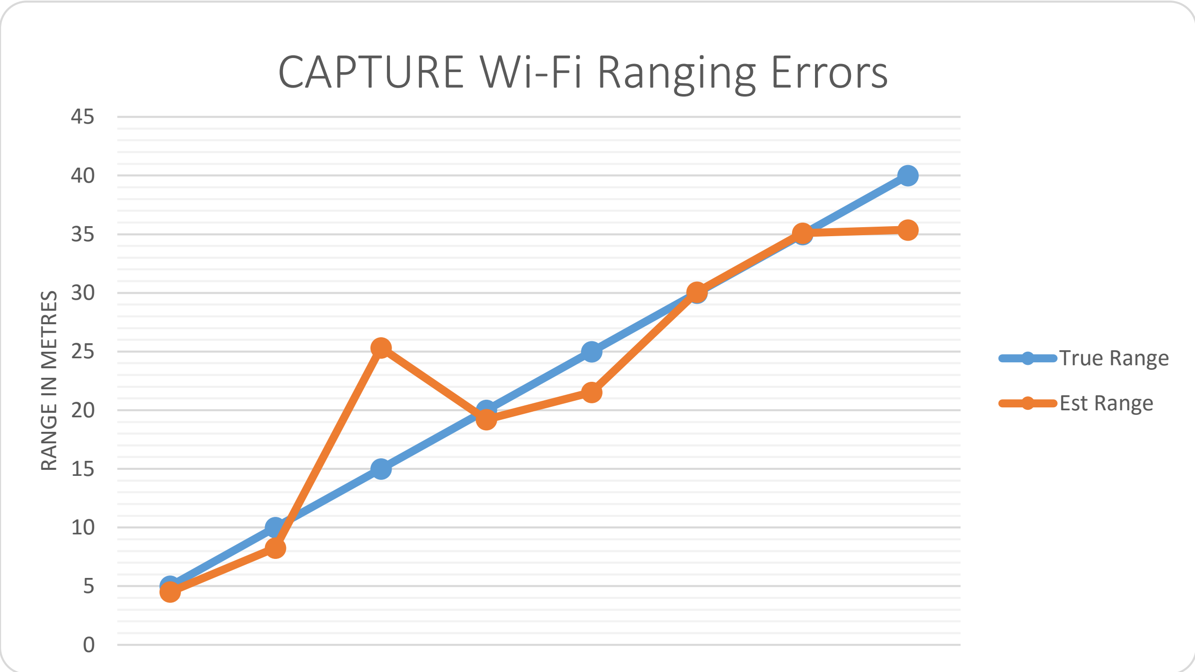


Figure 5-2: CAPTURE Wi-Fi Ranging Errors

Figure 5-2 illustrates the numbers shown in Table 5-1 and highlights this spike in readings. This is most likely due to signal reflection, or other multipath effects. It jumped dramatically at this distance, giving a RSS value higher than the 20 and 25-metre tests. This test at 15-metres was carried out at different areas of the hall, to rule out signal interference. Irrespective of where in the hall the readings were taken, the RSS value was always way out of proportion, especially so when considered against other readings at distances above and below this 15-metre range. These initial tests show the capacity to provide a coarse position estimate, to be able to determine the distance to a mobile device to within an approximate location.

The experiments carried out on CAPTURE when in Bluetooth mode, also used Testbed 1 to examine the capacity of Bluetooth to accurately range between mobile devices. The results of the Bluetooth tests can be seen in Table 5-2. Not all the readings in Table 5-1 or Table 5-2 offer what would be considered acceptable accuracy levels. Acceptable accuracy levels in the indoor environment can vary depending on their application but typically fall within a 5 – 10-metre error range. The average range errors with Wi-Fi was 2.66m, with Bluetooth not faring any better, offering an average of 4.91 metres, indeed some of the individual range estimates were nearly 10-metres out. At the time that these experiments were initially carried out however, they did offer at least an indication that these technologies could be used to estimate range. Indoor positioning research at the time was primarily focused on methods to further hone the accuracy of these technologies to determine range to more useable levels.

Distance	5m	10m	15m	20m	25m	30m	35m	40m
Average RSS	- 75.39 (dBm)	-80.05 (dBm)	-82.56 (dBm)	-81.62 (dBm)	-88.72 (dBm)	-88.84 (dBm)	-88.49 (dBm)	-92.29 (dBm)
Std. Dev	4.12m	3.63m	3.96m	3.92m	4.11m	3.38m	4.28m	2.95m
Estimated Range	3.73m	7.62m	11.20m	9.69m	28.82m	29.38m	27.87m	49.95m

Table 5-2: CAPTURE Bluetooth Range Estimates

One notable aspect of the Bluetooth range tests is the large deviation in the recorded RSS readings, which was found to be a lot lower when using Wi-Fi.

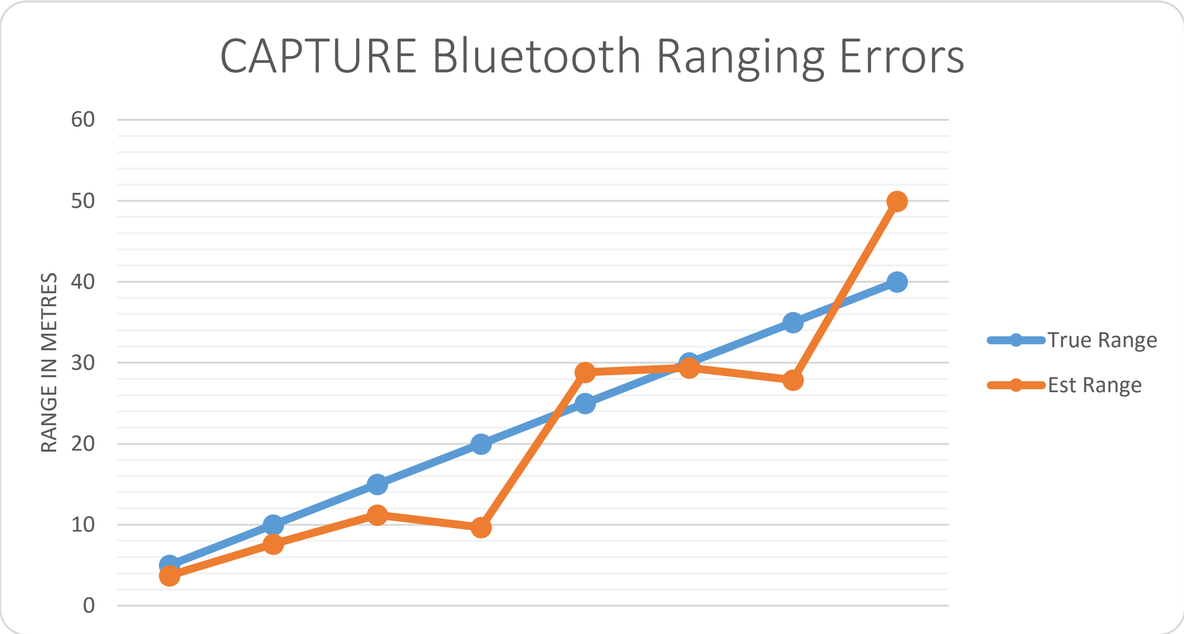


Figure 5-3: CAPTURE Bluetooth Ranging Errors

A large sample of recordings were used in the experiments with CAPTURE when in Wi-Fi and Bluetooth mode. Although the accuracy levels of these could not be considered sufficient to implement a positioning solution, it must be reemphasised that CAPTURE never espoused to offer the positioning accuracies that could compete with an IPS.

The cooperative methodology of using small battery powered mobile devices to position could never match the precision of custom designed, mains powered and costly infrastructure of an IPS. The results of these experiments do however, address the research questions set out in RQ1 and RQ2 and allow the project to continue, by looking at some newer technologies and better techniques to position mobile devices.

Most mobile devices come coupled with both Wi-Fi and Bluetooth sensors on board. As mentioned in the literature survey in Section 2.7, fusing the results of different sensors can have an impact on positioning accuracy. The range estimates evaluated using CAPTURE in Wi-Fi and Bluetooth mode were fused to evaluate any perceived benefit when estimating the range between two mobile devices. Table 5-3 illustrates the benefits of this sensor fusion when applied in the CAPTURE algorithm.

Range	Wi-Fi Error	Bluetooth Error	Fusion
5-metres	-0.49m	-1.27m	-0.88m
10-metres	1.73m	-2.38m	-0.33m
15-metres	10.03m	-3.8m	3.12m
20-metres	-0.78m	-10.31m	-5.55m
25-metres	-3.46m	3.82m	0.18m
30-metres	0.06m	-0.62m	-0.28m
35-metres	0.1m	-7.13m	-3.15m
40-metres	-4.62m	9.95m	2.67m
Overall Avg	2.57m	4.91m	2.02m

Table 5-3: CAPTURE Sensor Fusion Results

5.2.2 Experimental Testbed 2 – Main Campus

The first test environment offered a clean, somewhat clinical test area to conduct experiments without any intrusions during experiments whilst also offering LoS views between devices. These initial tests helped establish some fundamentals and baselines for all subsequent tests, providing a preliminary testing environment that helped iron out some early teething issues. It also helped highlight the type of tests that were required to adequately evaluate a positioning system.

The hallways in the main campus were used as the second testbed environment. These provided access to a more real-world setting with narrow corridors and passageways that more accurately reflected the type of environment that CAPTURE would be exposed to during any large-scale implementation. The Sports hall also had a limited range, in that the furthest that two devices could be placed apart was 40-metres, when using the diagonal of the hall. The hallways in Testbed 2 stretched for up 110-metres, providing the capacity to evaluate CAPTURE at much greater distances. One notable question that arose out of the original hypothesis, was just how far an IPS could be extended when using an implementation of CAPTURE.

This was outlined in Research Question 2:

- What range can these mobile devices reach, i.e. how far can they possibly extend a system, and can these range estimates be used to then position devices?

To address this question, a set of experiments were established to measure the precise range of CAPTURE, rather than the theoretical bounds of each technology used therein. The first experiment used Bluetooth which was carried out on two Sony Xperia Z1 C6943 Smart Phones. The largest distance that a reading was recorded between the phones was 173 metres, giving an RSS reading of -93.18 dBm at that position. After passing that through the path loss algorithm described in (4), a range estimate of 196.56 metres was achieved. Although this gave an error of 23.56 metres, it still provided an insight into just how far CAPTURE could extend an IPS. Furthermore, this accuracy level needs to be put into context.

Although 23.56 metres is a very large error, considering an IPS without CAPTURE could not extend into that area, then that mobile device would not be locatable at all. Depending on its application, that knowledge of understanding that a device is somewhere between 173 metres and 196 metres, as opposed to not knowing where that device is could be critical.

A range experiment was also carried out with this implementation to see how far it could potentially extend an IPS. The furthest that CAPTURE when in UWB mode could extend was 103.4 metres, although this was limited in relation to the other CAPTURE modes, its accuracy was to within 0.004 metres. The absolute range of Wi-Fi mode was also tested, and two mobile devices could *'sense'* each other up to 217 metres apart. The estimated range at this point was 189.62 metres, an error bound of 27.38 metres.

Again, as with the Bluetooth readings the errors are very large, making it problematic to use in any meaningful way in a traditional positioning system. However, there is still the argument that if CAPTURE can *'sense'* these devices this far beyond the IPS, surely knowing it is within the vicinity of these error margins as opposed to not knowing where in the world the device is, could be critical for certain utilities. Consider an IPS that cannot extend beyond its given range and a user is located beyond that. The IPS cannot *'sense'* the user and therefore does not know where they are. With CAPTUREs ability to extend this IPS into an area some 200 meters beyond its given range, describing the users as being within the vicinity of 27.38 metres of an area could still be useful information.

CAPTURE was initially tested in the main hallways, to evaluate it at larger ranges, where the sports hall was limited to 40-metres. The college canteen Testbed 3 provided an optimal environment for the evaluation of the positioning accuracy of the centroid positioning algorithm with CAPTURE. The testing environment was initially sampled to obtain a metre read for the path loss algorithm described in (5). The meter read is calibrated from the environment and used as input 'A' for the path loss algorithm. Over 500 samples were gathered to properly evaluate what a 1 metre RSS reading should be in this setting, sampling at different locations throughout the testing area. This provides a way to train the algorithm for a 1 metre read in this environment. All the recorded values for this sample are presented in Appendix 2.2.

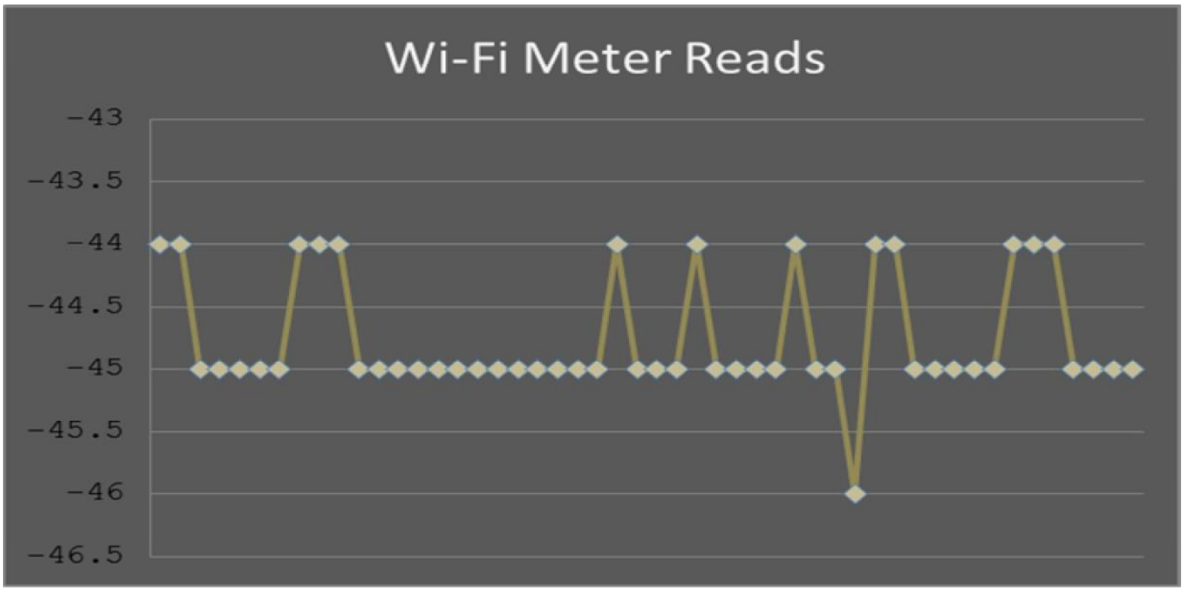


Figure 5-4: CAPTURE Wi-Fi metre reads

A graph illustrating these calibrating metre readings can be seen in Figure 5-4 for Wi-Fi and Figure 5-5 for Bluetooth. One notable aspect of this initial sample and one that continued throughout all the experiments was the smoothness of the results in the Wi-Fi tests relative to the Bluetooth. This can be seen when comparing the chart depicted in Figure 5-4 and Figure 5-5. The Wi-Fi RSS reads range from -44 dBm through to -46 dBm for all of the metre reads, a deviation of 2. Whereas the Bluetooth metre reads the highest read recorded was at -59 dBm and the smallest read was -54 dBm giving an overall deviation of 5. This is characteristic of Bluetooth signals and is noted in the following literature (Subhan *et al.,* 2011; Wang *et al.,* 2013; Faragher and Harle, 2014). All of the recorded values for this sample are presented in Appendix 2.3.

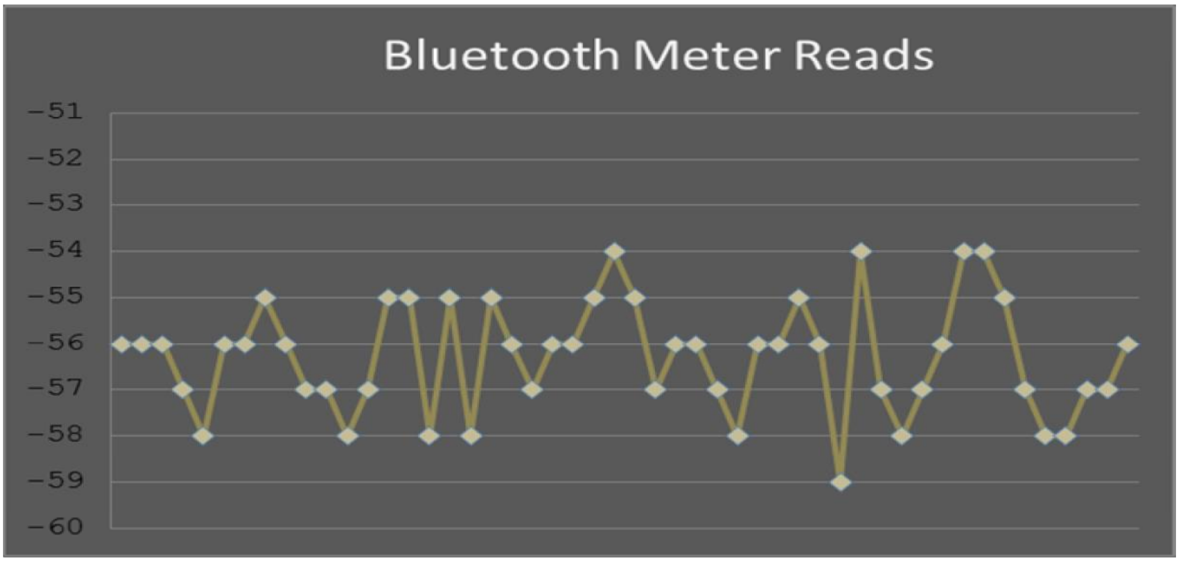


Figure 5-5: CAPTURE Bluetooth metre reads

Any outliers were removed with a simple filter to take out noise, smoothing the results. This filter is described in Appendix 1. After the calibration reads were calculated, a series of tests were carried out to evaluate the accuracy of the ranging aspect of the CAPTURE system. Two mobile devices were placed at specified distance intervals within the hallway. Readings were then recorded at these points and range estimates between the two devices were evaluated.

CAPTURE Wi-Fi Long-Range Estimates												
Distance	**5 m**	**10 m**	**15 m**	**20 m**	**30 m**	**40 m**	**50 m**	**60 m**	**70 m**	**80 m**	**90 m**	**100 m**
Avg RSS	-55.76 (dBm)	-63.16 (dBm)	-64.74 (dBm)	-64.93 (dBm)	-65.60 (dBm)	-67.66 (dBm)	-71.73 (dBm)	-70.68 (dBm)	-68.78 (dBm)	-69.14 (dBm)	-67.29 (dBm)	-69.68 (dBm)
Std. Dev	1.86m	0.97m	2.06m	0.54m	0.49m	0.94m	1.09m	1.39m	1.1m	1.25m	1.28m	1.00m
Estimate	4.84	14.04m	17.62m	18.09m	19.97m	26.84m	48.18m	41.43m	31.50m	33.20m	25.41m	35.86m

Table 5-4 : CAPTURE Wi-Fi Long-range estimates

As with all other implementations, any outliers were removed with a simple filter, this allowed for the accurate depiction of this reading to be used for the ranging algorithm described in (5). Table 5-4 and Table 5-5 detail the readings and the corresponding range estimates achieved during these tests.

CAPTURE Bluetooth Long-Range Estimates												
Distance	**5 m**	**10 m**	**15 m**	**20 m**	**30 m**	**40 m**	**50 m**	**60 m**	**70 m**	**80 m**	**90 m**	**100 m**
Avg RSS	-71.54 (dBm)	-73.86 (dBm)	-75.56 (dBm)	-74.42 (dBm)	-79.10 (dBm)	-82.63 (dBm)	-83.64 (dBm)	-82.70 (dBm)	-82.04 (dBm)	-81.70 (dBm)	-82.15 (dBm)	-87.91 (dBm)
Std. Dev	3.73m	3.71m	3.06m	3.12m	6.12m	3.81m	3.75m	4.60m	4.69m	2.87m	3.29m	3.02m
Estimate	8.7m	12.19m	15.56m	13.22m	25.92m	43.08m	49.83m	43.49m	39.60m	37.70m	40.19m	92.15m

Table 5-5: CAPTURE Bluetooth Long-range estimates

The initial Wi-Fi range estimations recorded in Table 5-4 are reasonable, showing 0.16 metres error in the 5-metre range. The next 3 readings from 10, through 15 to 20-metres have errors from 4.04 metres at the 10-metre read, to approximately 2 metres for 15 and 20-metres. The next 4 readings for 30, 40, 50 and 60-metres have errors from 0.82 metres for the 50-metre range, through to as large as 18.57 metres out on range estimate for 60-metres. After this point, the subsequent 4 readings get progressively worse as illustrated in Figure 5-6. These final readings from 60 to 70-metres are basically unusable in any standard positioning solution. The Bluetooth readings follow a similar pattern to the Wi-Fi readings, in that they begin well for the smaller ranges but then become mostly unusable after about 70-metres, although the 100-metre read is only 7.85-metres out, which would place it back into bounds of error that would be quite usable again.

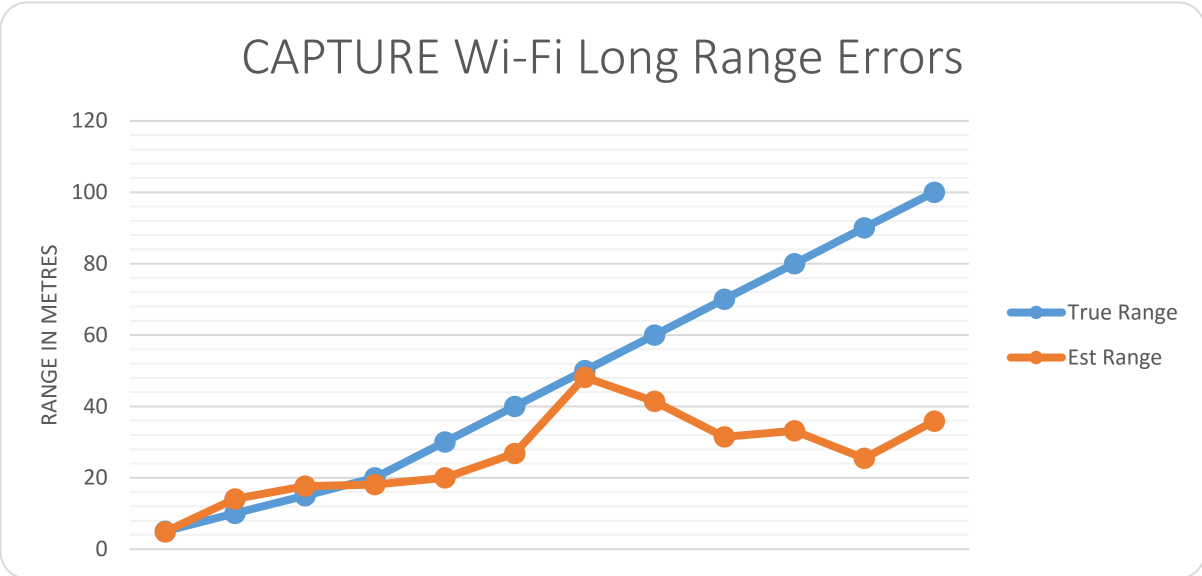


Figure 5-6: CAPTURE Wi-Fi Long Range Errors

Figure 5-6 and Figure 5-7 graphically depict these large variances in range estimates at distances above 40 to 50-metres, illustrating where these technologies prove challenging in any IPS implementation.

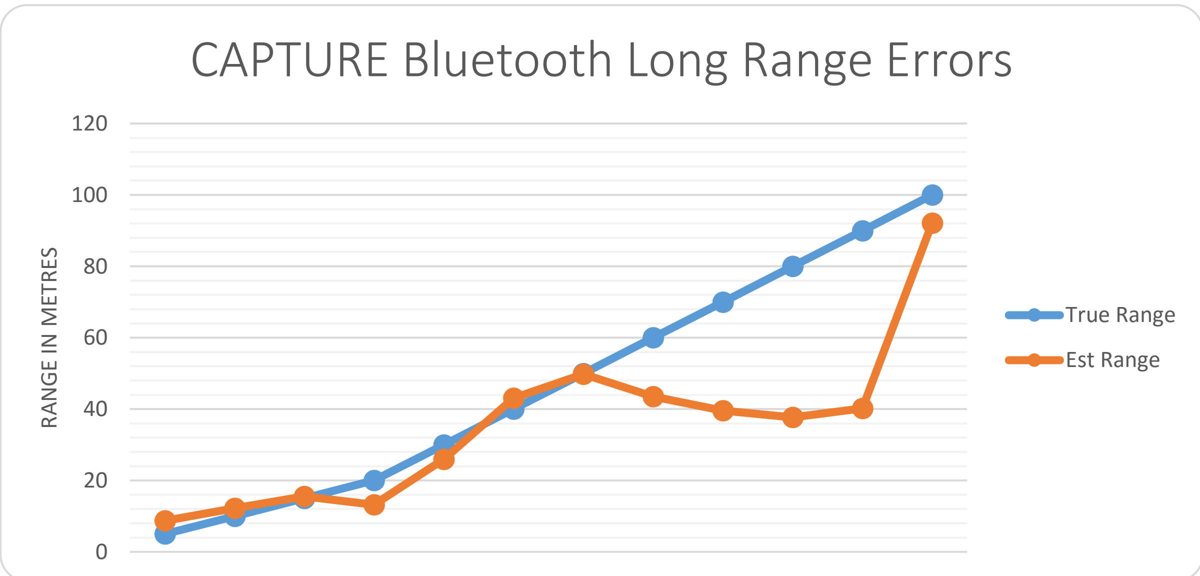


Figure 5-7: CAPTURE Bluetooth Long Range Errors

Range	Wi-Fi Error	Bluetooth Error	Fusion
5-metres	-0.16m	3.7m	1.77m
10-metres	-0.96m	2.19m	0.62m
15-metres	2.62m	0.56m	1.59m
20-metres	-1.91m	-6.78m	-4.35m
30-metres	-11.03m	-4.08m	-7.55m
40-metres	-13.16m	3.08m	-8.12m
50-metres	-1.82m	-0.17m	-1.0m
60-metres	-18.57m	-16.51m	-17.54m
70-metres	-38.5m	-30.4m	-34.45m
80-metres	-46.8m	-42.3m	-44.55m
90-metres	-64.59m	-49.81m	-57.2m
100-metres	-64.14m	-7.85m	-35.00m
Overall Avg	-22.02m	-13.95m	17.81m

Table 5-6: CAPTURE Fusion results

Table 5-6 illustrates the results achieved when fusing the readings from both the Bluetooth and Wi-Fi sensors range estimates. Once the experiments pass the 50-metre threshold range estimate accuracies drop dramatically. The fusion results do however smooth the errors of both technologies when used in combination.

5.2.3 Experimental Testbed 3 – Canteen

The hallways in the main LyIT Campus building offered a great location to carry out experiments to measure range, with its many long halls providing test areas that could extend over 100-metres in distance. After completing the range experiments in Testbeds 1 and 2, CAPTURE needed to be tested to evaluate its capacity to obtain a position fix. The main canteen in LyIT was chosen for these experiments.

The canteen offers a large test area, with a large congregation of people at key times throughout the day, thereby offering both LoS and NLoS conditions for tests. This provided the ability to evaluate the performance of CAPTURE when using a centroid positioning algorithm.

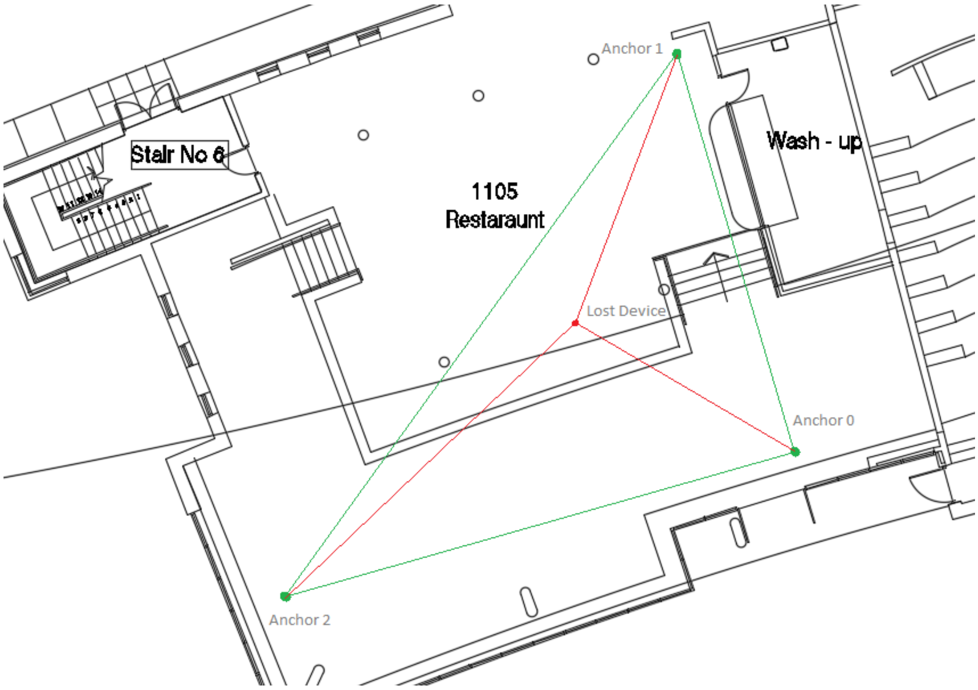


Figure 5-8: Testbed 3 Experiment Plan Overview

CAPTURE used Bluetooth and Wi-Fi to estimate the range between mobile devices. Some issues around the accuracies of these range estimates were highlighted in earlier experiments when the distance between the mobile devices exceeded 40 to 50-metres. The canteen provided a testbed to evaluate the positioning capabilities of the centroid positioning algorithm used in it by not encroaching into these problematic ranges.

Figure 5-8 shows one of the experiments where CAPTURE locates a mobile device to within 2.89 metres of its actual position in the canteen, during LoS conditions. Anchor 0, Anchor 1, Anchor 2 have a prior knowledge of their relative location, (Anchor 0 - Anchor 1 = 20-metres, Anchor 0 - Anchor 2 = 20-metres). The Bluetooth RSS readings from the Lost Phone to Anchor 0 is -75.51 dBm, from the Lost Phone to Anchor 1 is -77.06 dBm and from the Lost Phone to Anchor 2 is -17.52 dBm. These RSS readings translate to a ranging estimate of 15.47 metres, 15.42 metres and 19.37 metres respectively when evaluated by the ranging algorithm. The actual distance between Anchor 0 and the lost phone is 14.17 metres, between Anchor 1 and the lost phone is 17.9 metres and Anchor 2 and the Lost Phone is 14.19. When incorporating the centroid algorithm with these figures, this gives an approximate error rate of 2.89 metres.

The canteen can seat up to 350 students at any one time. The experiments carried out in the canteen were carried out at specific times, this allowed the experiments to measure the impact of both LoS and NLoS situations. The canteen closes at 10pm, therefore any experiments recorded after this time would not encounter human traffic within the canteen area at those times. Different configurations to those illustrated in Figure 5-9 were used in the canteen setting and the results of all the experiments were recorded for both LoS and NLoS situations. Within the configuration illustrated in Figure 5-9, the resulting error rate was recorded at 2.96 metres with people moving around in the canteen. A further four configurations of reference devices similar to those in Figure 5-9 were used to evaluate CAPTURE in Testbed 3, each of these tests were recorded during both LoS and NLoS situations, these can be seen in Appendix 3.

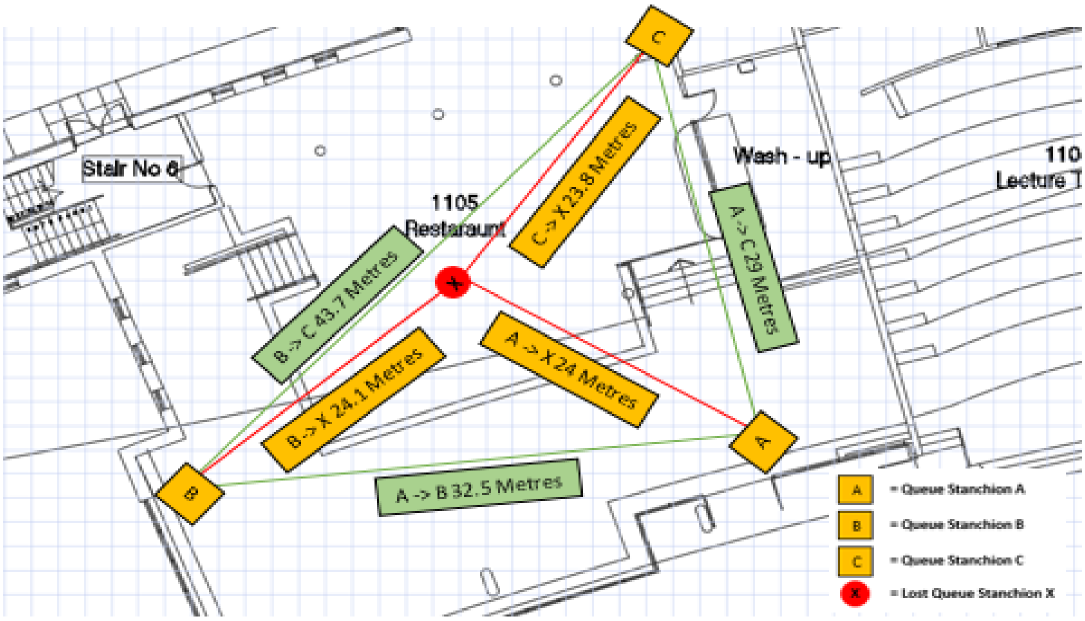


Figure 5-9: Schematic 1 Testbed 3

The results of these experiments are detailed in Table 5-7 and show a combined average error range of 2.36 metres for CAPTURE using Wi-Fi in LoS situations and 2.83 metres in NLoS situations. The corresponding results for Bluetooth were 2.76 metres in LoS and 3.1 in NLoS. The LoS reading were more accurate due to the lack of people in the environment while the tests were being run. This would be in line with findings by (Rowe *et al.*, 2007; Yang *et al.*, 2009) where they highlighted issues with radio signal propagation in environments where people were present. This is due to the fact that our bodies are 60-80% water and radio signals operating in the 2.4 GHz channel resonate at that frequency affecting the signal attenuation.

Experiment	Wi-Fi LoS	Wi-Fi NLoS	Bluetooth LoS	Bluetooth NLoS
Experiment 1	2.17m	2.74m	2.89m	3.17m
Experiment 2	2.59m	2.87m	2.67m	3.05m
Experiment 3	1.84m	2.79m	2.47m	2.82m
Experiment 4	2.75m	3.11m	3.11m	3.53m
Experiment 5	2.44m	2.65m	2.67m	2.93m
Average error	2.36m	2.83m	2.76m	3.1m

Table 5-7: CAPTURE Centroid Algorithm Errors

5.2.4 Experimental Testbed 4 – Library

The Library in LyIT was the penultimate testing area for CAPTURE. An implementation of CAPTURE, incorporating a trilateration algorithm to position was used during these tests. As with Testbed 3, Testbed 4 offered an experimental setting where tests could be carried out while people moved throughout the testing environment. The experiments were conducted during Library opening hours as well as when the Library was closed. This offered the capacity to measure the effect on accuracy of people moving throughout the test area while a position estimate was being evaluated. Figure 5-10 shows the Library area used for these experiments.

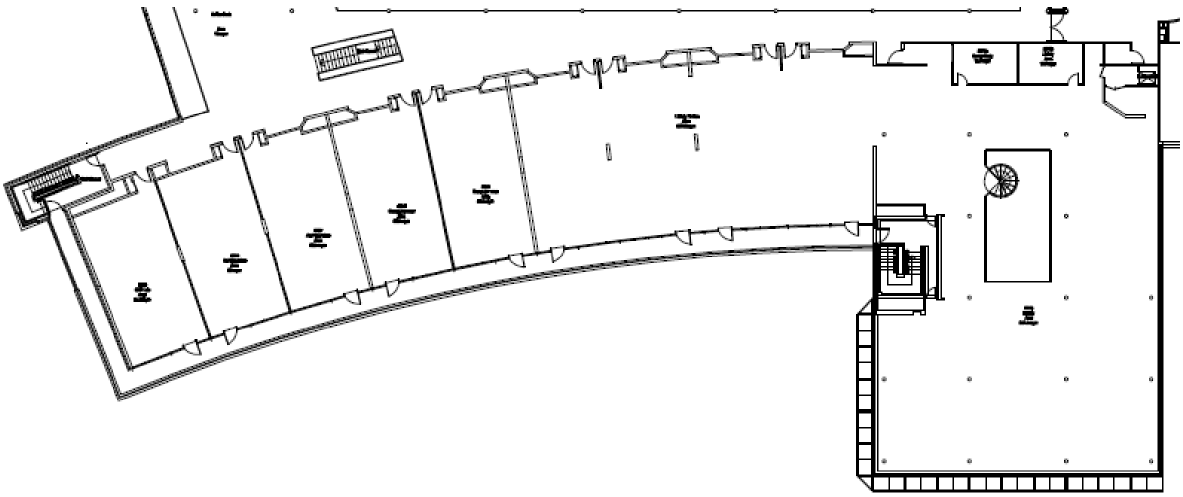


Figure 5-10: Library Plans

To evaluate the performance of CAPTURE, the estimated position versus the true position of the Lost Device is initially plotted. The positioning error metric is defined as the Euclidian distance between these true and estimated positions.

$$Positioning\ Error = \sqrt{(X_{EST} - X_{TRUE})^2 + (Y_{EST} - Y_{TRUE})^2} \qquad (6)$$

where X_{EST} and Y_{EST} are the coordinates of the estimated position of the mobile device and X_{TRUE} and Y_{TRUE} are the known coordinates of the actual positions of the mobile device.

Figure 5-11 shows CAPTURE test results being recorded in the Library testbed. The left-hand side of the screen illustrates the position of the reference devices (Anchor 0, Anchor 1 and Anchor 2) in blue, along with the true position of the Lost Device in green, together with as the estimated position in red[2]. The x and y coordinate values of the anchors are hardcoded into their respective textboxes at the bottom of the screen. The range between these anchors and the Lost Device is shown beneath this in metres. Live data from each anchor is streamed in the top textbox. While the estimated coordinate information of the Lost Device along with the difference between the estimate and the actual position is recorded in the textbox in the middle of the screenshot.

[2] https://captureips.com/videos/distance-plotter.mp4

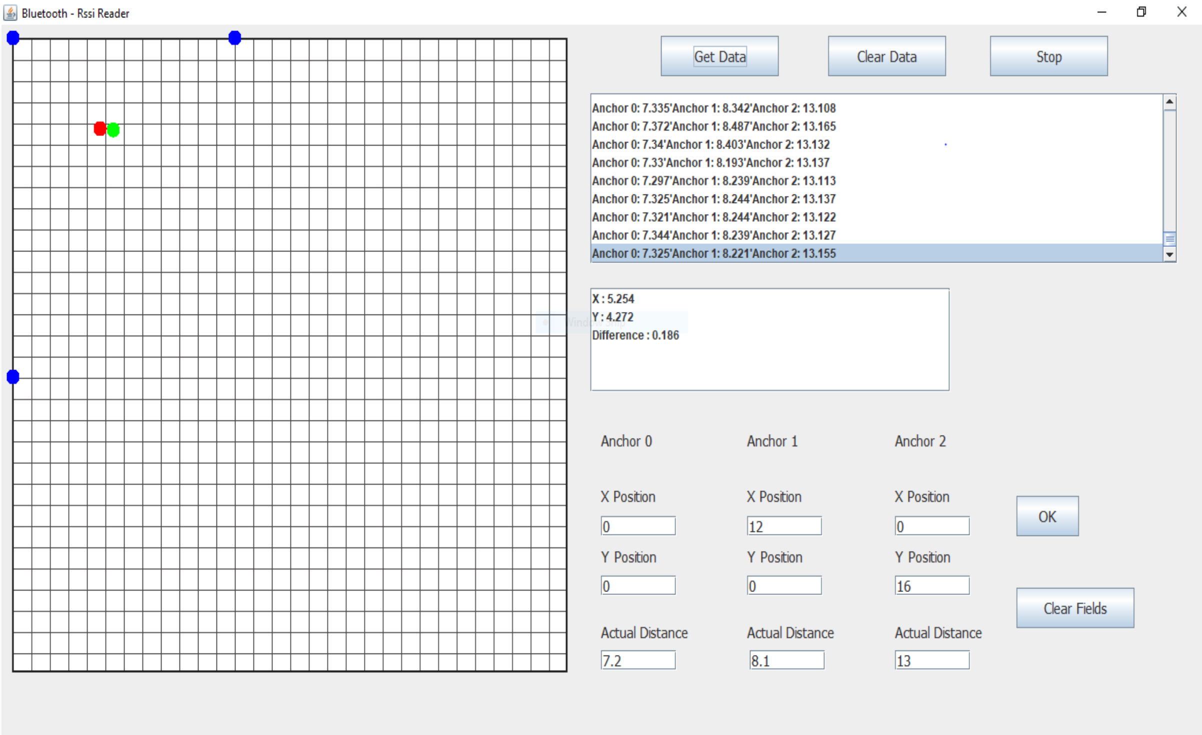


Figure 5-11: CAPTURE Test Results

Figure 5-12 illustrates these experiments in the Library setting, phones were placed at desk height with LoS views when the Library was closed. Student traffic distorted the views to and from the phones during Library opening times. The results of this are illustrated in Table 5-8.

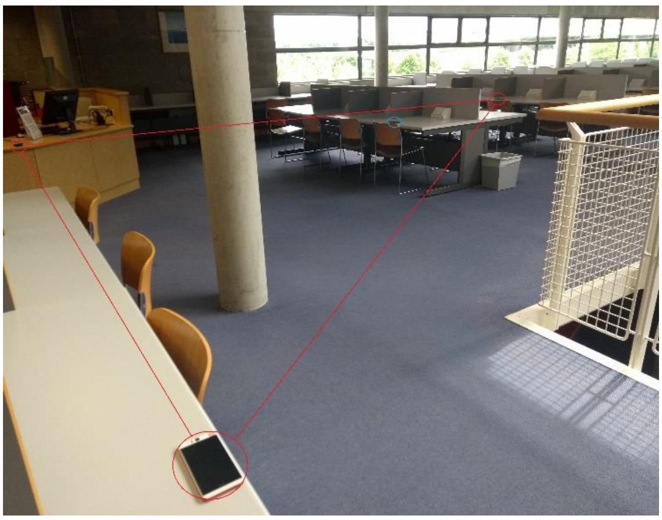


Figure 5-12: Library Bluetooth test

Figure 5-13: Pole Star Integration

The Cartesian coordinate values that were obtained from the trilateration algorithm were then used as input for the JavaScript that allowed CAPTURE to display the position onto the screen of the mobile device. This is described through its implementation in Section 4.4.4 and is illustrated in Figure 5-13.

The results of the trilateration for the five separate experiments carried out in the Library are detailed in Table 5-8. The NLoS tests relate to a time when the Library was open and was frequently used by students. Both Wi-Fi and Bluetooth performed reasonably well in these tests, the largest error recorded was 3.89 metres and the closest estimate was within 1.11 metres. The NLoS and LoS errors again, as with previous test align with results found in (Rowe *et al.*, 2007; Yang *et al.*, 2009).

Experiment	**Wi-Fi LoS**	**Wi-Fi NLoS**	**Bluetooth LoS**	**Bluetooth NLoS**
Experiment 1	3.11m	2.82m	2.12m	3.86m
Experiment 2	1.39m	2.18m	2.58m	3.47m
Experiment 3	2.16m	2.22m	3.87m	2.96m
Experiment 4	2.14m	2.35m	1.25m	3.89m
Experiment 5	2.57m	1.11m	2.34m	3.58m
Average error	2.27m	2.14m	2.43m	3.55m

Table 5-8: CAPTURE Library Results

Figure 5-14 provides an outline of the schematic for one of the experiments carried out in the Library. Three mobile devices (Anchors 0, 1 and 2) acted as fixed reference devices, they then located the Lost Device illustrated with the red dot in the diagram. The actual results recorded for this experiment can be seen in Section 1.5 of Appendix 2.

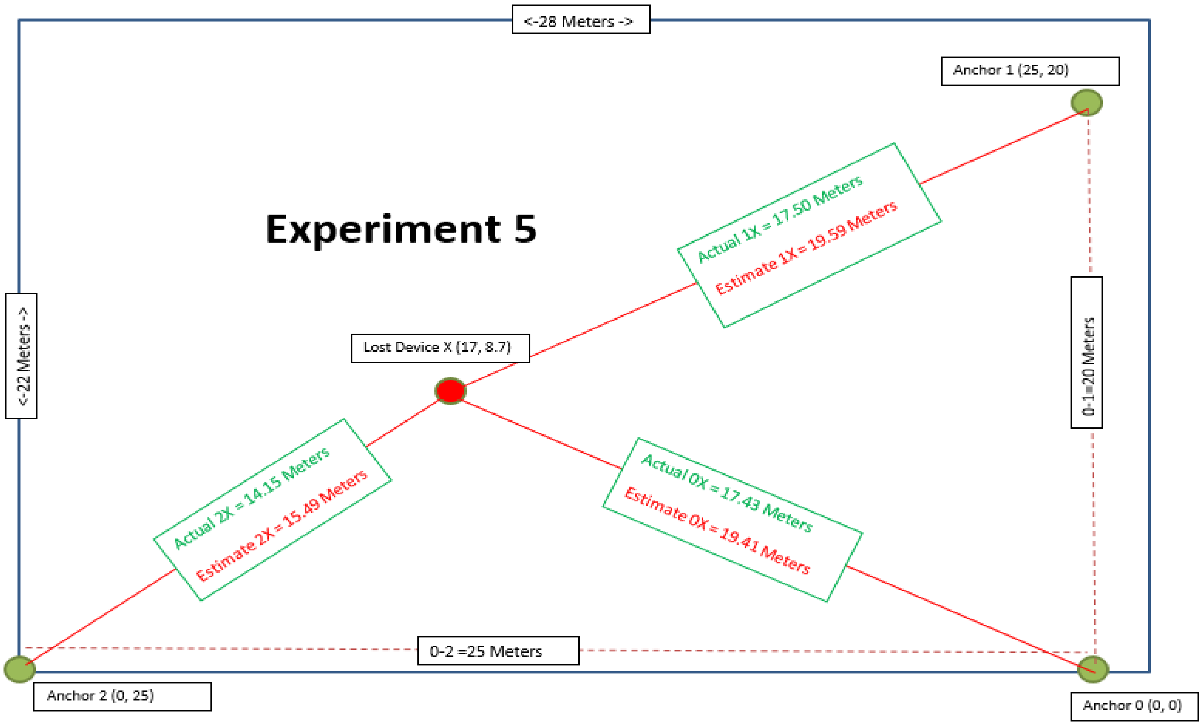


Figure 5-14: Schematic 5 Testbed 4

Figure 5-15 provides a further graphical illustration of this test as it was carried out in the setting for Testbed 4. The three reference devices can be seen with the red triangle line. The Lost Device is at the edge of the middle table, highlighted with the green circle.

Figure 5-15: Library Experiment 5

5.3 Preliminary Tests

Before carrying out the experiments, some preliminary tests were recorded in the college in Testbed 3 and 4. These testbeds best emulated the type of setting that would be encountered in a real-world environment and therefore allowed teething issues to be teased out more effectively here. The UWB tags were attached to the top of queue stanchions which replicated mobile reference devices, as can be seen in Figure 5-16 and are powered by a PNY Curve 5200 Portable Power Bank. The Power Bank uses a micro USB cable to connect to the tag and has a capacity of 5200 mAh. It is slender in size being 152mm high, 84mm wide and 34mm deep. This allows it to fit comfortably around the stanchion. The completed solution proposes to locate the power banks inside the hollow core of the stanchion. Figure 5-16 illustrates the prototype system in action as its being tested in the canteen area of the LyIT Campus.

Figure 5-16: Stanchion mounted UWB Tag

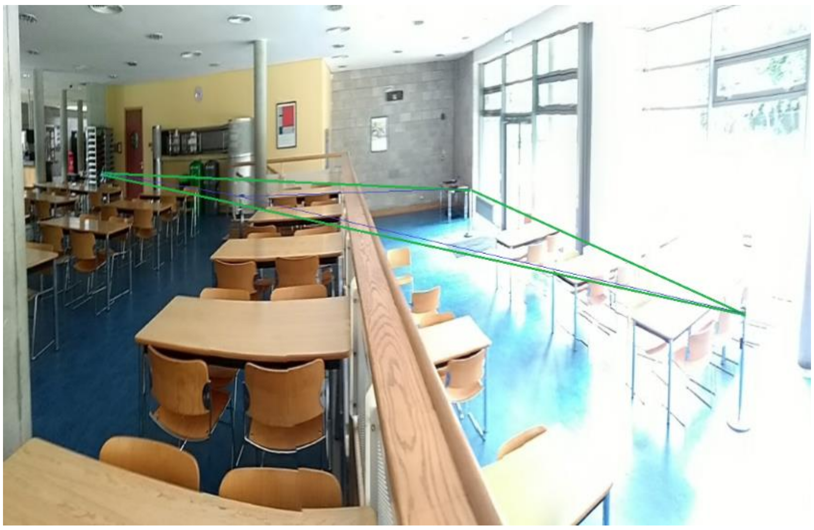


Figure 5-17: Testbed 3 Configuration - CAPTURE preliminary experiments

Figure 5-17 shows one of the tests being recorded in the canteen. Three anchor tags are placed on top of stanchions at pre-recorded positions. These anchor tags then collaborate to locate the fourth stanchion. This replicates as closely as possible the situations in a cooperative positioning methodology. Some range estimates were first recorded. These highlighted some very accurate measurements as can be seen in Table 5-9. Even at distances up to 90-metres the errors were as low as 0.12 of a metre. It is not perceived at this stage that any of the stanchions would ever be this far away from other stanchions. The largest error recorded was at 25-metres and was only out by 0.44 metres.

CAPTURE UWB Range estimates												
Distance	5 m	10 m	15 m	20 m	25 m	30 m	40 m	50 m	60 m	70 m	80 m	90 m
Std. Dev	0.01	0.03	0.03	0.03	0.02	0.03	0.03	0.01	0.09	0.03	0.05	0.03
Estimate	5.10	10.08	15.07	19.90	25.44	30.52	40.14	50.21	60.22	70.15	80.19	90.12

Table 5-9: CAPTURE UWB Range Estimates

Earlier experiments with Wi-Fi and Bluetooth showed very large ranging errors as can be seen in Figure 5-2, Figure 5-3, Figure 5-6 and Figure 5-7. In Figure 5-18 the dramatic impact UWB has compared to these results can be seen. This is particularly evident where the blue line of the True Range values cannot be seen because the orange line of the estimates is so accurate it completely covers it. All of the recorded readings taken during these tests are presented in Section 2.1 of Appendix 2.

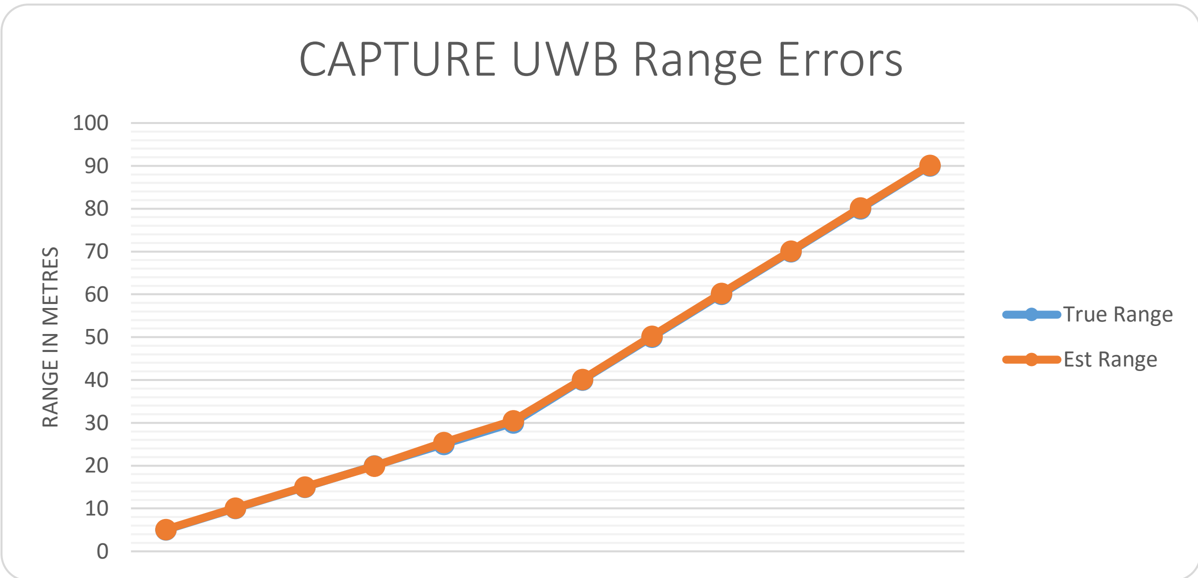


Figure 5-18: CAPTURE Range Errors

Three stanchions acted as anchor stanchions. Once the lost stanchion can be seen by all three of these anchors, they can position the lost stanchion. The lost stanchion is attached to a laptop during experiments. CAPTURE is running on the laptop and takes in the range estimates before putting them through the CAPTURE positioning algorithm.

CAPTURE then returns the position estimate of the lost stanchion. The completed solution would have multiple stanchions locate other stanchions. Once all of the stanchions within an area are located, the Bluetooth and Wi-Fi chips on stanchions are then used to locate mobile devices as they move through the stanchions. It must be remembered that the configuration of a queue can regularly change and that stanchions themselves are mobile objects within these configurations.

Table 5-10 details the results of the preliminary experiments carried out in the Library. These results were recorded when the Library was closed. There were no obstacles or people between each of the UWB tags during the tests. The true position of the tag that CAPTURE was attempting to locate is at (5.06, 0.46). The read column signifies an average of twenty recorded position estimates. The application processes approximately eight reads per second. These reads therefore relate to 2.5 seconds of reads. Twenty position estimates were determined by CAPTURE. These were then averaged, and the results can be seen in the table. This would provide a refresh rate of approximately 2.5 seconds, updating any newly estimated position at that rate. A full record of all of these results can be seen in Section 1.6 and Section 1.7 of Appendix 2.

Read	True Position		Estimated Position		Error
	X	Y	X	Y	Metres
1	5.06	0.46	5.01	0.35	0.12
2	5.06	0.46	4.99	0.36	0.12
3	5.06	0.46	5.00	0.36	0.12
4	5.06	0.46	4.99	0.34	0.14
5	5.06	0.46	5.00	0.36	0.12
6	5.06	0.46	4.96	0.36	0.14
7	5.06	0.46	5.00	0.35	0.12
8	5.06	0.46	4.99	0.36	0.11
9	5.06	0.46	5.00	0.36	0.12
10	5.06	0.46	5.00	0.36	0.12
Avg	5.06	0.46	**4.99**	**0.36**	**0.12**

Table 5-10: CAPTURE UWB LoS Position Estimates Library

Read	True Position		Estimated Position		Error
	X	Y	X	Y	Metres
1	5.06	0.46	5.00	0.35	0.12
2	5.06	0.46	4.99	0.36	0.13
3	5.06	0.46	5.00	0.35	0.12
4	5.06	0.46	4.99	0.34	0.14
5	5.06	0.46	4.98	0.35	0.14
6	5.06	0.46	4.98	0.36	0.13
7	5.06	0.46	5.00	0.35	0.13
8	5.06	0.46	5.00	0.37	0.12
9	5.06	0.46	5.00	0.36	0.12
10	5.06	0.46	5.00	0.36	0.12
Avg	**5.06**	**0.46**	**4.99**	**0.36**	**0.13**

Table 5-11: CAPTURE UWB NLoS Position Estimates Library

The “Error Metres” column details the errors that were recorded between the true position of the tag and the estimated position. As can be seen, these were very low. The highest reading being 0.14 metres out, giving an average error bounds of 0.12 metres with a sample of over 200 position estimates. Table 5-11 lists the results of the same experiment in the Library with the tags positioned at the same locations, but this time the experiment was carried out while the Library was open. The results of the experiment were still very accurate giving an average error bounds of 0.13 metres. A full record of all of these results can be seen in Section 1.7 of Appendix 2.

The tags were all placed within 25-metres of each other during these experiments. The second testbed that was used for these preliminary tests was the canteen area in LyIT. This testbed is described in Section 5.2.3 and provides a large test area to evaluate the capacity for CAPTURE to locate tags on queue stanchions, via tags on other queue stanchions. The canteen also closed in the evening this offered the opportunity to run the experiment while people were in the area of the tests, whilst also being able to measure the effect of people within the test area.

Read	True Position		Estimated Position		Error Metres
	X	Y	X	Y	
1	5.43	4.34	5.21	4.30	0.22
2	5.43	4.34	5.20	4.32	0.23
3	5.43	4.34	5.19	4.30	0.24
4	5.43	4.34	5.20	4.32	0.22
5	5.43	4.34	5.25	4.33	0.18
6	5.43	4.34	5.20	4.43	0.26
7	5.43	4.34	5.28	4.31	0.15
8	5.43	4.34	5.19	4.29	0.25
9	5.43	4.34	5.28	4.32	0.15
10	5.43	4.34	5.23	4.42	0.24
Avg	**5.43**	**4.34**	**5.22**	**4.33**	**0.22**

Table 5-12: CAPTURE UWB LoS Position Estimates Canteen

Being able to measure the difference between reads while people were in between tags, allowed the experiment to evaluate the impact that people in a queue situation would have on position estimates. Considering all the tags e.g. UWB, Wi-Fi or Bluetooth would eventually be placed on top of the stanchions and transmitting between each other on a horizontal plane, therefore, any people in the vicinity would obscure any views to and from tags. The configuration of the tags for the experiments in the canteen maintained the distance threshold of 25-metres, like the earlier tests. The error bounds recorded during these experiments were slightly larger than those recorded in the Library Testbed. The Steel Mesh partitions in the canteen impacted on these error bounds. Two of the tags had to transmit through this Steel Mesh partition to be able to determine the range between themselves and the lost tag. The impact of this Steel Mesh on the ranging accuracy of the DecaWave tags can be seen in Table 4-3. Nonetheless, the results achieved were still impressive giving an average error of 0.22 metres as can be seen in Table 5-12.

Table 5-13 the results carried out in the canteen Testbed for the same experiment that was carried out in Table 5-12, but this time the canteen was open, so people were moving freely around while the experiments were being recorded. Strangely, the results achieved with this experiment where people are obstacles between the tags, are better that the same experiment when there was no interference from people. (Jimenez and Seco, 2016) found similar results in crowded environments, this is due to the operating frequency of UWB (3-5GHz) thereby overcoming the effects of signal attenuation due to resonance (Rowe *et al.*, 2007; Yang *et al.*, 2009).

Read	True Position		Estimated Position		Error
	X	Y	X	Y	Metres
1	5.43	4.34	5.20	4.28	0.25
2	5.43	4.34	5.06	4.29	0.37
3	5.43	4.34	5.07	4.31	0.36
4	5.43	4.34	5.37	4.29	0.08
5	5.43	4.34	5.36	4.29	0.09
6	5.43	4.34	5.33	4.31	0.10
7	5.43	4.34	5.30	4.29	0.14
8	5.43	4.34	5.34	4.30	0.12
9	5.43	4.34	5.23	4.29	0.20
10	5.43	4.34	5.36	4.30	0.08
Avg	**5.43**	**4.34**	**5.26**	**4.30**	**0.18**

Table 5-13: CAPTURE UWB NLoS Position Estimates Canteen

The 3-5 GHz also moves the signal out of the noisy 2.4 GHz channel lessening the impact of other indoor signals such as Wi-Fi, Bluetooth and Microwave ovens that operate in that band. The DecaWave tags were also configured to be used in crowded indoor environments and were calibrated to negate for human interference. The only explanation for this is the effect that the Steel Mesh was having on results. It is the only variable in each of the different Testbeds. Irrespective, the results are still very impressive with four experiments giving an average error bounds of 0.16 metres. This provides conclusive evidence that UWB can be used with enough precision to position these stanchions and allow them to act as reference devices to then cooperatively locate people as they move between these queues.

To improve on this accuracy, the results achieved were passed through a Kalman Filter. Considering the results were already very accurate improvements on those levels were going to be difficult. The source code for the filter can be seen in Section 1.2 of Appendix 1. The implementation focused on using the Kalman Filter to screen measured/estimated ‘x’ and ‘y’ coordinate values to estimate the position of an object on a Cartesian plane. The filter was applied to evaluate ‘x’ and ‘y’ coordinates using different measurement models. It was first applied on each coordinate separately and then applied on both coordinates simultaneously. The process noise covariance matrix was modified several times during testing to evaluate which model resembled the real-world process, this model was then used for the final filter application. A standalone application was developed for initial testing to read the measured coordinates from a database, filter the coordinates and write the filtered values back out to a database. An open source Java API was used to implement the filter (Apache, 2018). The data was imported directly into an excel spreadsheet from the database and visualised using line charts as illustrated in Figure 5-19 and Figure 5-20.

The program was designed in a way that allowed the following variable inputs (process noise, measurement noise, error covariance and discrete time) to be altered using a single variable value for each input. Various measurement and process models were evaluated to determine an optimal configuration for the specific real-world measurement and process models. The error covariance matrix and the number of discrete time steps were altered to model this configuration. The coordinates are updated at a rate of 4 per second, therefore 10 coordinate reads are equivalent to 2.5 seconds and 100 coordinate reads are equivalent to 25 seconds. The preliminary tests produced clear results in terms of which variable changes were improving the filter.

ID	Noise	Process Noise	Error Rate	Discrete Time	Estimated Distance Error	Filtered Distance Error	Improved By metres	Estimated Distance Error	Filtered Distance Error	Improved By metres
Preliminary Tests										
0	1	1	1.00m	1.00m	0.096m	0.090m	0.006m	0.3223m	0.323m	-0.001m
1	1	1	1.00m	0.10m	0.096m	0.069m	0.027m	0.3223m	0.326m	-0.003m
2	1	1	1.00m	0.01m	0.096m	0.066m	0.030m	0.3223m	0.307m	0.016m
3	1	1	1.00m	0.00m	0.096m	0.066m	0.030m	0.3223m	0.223m	0.099m
4	1	1	1.00m	0.00m	0.096m	0.066m	0.030m	0.3223m	0.220m	0.102m
5	1	1	0.10m	1.00m	0.096m	0.088m	0.008m	0.3223m	0.323m	0.000m
6	1	1	0.01m	1.00m	0.096m	0.088m	0.008m	0.3223m	0.323m	0.000m
7	1	1	0.00m	1.00m	0.096m	0.088m	0.008m	0.3223m	0.323m	0.000m
8	1	1	0.00m	1.00m	0.096m	0.088m	0.008m	0.3223m	0.323m	0.000m
9	1	0.1	1.00m	1.00m	0.096m	0.090m	0.006m	0.3223m	0.323m	-0.001m
10	1	0.01	1.00m	1.00m	0.096m	0.090m	0.006m	0.3223m	0.323m	-0.001m
11	1	10	1.00m	1.00m	0.096m	0.090m	0.006m	0.3223m	0.323m	-0.001m
12	1	100	1.00m	1.00m	0.096m	0.090m	0.006m	0.3223m	0.323m	-0.001m
13	0.1	1	1.00m	1.00m	0.096m	0.096m	0.000m	0.3223m	0.325m	-0.003m
14	0.01	1	1.00m	1.00m	0.096m	0.097m	-0.001m	0.3223m	0.326m	-0.004m
15	10	1	1.00m	1.00m	0.096m	0.074m	0.022m	0.3223m	0.322m	0.001m
16	100	1	1.00m	1.00m	0.096m	0.059m	0.037m	0.3223m	0.316m	0.007m
Custom Tests										
17	100	1	0.00m	0.00m	0.096m	0.059m	0.037m	0.3223m	0.059m	0.264m
18	100	100	0.10m	0.00m	0.096m	0.059m	0.037m	0.3223m	0.059m	0.264m
19	100	1	0.50m	0.00m	0.096m	0.059m	0.037m	0.3223m	0.058m	0.264m
20	1000	1	0.00m	0.00m	0.096m	0.059m	0.037m	0.3223m	0.059m	0.264m

Table 5-14: Parameter configuration test results

The preliminary tests indicated that the process noise and measurement noise are inversely related as the input for the process noise increases and the input for the measurement noise increases, the numbers remain constant. However, if either one increases, there is a dramatic impact on results.

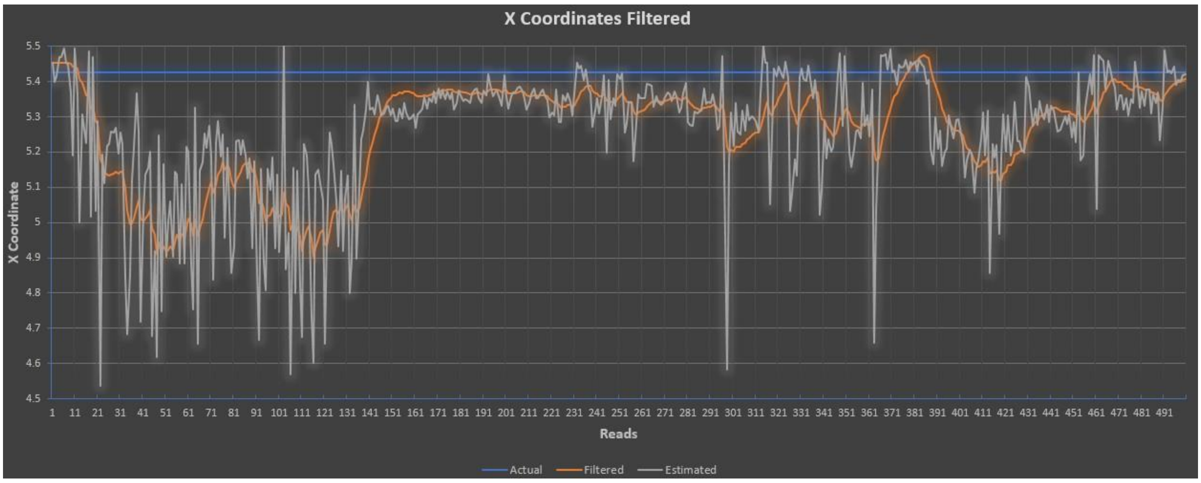


Figure 5-19: 'x' coordinate filtered results

These results are highlighted in Figure 5-19 and Figure 5-20. The blue line represents the actual coordinates, the grey line represents the estimated coordinates and the orange line represents the filtered coordinates.

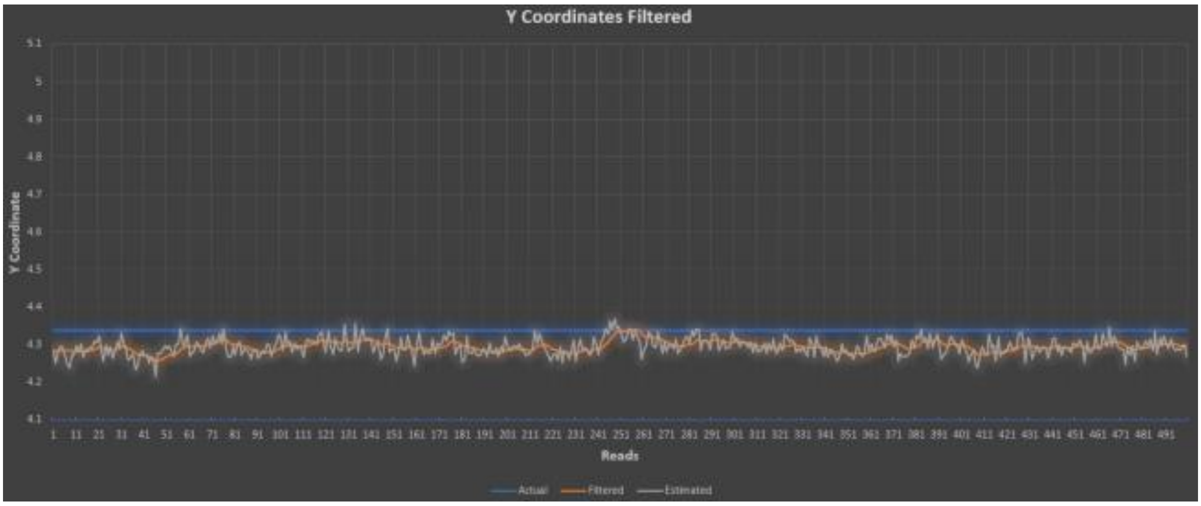


Figure 5-20: 'y' coordinate filtered results

The following outcomes were observed from these tests:

1. The process noise and measurement noise are inversely related; therefore, the process noise can be left at a constant of 1.
2. The error covariance has negligible impact when observing only two Cartesian coordinates; therefore, it can be left at a constant of 0.5.
3. The discrete time significantly improves the filter as it is reduced by a factor of 10.

5.4 Battery Consumption

Convincing users of other devices to cooperatively assist in locating Lost Devices, would be impossible, if as part of that cooperation, the assisting devices had to sacrifice copious amounts of battery power to do so. CAPTURE relies on the *'cooperative goodwill'* of other users, to assist in the location of Lost Devices. In any cooperative ethos such as this, it is imperative that no burden be placed on any users' involvement in such an arrangement. Constantly pinging devices to ascertain ranging information between each other can have a dramatic effect on battery life, irrespective of the technology adopted to determine this. Accepting that a device would lose such a vital commodity, in a world where battery consumption is such an essential commodity, would seem an unreasonable demand from any application or service. The technological advancements required to drive modern smart phones, with the myriad of sensors and brightly lit screens that come bundled with them, further exacerbate this issue. It was for this reason that sample test implementations of both the Wi-Fi Direct and Bluetooth LE versions of CAPTURE, were conducted to measure their respective impact on battery consumption.

The tests were carried out on Sony Xperia Z1 C6943 Smart Phones running Android v5.1 (Lollipop) with a total battery lifetime of 2980 mA.h (milliampere hours). At the beginning of each test, the phones were placed into Airplane mode. Wi-Fi was then switched on for the Wi-Fi Direct test and Bluetooth switched on for the BLE test. This provided a more accurate measurement of each technology in isolation. By switching off all the other sensors on each phone during each test, the respective sensors that were to be measured, were isolated with regards to battery consumption.

A simple program was created to capture the battery readings at the beginning, end and throughout the test. The application used the `BatteryManager` class, to access the battery levels at pre-recorded intervals, throughout the testing period. An SQLite database was used to record each of the battery level readings throughout the test. The local database was used, because network connectivity was not available for each of the tests due to Wi-Fi being switched off. A sample of the Wi-Fi Direct version of CAPTURE was recorded running over a period of 10 hours. An estimate of 1.5 seconds per range estimate of each device, was then evaluated from this sample. This displayed a total battery consumption of 0.004967 mA.h, per range estimate, or 0.000167% of the overall lifetime of the battery, as can be seen in Table 5-15.

Wi-Fi Battery Consumption	
Total Battery	2980 mA.h
Battery Start Level	2488.3 mA.h
Battery End Level	2369.1 mA.h
Total Consumption	119.2 mA.h
Per range estimate	0.00497 mA.h
% of Battery Usage	0.00017%

Table 5-15: Battery Consumption - Wi-Fi

Bluetooth Battery Consumption	
Total Battery	2980 mA.h
Battery Start Level	2711.8 mA.h
Battery End Level	2324.4 mA.h
Total Consumption	387.4 mA.h
Per range estimate	0.0161417
% of Battery Usage	0.00054%

Table 5-16:Battery Consumption - Bluetooth

Again, as with the Wi-Fi Direct test, a sample of the BLE version of CAPTURE was recorded taking RSS readings over a period of 10 hours. 1.5 seconds was determined as the time required to record enough BLE RSS readings, to obtain a range estimate. Since each mobile device utilised in the CAPTURE framework merely assists in the localisation of Lost Devices, each device only assists with the range estimate between itself and the Lost Device.

Therefore, this was the only impact on battery consumption with cooperating devices. The battery consumption to estimate the range between two devices, was calculated at 0.016142 mA.h, 0.0005417% of the overall lifetime of the battery, as can be seen in Table 5-16. The BLE version of the application proved more battery intensive, but this had more to do with the implementation process rather than the technology itself being power hungry. One of the characteristics of Bluetooth is that it is designed to search the local area for other Bluetooth enabled devices. To be in a position to receive and record the signal strength from neighbouring devices, CAPTURE needs to carry out a scanning procedure, called Device Discovery. Bluetooth adopts Device Discovery to search for neighbouring devices. The cooperating device does not establish a link with any of these neighbouring devices when recording an RSS value. To be able to record other RSS values from the same device, CAPTURE was designed to loop this device discovery method. The problem with this is that the Device Discovery procedure is battery intensive, as can be seen in Table 5-16. CAPTURE imports the Bluetooth package, it then applies the `BluetoothDevice` and the `BluetoothAdapter` to get the RSS from each scan.

5.5 Summary

In this chapter, results from the different test environments used to evaluate CAPTURE were presented. Each of these tests were in progressively more challenging and in more real-world environments, allowing the tests to better reflect how CAPTURE would perform in those environments. The experiments were designed to address the main research questions laid out at the beginning of this thesis.

The first and second experiments carried out in the LyIT Sports Hall and main LyIT Campus Hallways, provided a LoS scenario to test the capacity to measure range using mobile devices. The accuracy levels obtained in these experiments, although not at the level of an IPS, did offer the ability to address RQ1. Being able to read devices up to 173, 217 and 104 metres away, using Bluetooth, Wi-Fi and UWB respectively, proved RQ2. Using the range estimate in both centroid and trilateration algorithms, implemented in testbeds 3 and 4, substantiated the claims set out in RQ2 and RQ3. Integrating CAPTURE with the Pole Star IPS in testbed 4, further corroborated the claims made in RQ3. The chapter also provided an insight into the capacity for CAPTURE to solve a positioning problem using its cooperative methodology, in a novel fashion. Some of the successes of earlier implementations of CAPTURE were used to create a solution, using Wi-Fi, Bluetooth and UWB to do so.

The use of a Kalman Filter to further refine results was also described here. The proposed solution involved the use of queue stanchions to cooperatively locate other queue stanchions using UWB. BluFi chips on key queue stanchions then positioned passengers as they moved through the queues. This work highlighted a novel implementation of CAPTURE one that would allow for the setup and teardown of an ad-hoc positioning system using the cooperation of mobile devices that already know their position to do so. Collectively, all of the experiments addressed the overall thesis hypothesis by providing quantifiable evidence that backed up the assertion that mobile devices could, in effect cooperatively extend the range of an IPS.

6 Conclusion & Future Work

The main hypothesis of this work was that cooperating mobile devices could extend the range of an IPS. The development of the CAPTURE prototype and the results presented therein helped prove this hypothesis. Moreover, the capacity to use the cooperative methodology of CAPTURE to solve real-world problems. This opened some more interesting opportunities for CAPTURE to provide a solution in specific niche areas. The ability to set up an instance of CAPTURE, a sort of pop-up IPS, by exploiting local mobile devices to provide the necessary cooperative positioning infrastructure warrants further exploration. The capacity to position in all areas of the indoor environment has been an important aspect of research in this area over the past number of years.

As people become more accustomed to an application or a system's capacity to position in the outdoor arena, the more they will demand to be able to replicate this while indoors. Considering people spend more time indoors and carry out most commerce indoors, this demand looks unlikely to abate in the near future. The proliferation of mobile devices available today mandate the need to position in all environments, whilst also offering a possible solution to the positioning problem when operating as cooperating devices themselves.

6.1 Thesis Summary

The primary objective of this study was to design, develop and test a cooperative methodology to extend the range of IPSs. Platform requirements for the system needed to fall within the technological limitations of standard off the shelf mobile phones, with no requirements for hardware or software modifications therein. These requirements limited the technological solutions to those available on consumer mobile devices.

An introduction to positioning was presented in Chapter 2. How current technologies mimic the way humans have historically positioned was illustrated. An overview of coordinate systems was provided along with positioning measurements and how these measurements can be used to help with a technological solution to the positioning problem. A detailed overview of current positioning technologies was also described in Chapter 2.

Ranging techniques used with these technologies was also presented. Position estimation algorithms were evaluated and the sources of positioning errors in the indoor environment were described. Metrics used to evaluate the performance of a positioning system were outlined. Filtering techniques were detailed as well as an in-depth look at GPS and how from its early conception it got to be the ubiquitous system that is used today. Chapter 2 concluded by stating that to date, no technology using a cooperative framework existed to solve the problem of indoor positioning coverage. In Chapter 3, the CAPTURE methodology was presented, outlining how this cooperative approach has been utilised in computing for quite some time. Evidence was presented via experiments in Section 3.2 illustrating coverage issues in the indoor environment when using an endogenous solution, further backing this work's hypothesis. Issues relating to device selection were documented in Section 3.3. Specific scenarios where CAPTURE can help extend IPS range were described.

The CAPTURE model was detailed in Chapter 4, illustrating the design of CAPTURE. Chapter 4 also describes how CAPTURE was implemented outlining the different technologies and algorithms that were incorporated. An overview of the mobile devices that were used with CAPTURE were also presented here along with some evidential evaluation surrounding device heterogeneity. Chapter 5 provides an evaluation of CAPTURE with a complete testbed description and an account of a case study implementation. The hypothesis of this thesis looks at how mobile devices can assist in the positioning of other mobile devices in a cooperative methodology. Evidence for this hypothesis has been presented through the design, development and evaluation of the proof of concept application - CAPTURE. This thesis has answered the research questions outlined in Chapter 1, proving that the range of an IPS can be extended by mobile devices using a cooperative methodology.

6.2 Relation to other work

CAPTURE was inspired through previous and current research carried out in cooperative positioning. It relates broadly to the work carried out by (Patwari *et al.,* 2005; Wymeersch *et al.,* 2009; Shen *et al.,* 2010; Kloch *et al.,* 2011b; Kaltiokallio *et al.*, 2012; Meyer *et al.,* 2015). Although these works inspired CAPTURE, the unique contribution of CAPTURE remains, in its capacity to extend the coverage of an IPS, rather than further hone the accuracy levels of indoor positioning.

In this work, a novel approach to the coverage issue in indoor positioning is presented. There are two key contributions within the technical work of this thesis. The primary contribution is the CAPTURE model which uses a cooperative methodology to locate devices outside the coverage area of an indoor positioning solution. The model offers the capacity to act as a plugin to an existing IPS, to extend its range. CAPTURE could be implemented in key areas of a building, to position mobile devices that could not ordinarily be positioned in those areas with the existing IPS infrastructure. IPS users could download CAPTURE which would then cooperatively locate itself or other CAPTURE users within an indoor environment.

The second contribution of this thesis lies in the ability to use the cooperative methodology of CAPTURE to create an impromptu IPS in strategic areas. The initial concept of cooperative localisation involved the use of mobile devices such as phones or tablets as cooperating devices. With the recent advent of wireless devices, such as Headphones, Smartwatches and Fitbits along with the proliferation of devices within the realm of IoT, the definition of cooperating devices broadened (Tsai and Teng, 2012; Safavi *et al.*, 2018). CAPTURE aimed to exploit the availability of such devices. The ability to use a device in such an opportunistic fashion whilst retaining a cooperative methodology offered the capacity to expand the application of CAPTURE.

Cooperative positioning is very similar to conventional IPSs and only differs in that the reference devices are typically mobile, initially positioned by an IPS and cooperate by being used as a reference frame. The reference devices are initially located by the UWB ceiling mounted tags and when Wi-Fi, Bluetooth or UWB chips are attached to them, they cooperate to locate mobile devices as they manoeuvre between them.

This concept of a '*pop-up*' IPS could be extended to any environment that required an improvised positioning system. It could be constructed at key times or in key locations in either an indoor or outdoor setting, in scenarios where devices could not ordinarily be located. Achieving a position fix in the indoor environment, still poses particularly challenging problems mainly due to the following factors:

- Multi-path errors and Non-Line of Sight surroundings.
- A propagation channel being obstructed, due to the presence of people.
- A higher density of obstacles that affect attenuation of signals travelling through or bouncing off them.
- The requirement to deliver greater precision accuracy, in what is, a smaller domain.
- Propagation paths, which are horizontal rather than vertical, further exacerbating the issues above.

Most of these factors still remain, but as of writing, positioning in the indoor domain is a problem that has somewhat been solved (Jimenez and Seco, 2016). Obtaining accuracy levels in the millimetre realm still poses a challenge, however this is primarily the focus of more specialist systems. This is not to say that challenges themselves do not exist. GPS for example, although invented in the 90's is still actively researched today. It is envisaged that new and current research will focus on niche areas within the area of indoor positioning, areas such as coverage. For this reason, studies such as CAPTURE remain as relevant today as they were when this research initially began in 2010. Future implementations of CAPTURE can be envisaged offering cooperative solutions to these niche indoor positioning challenges.

Following on from the experiments carried out with the different implementations of CAPTURE, along with investigations carried out in the review of the literature surrounding IPSs and the techniques used therein, cooperative range estimation techniques using UWB, Bluetooth and Wi-Fi were identified as possible solutions. In combination with this, trilateration was identified as providing the most appropriate positioning algorithm to use with this cooperative framework, due to its ability to work with the RSS range estimation techniques as described in Section 2.9.1. Thereby, offering a feasible and novel approach to the coverage issue within IPSs. This builds on existing research in this field when using a cooperative paradigm as demonstrated by (Howard *et al.*, 2003; Patwari *et al.*, 2005; Chen *et al.*, 2006; Wymeersch *et al.*, 2009; Rantakokko *et al.*, 2011; Win *et al.*, 2011; Kaltiokallio *et al.*, 2012; Meyer *et al.*, 2015).

6.3 Future Work

Several aspects of this research have emerged as having the potential to be expanded upon. These areas would still utilise the underlying methodology and technologies within CAPTURE but would do so to solve problems other than the issue of yield or range in an IPS. Investigations into the use of smoothing algorithms, could be done to better remove the noise from RSS values. The focus would be on finding an algorithm which best suits the cooperative nature of CAPTURE, such as Bayesian filters to remove some of the noise in a more comprehensive manner than the current filtering algorithm.

Node censorship (Wymeersch *et al.,* 2009) warrants further investigation in order to improve the positioning accuracy of CAPTURE. This could offer the capacity to improve the intelligence of the system as by first evaluating the truth of range estimates from cooperating mobile devices, a decision could be made, whether to use this information or discard it.

Co-operative hotspots can be used to allow users of CAPTURE to avail of the benefit of extending a networks location coverage, whilst also allowing them to extend the coverage of their Wi-Fi access to that network. This could mean that a device using Wi-Fi Direct could be connected to the network and then connect to other devices beyond the network's reach, thereby extending that network's range. This, although not a particularly novel concept on its own, could be incorporated as an add-on, allowing CAPTURE to extend both the range of an IPS and the range of that network's wireless infrastructure.

CAPTURE can be used as a pop-up positioning system extended to the outdoor arena in a setting where GPS could not accurately locate all required devices. For example, a group of scouts on a camping trip in a cavernous terrain, with trees and rock faces, obscuring views to satellites. A network of collaborating devices could be used to implement CAPTURE and assist in extending the range of GPS into that environment. This could also provide a solution to the urban canyon effect (Xie and Petovello, 2015) where manmade metropolitan canyons of buildings obscure the line of sight of mobile devices to an adequate amount of satellites. Devices located at the outskirts of these barriers that are already positioned via GPS, could help locate devices inside these areas.

6.4 Summary

This chapter delivers a synopsis of the thesis which provides a cooperative methodology and framework to extend the range of IPSs. Furthermore, it offers the ability to use this methodology in a novel concept to provide a pop-up IPS in niche areas or impromptu settings. Evidence for the thesis hypothesis is validated through the results obtained during the testing of CAPTURE, whilst the limitations in this approach are also acknowledged.

The incorporation of more complex filtering techniques to assist with the accuracy of CAPTURE are emphasised. The link between CAPTURE and similar research is presented, emphasising the uniqueness of CAPTURE whilst recognising the importance of the cooperative methodology and the research therein.

The results achieved by CAPTURE enhance the existing work in this field of cooperative positioning by (Howard *et al.,* 2003; Patwari *et al.,* 2005; Chen *et al.,* 2006; Wymeersch *et al.,* 2009; Rantakokko *et al.,* 2011; Win *et al.,* 2011; Kaltiokallio *et al.,* 2012; Meyer *et al.,* 2015). Further work in this field is detailed, outlining examples where CAPTURE could offer a potential solution. CAPTURE proves this study's hypothesis by providing a framework whereby devices can, in a cooperative methodology, assist in the locating of other devices beyond the range of an IPS.

References

Akyildiz, I.F., Su, W., Sankarasubramaniam, Y. and Cayirci, E. (2002) 'Wireless sensor networks: a survey', *Computer networks*, 38(4), 393-422.

Alliance, W.-F. (October 2010) 'Wi-Fi Certified Wi-Fi Direct', *White paper*.

Aloudat, A., Michael, K., Chen, X. and Al-Debei, M.M. (2014) 'Social acceptance of location-based mobile government services for emergency management', *Telematics and Informatics*, 31(1), 153-171.

Aly, M. and Bouguet, J.Y. (2012) 'Street view goes indoors: Automatic pose estimation from uncalibrated unordered spherical panoramas', in *Applications of Computer Vision (WACV), 2012 IEEE Workshop, Breckenridge, CO, USA*, 9 - 11 Jan, Piscataway, New Jersey: IEEE, 1-8, available: http://dx.doi.org/10.1109/WACV.2012.6162996.

Apache (2018) *Apache Commons Math 4.0-SNAPSHOT API*, available: http://commons.apache.org/proper/commons-math/apidocs/org/apache/commons/math4/filter/KalmanFilter.html [accessed 03/04/2018].

Araghi, B., Christensen, L., Krishnan, R., Olesen, J. and Lahrmann, H. (2013) 'Use of low-level sensor data to improve the accuracy of bluetooth-based travel time estimation', *Transportation Research Record: Journal of the Transportation Research Board*, (2338), 29-34.

Atyabi, A., Nefti-Meziani, S. (2016) ‘Applications of Computational Intelligence to Robotics and Autonomous Systems’, in *Handbook on Computational Intelligence*, WORLD SCIENTIFIC, 821–863, available: http://www.worldscientific.com/doi/abs/10.1142/9789814675017_0025 [accessed 12 Mar 2018]

Bahl, P. and Padmanabhan, V.N. (2000) 'RADAR: an in-building RF-based user location and tracking system', in *INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE*, 2000, Tel Aviv, Israel, 26 – 30 Mar, Piscataway, New Jersey: IEEE, 775-784, vol.2, available: http://dx.doi.org/10.1109/INFCOM.2000.832252.

Bai, Y., Jia, W., Zhang, H., Mao, Z.H. and Sun, M. (2013) 'Helping the blind to find the floor of destination in multistory buildings using a barometer', in *Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE*, Osaka, Japan, 3-7 July 2013, Piscataway, New Jersey: IEEE, 4738-4741, available: http://dx.doi.org/10.1109/EMBC.2013.6610606.

Balazs, A. (2008) ‘International Vocabulary of Metrology–Basic and General Concepts and Associated Terms’, *Chemistry International -- Newsmagazine for IUPAC*, 30(6), 21–22.

Barrett, J.H.a.Y. and Yonge, C.M. (1958) *Collins Pocket Guide to the Sea Shore. Illustrated by Elspeth Yonge [and others], etc*, London: Collins.

Bashore, F. (2000) 'The Essential Guide to RF and Wireless', *Microwave Journal*, 43(5), 410-410.

Basili, V.R. (1980) ‘Qualitative software complexity models: A summary’, in *Tutorial on Models and Methods for Software Management and Engineering.*, Los Alamitos: IEEE Computer Society Press.

Becker, B., Huber, M. and Klinker, G. (2008) 'Utilizing RFIDs for location aware computing' in *Ubiquitous Intelligence and Computing: 5th International Conference, UIC 2008*, Oslo, Norway, 23 – 25 Jun, Berlin, Heidelberg: Springer-Verlag, 216 – 228, available: https://doi.org/10.1007/978-3-540-69293-5_18.

Bekö, G., Kjeldsen, B.U., Olsen, Y., Schipperijn, J., Wierzbicka, A., Karottki, D.G., Toftum, J., Loft, S. and Clausen, G. (2015) 'Contribution of various microenvironments to the daily personal exposure to ultrafine particles: Personal monitoring coupled with GPS tracking', *Atmospheric Environment*, 110, 122-129, available: http://dx.doi.org/http://dx.doi.org/10.1016/j.atmosenv.2015.03.053.

Belloni, F., Ranki, V., Kainulainen, A. and Richter, A. (2009) 'Angle-based indoor positioning system for open indoor environments', in *2009 6th Workshop on Positioning, Navigation and Communication*, Hannover, Germany, 19 – 19 Mar, Piscataway, New Jersey: IEEE, 261-265 available: http://dx.doi.org/ 10.1109/WPNC.2009.4907836.

Blumenthal, J., Grossmann, R., Golatowski, F. and Timmermann, D. (2007) 'Weighted Centroid Localization in Zigbee-based Sensor Networks', in *2007 IEEE International Symposium on Intelligent Signal Processing*, Alcala de Henares, Spain, 3-5 Oct, Piscataway, New Jersey: IEEE, 1-6, available: http://dx.doi.org/10.1109/WISP.2007.4447528.

Bolanakis, D.E., Kotsis, K.T. and Laopoulos, T. (2015) 'A prototype wireless sensor network system for a comparative evaluation of differential and absolute barometric altimetry', *IEEE Aerospace and Electronic Systems Magazine*, 30(11), 20-28, available: http://dx.doi.org/10.1109/MAES.2015.150013.

Borriello, G., Liu, A., Offer, T., Palistrant, C., Sharp, R. (2005) ‘WALRUS: Wireless Acoustic Location with Room-level Resolution Using Ultrasound’, in *Proceedings of the 3rd International Conference on Mobile Systems, Applications, and Services, MobiSys ’05*, New York, NY, USA: ACM, 191–203, available: http://doi.acm.org/10.1145/1067170.1067191.

Bossler, J.D., Campbell, J.B., McMaster, R.B. and Rizos, C. (2010) *Manual of geospatial science and technology*, 2nd ed. ed., Boca Raton, Fla.: CRC ; London : Taylor & Francis [distributor].

Bouhdid, B., Akkari, W. and Belghith, A. (2017) 'Energy-aware cooperative localization approach for wireless sensor networks', in *2017 13th IEEE International Conference on Intelligent Computer Communication and Processing (ICCP)*, Cluj-Napoca, Romania, 7-9 Sept. 2017, Piscataway, New Jersey: IEEE, 429-435, available: http://dx.doi.org/10.1109/ICCP.2017.8117043.

Brooks, T., Bakker, H., Mercer, K., Page, W. (2005) ‘A Review of Position Tracking Methods’, Presented at the 1st International Conference on Sensing Technology, November 21-23, 2005 Palmerston North, New Zealand.

Bullo, F., Cortes, J. and Martinez, S. (2009) *Distributed control of robotic networks: a mathematical approach to motion coordination algorithms*, Princeton University Press.

Bulusu, N., Heidemann, J. and Estrin, D. (2000) 'GPS-less low-cost outdoor localization for very small devices', *Personal Communications, IEEE*, 7(5), 28-34, available: http://dx.doi.org/10.1109/98.878533.

Caruso, M.J. (1997) Applications of Magnetoresistive Sensors in Navigation Systems, SAE Technical Paper 970602, SAE International, Warrendale, PA, available: https://www.sae.org/publications/technical-papers/content/970602/ [accessed 13 Nov 2018].

Casas, R., Cuartielles, D., Marco, A., Gracia, H.J. and Falco, J.L. (2007) 'Hidden Issues in Deploying an Indoor Location System', *IEEE Pervasive Computing*, 6(2), 62-69, available: http://dx.doi.org/10.1109/MPRV.2007.33.

Cassioli, D., Giuliano, R. and Mazzenga, F. (2005) 'Performance evaluation of high data rate UWB systems based on IEEE 802.15. 3', in *2005 IEEE International Conference on Ultra-Wideband, IEEE, Zurich, Switzeland*, 5 – 8 Sep, Piscataway, New Jersey: IEEE, 678-683, available: http://dx.doi.org/ 10.1109/ICU.2005.1570070.

Catedra, M.F., Perez, J., Adana, F.S.d. and Gutierrez, O. (1998) 'Efficient ray-tracing techniques for three-dimensional analyses of propagation in mobile communications: application to picocell and microcell scenarios', *IEEE Antennas and Propagation Magazine*, 40(2), 15-28, available: http://dx.doi.org/10.1109/74.683539.

Chen, C., Chen, Y., Lai, H.Q., Han, Y. and Liu, K.J.R. (2016) 'High accuracy indoor localization: A WiFi-based approach', in *2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Shangai, China, 20-25 March, Piscataway, New Jersey: IEEE, 6245-6249, available: http://dx.doi.org/10.1109/ICASSP.2016.7472878.

Chen, R. (2012) *Ubiquitous Positioning and Mobile Location-Based Services in Smart Phones*, 1st ed, Hershey, PA: IGI Global.

Chen, R., Guinness, R. (2014) *Geospatial Computing in Mobile Devices*, Norwood M.A: Artech House.

Chen, X., Chen, Y., Rao, F. (2003) ‘An Efficient Spatial Publish/Subscribe System for Intelligent Location-based Services’, in *Proceedings of the 2nd International Workshop on Distributed Event-Based Systems, DEBS ’03*, New York, NY, USA: ACM, 1–6, available: http://doi.acm.org/10.1145/966618.966625.

Chen, Z., Zhu, Q. and Soh, Y.C. (2016) 'Smartphone Inertial Sensor Based Indoor Localization and Tracking with iBeacon Corrections', *IEEE Transactions on Industrial Informatics*, PP(99), 1-1, available: http://dx.doi.org/10.1109/TII.2016.2579265.

Coleman, D.D., Westcott, D.A. (2015) CWNA Certified Wireless Network Administrator Official Deluxe Study Guide: Exam CWNA-106, 1st ed, Indianapolis, IN: Sybex.

Comaniciu, D., Ramesh, V. and Meer, P. (2003) 'Kernel-based object tracking', *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 25(5), 564-577, available: http://dx.doi.org/10.1109/TPAMI.2003.1195991.

Corke, P., Wark, T., Jurdak, R., Hu, W., Valencia, P. and Moore, D. (2010) 'Environmental Wireless Sensor Networks', *Proceedings of the IEEE*, 98(11), 1903-1917, available: http://dx.doi.org/10.1109/JPROC.2010.2068530.

Dammann, A., Sand, S. and Raulefs, R. (2012) 'Signals of opportunity in mobile radio positioning', in *2012 Proceedings of the 20th European Signal Processing Conference (EUSIPCO)*, 27-31 Aug. 2012, 549-553.

Deng, Z.-A., Hu, Y., Yu, J. and Na, Z. (2015) 'Extended kalman filter for real time indoor localization by fusing WiFi and smartphone inertial sensors', *Micromachines*, 6(4), 523-543.

Di Benedetto, M.-G. (2006) *UWB communication systems: a comprehensive overview*, Hindawi Publishing Corporation.

EIA (1969) *EIA RS-232-C Interface between data terminal equipment change*: (EIA) Electronic Industries Alliance.

Ekahau Inc (2016) *Ekahau Wi-Fi RTLS, Active RFID Tracking Solutions, and Wi-Fi Site Survey, WLAN Planning Tools*, available: http://www.ekahau.com/ [accessed 29th March].

Fahy, R.F. (2002) *US Fire Service fatalities in structure fires, 1977-2000*, NFPA.

Fantuzzi, C., Simani, S., Beghelli, S. and Rovatti, R. (2002) 'Identification of piecewise affine models in noisy environment', *International Journal of Control*, 75(18), 1472-1485.

Faragher, R., Harle, R. (2014) 'An Analysis of the Accuracy of Bluetooth Low Energy for Indoor Positioning Applications', in *Proceedings of the 27th International Technical Meeting of The Satellite Division of the Institute of Navigation (ION GNSS+ 2014)*, ION Publications: Tampa, Florida, September 2014, 201–210.

Farid, Z., Nordin, R. and Ismail, M. (2013) 'Recent advances in wireless indoor localization techniques and system', *Journal of Computer Networks and Communications*, 2013.

Filonenko, V., Cullen, C. and Carswell, J. (2010) 'Investigating ultrasonic positioning on mobile phones', in *Indoor Positioning and Indoor Navigation (IPIN), 2010 International Conference on*, 15-17 Sept. 2010, 1-8, available: http://dx.doi.org/10.1109/IPIN.2010.5648235.

Gezici, S. (2008) 'A survey on wireless position estimation', *Wireless personal communications*, 44(3), 263-282.

Giorgetti, G., Farley, R., Chikkappa, K., Ellis, J. and Kaleas, T. (2011) 'Cortina: Collaborative indoor positioning using low-power sensor networks', in *Indoor Positioning and Indoor Navigation (IPIN), 2011 International Conference on*, 21-23 Sept. 2011, 1-10, available: http://dx.doi.org/10.1109/IPIN.2011.6071938.

Grewal, M.S., Andrews, A.P. (2010) 'Applications of Kalman Filtering in Aerospace 1960 to the Present [Historical Perspectives]', IEEE Control Systems Magazine, 30(3), 69–78.

Grossmann, U., Schauch, M. and Hakobyan, S. (2007) 'RSSI based WLAN Indoor Positioning with Personal Digital Assistants', in *2007 4th IEEE Workshop on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications*, Dortmund, Germany, 6-8 Sept., Piscataway, New Jersey: IEEE, 653-656, available: http://dx.doi.org/10.1109/IDAACS.2007.4488503.

Grosz, A., Haji-Sheikh, M.J., Mukhopadhyay, S.C. (Eds.) (2017) High Sensitivity Magnetometers [online], Smart Sensors, Measurement and Instrumentation, Springer International Publishing, available: //www.springer.com/gp/book/9783319340685 [accessed 11 Mar 2018].

Gu, Y., Lo, A. and Niemegeers, I. (2009) 'A survey of indoor positioning systems for wireless personal networks', *IEEE Communications Surveys & Tutorials*, 11(1), 13-32, available: http://dx.doi.org/10.1109/SURV.2009.090103.

Guerrieri, J.R., Francis, M.H., Wilson, P.F., Kos, T., Miller, L.E., Bryner, N.P., Stroup, D.W. and Klein-Berndt, L. (2006) 'RFID-assisted indoor localization and communication for first responders', in *Antennas and Propagation, 2006. EuCAP 2006. First European Conference,* Nice, France, 6-10 Nov, Piscataway, New Jersey: IEEE, 1-6, available: http://dx.doi.org/10.1109/EUCAP.2006.4584714.

Guvenc, I. and Chong, C.C. (2009) 'A Survey on TOA Based Wireless Localization and NLOS Mitigation Techniques', *IEEE Communications Surveys & Tutorials*, 11(3), 107-124, available: http://dx.doi.org/10.1109/SURV.2009.090308.

Hadzic, S. and Rodriguez, J. (2011) 'Utility based node selection scheme for cooperative localization', in *Indoor Positioning and Indoor Navigation (IPIN), 2011 International Conference, Guimaraes, Portugal*, 21-23 Sep, Piscataway, New Jersey: IEEE, 1-6, available: http://dx.doi.org/10.1109/IPIN.2011.6071914.

Hall, T.J., Schwartz, M.A. and Hamer, S.M. (1996) 'GPS-based traffic control preemption system'.

Hauschildt, D. and Kirchhof, N. (2010) 'Advances in thermal infrared localization: Challenges and solutions', in *2010 International Conference on Indoor Positioning and Indoor Navigation*, Zurich, Switerland, 15-17 Sep, Piscataway, New Jersey: IEEE, 1-8, available: http://dx.doi.org/10.1109/IPIN.2010.5647415.

Hightower, J. and Borriello, G. (2001) 'Location systems for ubiquitous computing', *Computer*, 34(8), 57-66.

Hijikata, S., Terabayashi, K. and Umeda, K. (2009) 'A simple indoor self-localization system using infrared LEDs', in *2009 Sixth International Conference on Networked Sensing Systems (INSS)*, Pittsburgh, PA, USA, 17-19 Jun, Piscataway, New Jersey: IEEE, 1-7, available: http://dx.doi.org/10.1109/INSS.2009.5409955.

Hlinka, O., Hlawatsch, F. and Djuric, P.M. (2013) 'Distributed particle filtering in agent networks: A survey, classification, and comparison', *IEEE Signal Processing Magazine*, 30(1), 61-81, available: http://dx.doi.org/10.1109/MSP.2012.2219652.

Hossain, A.K.M.M., Jin, Y., Soh, W.S. and Van, H.N. (2013) 'SSD: A Robust RF Location Fingerprint Addressing Mobile Devices' Heterogeneity', *IEEE Transactions on Mobile Computing*, 12(1), 65-77, available: http://dx.doi.org/10.1109/TMC.2011.243.

Howard, A., Mataric, M.J. and Sukhatme, G.S. (2003) 'Putting the 'I' in 'team': an ego-centric approach to cooperative localization', in *Robotics and Automation, 2003. Proceedings. ICRA '03. IEEE International Conference*, Taipei, Taiwan, 14 - 19 Sep, Piscataway, New Jersey: IEEE, 868-874 vol.1, available: http://dx.doi.org/10.1109/ROBOT.2003.1241702.

Hu, H., Liu, Y., Li, G., Feng, J., Tan, K. (2015) ‘A location-aware publish/subscribe framework for parameterized spatio-textual subscriptions’, in *2015 IEEE 31st International Conference on Data Engineering*, Seoul, South Korea, 13 – 17 Apr, Piscataway, New Jersey: IEEE, 711–722, available: http://dx.doi.org/10.1109/ICDE.2015.7113327.

Huang, C.-H., Lee, L.-H., Ho, C.C., Wu, L.-L. and Lai, Z.-H. (2015) 'Real-time RFID indoor positioning system based on Kalman-filter drift removal and Heron-bilateration location estimation', *IEEE Transactions on Instrumentation and Measurement*, 64(3), 728-739.

Hui, L., Darabi, H., Banerjee, P. and Jing, L. (2007) 'Survey of Wireless Indoor Positioning Techniques and Systems', *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, 37(6), 1067-1080, available: http://dx.doi.org/10.1109/TSMCC.2007.905750.

Ibrahim, M. and Youssef, M. (2010) 'CellSense: A Probabilistic RSSI-Based GSM Positioning System', in *Global Telecommunications Conference (GLOBECOM 2010), 2010 IEEE*, Miami, FL, USA, 6-10 Dec, Piscataway, New Jersey: IEEE, 1-5, available: http://dx.doi.org/10.1109/GLOCOM.2010.5683779.

IEEE (2016) 'IEEE Standard for Low-Rate Wireless Networks', *IEEE Std 802.15.4-2015 (Revision of IEEE Std 802.15.4-2011)*, 1-709, available: http://dx.doi.org/10.1109/IEEESTD.2016.7460875.

Jacobson, E., Lee, T., Popeck, C., Martorana, M. and Sokolowski, S. (2003) 'SUO/SAS geolocation: land navigation using multiple integrated sensors', in *Military Communications Conference, 2003. MILCOM '03. 2003 IEEE*, Boston, MA, USA, 13-16 Oct, Piscataway, New Jersey: IEEE, 186-191 Vol.1, available: http://dx.doi.org/10.1109/MILCOM.2003.1290100.

Jeon, J.s., Kong, Y., Nam, Y. and Yim, K. (2015) 'An Indoor Positioning System Using Bluetooth RSSI with an Accelerometer and a Barometer on a Smartphone', in *2015 10th International Conference on Broadband and Wireless Computing, Communication and Applications (BWCCA)*, Kracow, Poland, 4-6 Nov, Piscataway, New Jersey: IEEE, 528-531, available: http://dx.doi.org/10.1109/BWCCA.2015.142.

Jie, S., Gang, M. and QiTai, G. (2002) 'Design and implementation of MIMU/GPS integrated navigation systems', in *2002 IEEE Position Location and Navigation Symposium (IEEE Cat. No.02CH37284)*, Palm Springs, CA, USA, 15-18 April, Piscataway, New Jersey: IEEE, 99-105, available: http://dx.doi.org/10.1109/PLANS.2002.998895.

Jimenez, A. and Seco, F. (2016) 'Comparing Decawave and Bespoon UWB location systems: Indoor/outdoor performance analysis', in *2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Alcala de Henares, Spain, 4-7 Oct, 1-8, Piscataway, New Jersey: IEEE, available: http://dx.doi.org/10.1109/IPIN.2016.7743686.

Jimenez Ruiz, A., Seco Granja, F., Prieto Honorato, J.C. and Guevara Rosas, J.I. (2012) 'Accurate Pedestrian Indoor Navigation by Tightly Coupling Foot-Mounted IMU and RFID Measurements', *IEEE Transactions on Instrumentation and Measurement*, 61(1), 178-189, available: http://dx.doi.org/10.1109/TIM.2011.2159317.

Jinghua, D., Sumana, D., Kazmi, S.A.A., Saxena, N. and Hasan, S.F. (2014) 'An outdoor assessment of scene analysis for Wi-Fi based positioning', in *2014 IEEE 3rd Global Conference on Consumer Electronics (GCCE)*, Tokyo, Japan, 7-10 Oct, Piscataway, New Jersey: IEEE, 658-659, available: http://dx.doi.org/10.1109/GCCE.2014.7031095.

Johnson, B.R., Cabuz, E., French, H.B. and Supino, R. (2010) 'Development of a MEMS gyroscope for northfinding applications', in *IEEE/ION Position, Location and Navigation Symposium*, Indian Wells, CA, USA, 4-6 May, Piscataway, New Jersey: IEEE, 168-170, available: http://dx.doi.org/10.1109/PLANS.2010.5507133.

Ju, H.J., Lee, M.S., Park, C.G., Lee, S. and Park, S. (2014) 'Advanced Heuristic Drift Elimination for indoor pedestrian navigation', in *2014 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Busan, South Korea, 27-30 Oct, Piscataway, New Jersey: IEEE, 729-732, available: http://dx.doi.org/10.1109/IPIN.2014.7275553.

Kaemarungsi, K. and Krishnamurthy, P. (2004) 'Properties of indoor received signal strength for WLAN location fingerprinting', in *Mobile and Ubiquitous Systems: Networking and Services, 2004. MOBIQUITOUS 2004. The First Annual International Conference, Boston, MA, USA*, 22-26 Aug, Piscataway, New Jersey: IEEE, 14-23, available: http://dx.doi.org/10.1109/MOBIQ.2004.1331706.

Kals, W.S. (2010) *Land Navigation Handbook: The Sierra Club Guide to Map, Compass and GPS*, Counterpoint.

Kaltiokallio, O., Bocca, M. and Patwari, N. (2012) 'Follow @grandma: Long-term device-free localization for residential monitoring', in *37th Annual IEEE Conference on Local Computer Networks - Workshops*, Clearwater, FL, USA, 22-25 Oct., Piscataway, New Jersey: IEEE, 991-998, available: http://dx.doi.org/10.1109/LCNW.2012.6424092.

Kendell, C.L., Lemaire, E.D. (2008) 'Effect of Mobility Devices on Orientation Sensors that Contain Magnetometers', *CMBES Proceedings, 31(1)*, available: https://proceedings.cmbes.ca/index.php/proceedings/article/view/335 [accessed 17 Apr 2018].

Kirson, A. (1992) 'ATIS-a modular approach [Advanced Traveler Information Systems]', in *IEEE PLANS 92 Position Location and Navigation Symposium Record*, Monterey, CA, USA, 23-27 Mar, Piscataway, New Jersey: IEEE,528-533, available: http://dx.doi.org/10.1109/PLANS.1992.185898.

Kloch, K., Lukowicz, P. and Fischer, C. (2011a) 'Collaborative PDR Localisation with Mobile Phones', in *2011 15th Annual International Symposium on Wearable Computers*, San Francisco, 12-15 Jun, Piscataway, New Jersey: IEEE, 37-40, available: http://dx.doi.org/10.1109/ISWC.2011.16.

Kloch, K., Pirkl, G., Lukowicz, P. and Fischer, C. (2011b) 'Emergent behaviour in collaborative indoor localisation: An example of self-organisation in ubiquitous sensing systems' in *Architecture of Computing Systems-ARCS 2011* Springer, 207-218.

Ko, J., Lu, C., Srivastava, M.B., Stankovic, J.A., Terzis, A. and Welsh, M. (2010) 'Wireless Sensor Networks for Healthcare', *Proceedings of the IEEE*, 98(11), 1947-1960, available: http://dx.doi.org/10.1109/JPROC.2010.2065210.

Konings, D., Faulkner, N., Alam, F., Noble, F. and Lai, E. (2017) 'Do RSSI values reliably map to RSS in a localization system?', in *2017 2nd Workshop on Recent Trends in Telecommunications Research (RTTR)*, Palmerston North, New Zealand, 10-10 Feb, Piscataway, New Jersey: IEEE, 1-5, available: http://dx.doi.org/10.1109/RTTR.2017.7887867.

Kortuem, G., Kawsar, F., Fitton, D. and Sundramoorthy, V. (2010) 'Smart objects as building blocks for the Internet of things', *Internet Computing, IEEE*, 14(1), 44-51, available: http://dx.doi.org/10.1109/MIC.2009.143.

Kouba, J., Popelar, J., Cannon, M.E. and Lachapelle, G. (1994) *Modern geodetic reference frames for precise satellite positioning and navigation*, University of Calgary, Department of Geomatics Engineering.

Kranz, M., Fischer, C. and Schmidt, A. (2010) 'A comparative study of DECT and WLAN signals for indoor localization', in *2010 IEEE International Conference on Pervasive Computing and Communications (PerCom)*, Mannheim, Germany, 29 Mar – 02 Apr, Piscataway, New Jersey: IEEE, 235-243, available: http://dx.doi.org/10.1109/PERCOM.2010.5466970.

Leca, C.L., Ciotirnae, P., Rincu, C.I. and Nicolaescu, I. (2017) 'Characteristics of crowdsourcing for outdoor radio fingerprinting positioning', in *2017 9th International Conference on Electronics, Computers and Artificial Intelligence (ECAI)*, Targoviste, Romania, 29 Jun – 01 Jul, Piscataway, New Jersey: IEEE, 1-4, available: http://dx.doi.org/10.1109/ECAI.2017.8166385.

Lee, S., Tewolde, G., Kwon, J. (2014) 'Design and implementation of vehicle tracking system using GPS/GSM/GPRS technology and smartphone application', in *2014 IEEE World Forum on Internet of Things (WF-IoT),* Seoul, South Korea, 6 – 8 Mar, Piscataway, New Jersey: IEEE, 353–358 available: http://dx.doi.org/ 10.1109/WF-IoT.2014.6803187.

Li, B., Cui, W. and Wang, B. (2015) 'A robust wireless sensor network localization algorithm in mixed LOS/NLOS scenario', *Sensors*, 15(9), 23536-23553.

Lisheng, X., Feifei, Y., Yuqi, J., Lei, Z., Cong, F. and Nan, B. (2011) 'Variation of Received Signal Strength in Wireless Sensor Network', in *Advanced Computer Control (ICACC), 2011 3rd International Conference* , Harbin, China, 18-20 Jan, Piscataway, New Jersey: IEEE, 151-154, available: http://dx.doi.org/10.1109/ICACC.2011.6016387.

Liu, J., Chen, R., Pei, L., Chen, W., Tenhunen, T., Kuusniemi, H., Kröger, T. and Chen, Y. (2010) 'Accelerometer assisted robust wireless signal positioning based on a hidden Markov model', in *IEEE/ION Position, Location and Navigation Symposium*, Indian Wells, CA, USA, 4-6 May, Piscataway, New Jersey: IEEE, 488-497, available: http://dx.doi.org/10.1109/PLANS.2010.5507251.

Liu, Y., Yang, Z., Wang, X. and Jian, L. (2010) 'Location, localization, and localizability', *Journal of Computer Science and Technology*, 25(2), 274-297.

Lui, G., Gallagher, T., Li, B., Dempster, A.G. and Rizos, C. (2011) 'Differences in RSSI readings made by different Wi-Fi chipsets: A limitation of WLAN localization', in *2011 International Conference on Localization and GNSS (ICL-GNSS),* Tampere, Finland, 29 – 30 June, Piscataway, New Jersey: IEEE, 53-57 available: http://dx.doi.org/10.1109/ICL-GNSS.2011.5955283

Ma, F., Liu, F., Zhang, X., Wang, P., Bai, H., Guo, H. (2018) ‘An ultrasonic positioning algorithm based on maximum correntropy criterion extended Kalman filter weighted centroid’, Signal, Image and Video Processing, 12, 1207–1215.

Martinez, S. (2010) 'UAV Cooperative Decision and Control: Challenges and Practical Approaches (Shima, T. and Rasmussen, S.; 2008) [Bookshelf]', *IEEE Control Systems*, 30(2), 104-107, available: http://dx.doi.org/10.1109/MCS.2010.935899.

Matta, D.M. (2000) ‘*Method and system for regulating switching of a traffic light’*, U.S. Pat. 6064319A.

Matz, C.J., Stieb, D.M., Davis, K., Egyed, M., Rose, A., Chou, B. and Brion, O. (2014) 'Effects of Age, Season, Gender and Urban-Rural Status on Time-Activity: Canadian Human Activity Pattern Survey 2 (CHAPS 2)', *International Journal Of Environmental Research And Public Health*, 11(2), 2108-2124.

Mautz, R. (2012) 'Indoor Positioning Technologies: Ph. D. Thesis. Zürich, 2012. 36 p'.

McCune, E. (2010) Practical Digital Wireless Signals, 1st ed, Cambridge, New York: Cambridge University Press.

Meyer, F., Wymeersch, H. and Hlawatsch, F. (2015) 'Cooperative localization with information-seeking control', in *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Brisbane, QLD, Australia, 19-24 April, 2854-2858, Piscataway, New Jersey: IEEE, available: http://dx.doi.org/10.1109/ICASSP.2015.7178492.

Micello (2018) *Micello*, available: https://www.micello.com/ [accessed 28/03/2018].

Miller, H. and Wagner, R.H. (1957) 'Flight Control System for Jet Transports', *IRE Transactions on Aeronautical and Navigational Electronics*, ANE-4(3), 118-126, available: http://dx.doi.org/10.1109/TANE3.1957.4201536.

Mischie, S. (2012) 'On using a gyroscope to measure the angular position', in *2012 10th International Symposium on Electronics and Telecommunications*, Timișoara, Romania, 15-16 Nov, 61-64, Piscataway, New Jersey: IEEE, available: http://dx.doi.org/10.1109/ISETC.2012.6408139.

Moder, T., Hafner, P., Wisiol, K. and Wieser, M. (2014) '3D indoor positioning with pedestrian dead reckoning and activity recognition based on Bayes filtering', in *Indoor Positioning and Indoor Navigation (IPIN), 2014 International Conference* , Busan, South Korea, 27-30 Oct, Piscataway, New Jersey: IEEE, 717-720, available: http://dx.doi.org/10.1109/IPIN.2014.7275549.

Mohri, K. (1984) 'Review on recent advances in the field of amorphous-metal sensors and transducers', *IEEE Transactions on Magnetics*, 20(5), 942-947.

Moore, T. and Stouch, D. (2016) 'A generalized extended kalman filter implementation for the robot operating system' in *Intelligent Autonomous Systems 13* Springer, 335-348.

Mrazovac, B., Bjelica, M.Z., Papp, I. and Teslic, N. (2011) 'Smart Audio/Video Playback Control Based on Presence Detection and User Localization in Home Environment', in *Engineering of Computer Based Systems (ECBS-EERC), 2011 2nd Eastern European Regional Conference on the*, Bratislava, Slovakia, 5-6 Sept, Piscataway, New Jersey: IEEE, 44-53, available: http://dx.doi.org/10.1109/ECBS-EERC.2011.16.

Muller, P., Wymeersch, H. and Piché, R. (2014) 'UWB Positioning with GeneralizedGaussian Mixture Filters', *IEEE Transactions on Mobile Computing*, (10), 2406-2414.

Nakazato, Y., Kanbara, M. and Yokoya, N. (2004) 'Discreet markers for user localization', in *Eighth International Symposium on Wearable Computers*, Arlington, VA, USA, 31 Oct.-3 Nov, Piscataway, New Jersey: IEEE, 172-173, available: http://dx.doi.org/10.1109/ISWC.2004.15.

Nayak, A., Stojmenovic, I. (2010) *Wireless Sensor and Actuator Networks: Algorithms and Protocols for Scalable Coordination and Data Communication*, Hoboken, New Jersey: John Wiley & Sons.

Ni, L.M., Yunhao, L., Yiu Cho, L. and Patil, A.P. (2003) 'LANDMARC: indoor location sensing using active RFID', in *Pervasive Computing and Communications, 2003. (PerCom 2003). Proceedings of the First IEEE International Conference*, Fort Worth, TX, USA, 26-26 March, Piscataway, New Jersey: IEEE, 407-415, available: http://dx.doi.org/10.1109/PERCOM.2003.1192765.

Nia, R., Erlandsson, F., Johnson, H. and Wu, S.F. (2013) 'Leveraging Social Interactions to Suggest Friends', in *2013 IEEE 33rd International Conference on Distributed Computing Systems Workshops*, Philadelphia, PA, USA, 8 - 11 July, Piscataway, New Jersey: IEEE, 386-391, available: http://dx.doi.org/10.1109/ICDCSW.2013.93.

Niculescu, D. and Badri, N. (2003) 'Ad hoc positioning system (APS) using AOA', in *INFOCOM 2003. Twenty-Second Annual Joint Conference of the IEEE Computer and Communications. IEEE Societies (IEEE Cat. No.03CH37428)*, San Francisco, CA, USA, 30 Mar - 3 Apr, Piscataway, New Jersey: IEEE, 1734-1743 vol.3, available: http://dx.doi.org/10.1109/INFCOM.2003.1209196.

Nievergelt, Y. (2001) 'A tutorial history of least squares with applications to astronomy and geodesy' in *Numerical Analysis: Historical Developments in the 20th Century*, Elsevier, 77-112.

Nikbakht, S., Mazlom, M. and Khayatian, A. (2005) 'Evaluation of solid-state accelerometer for positioning of vehicle', in *2005 IEEE International Conference on Industrial Technology*, Hong

Kong, China, 14 - 17 Dec, Piscataway, New Jersey: IEEE, 729-733, available: http://dx.doi.org/10.1109/ICIT.2005.1600732.

Odeh, I. and Hussein, T. (2016) 'Activity Pattern of Urban Adult Students in an Eastern Mediterranean Society', *International Journal of Environmental Research and Public Health*, 13(10), 960.

Oshin, T.O. and Poslad, S. (2013) 'ERSP: An Energy-Efficient Real-Time Smartphone Pedometer', in *2013 IEEE International Conference on Systems, Man, and Cybernetics*, Manchester, UK, 13-16 Oct, Piscataway, New Jersey: IEEE, 2067-2072, available: http://dx.doi.org/10.1109/SMC.2013.354.

Park, J.g., Curtis, D., Teller, S. and Ledlie, J. (2011) 'Implications of device diversity for organic localization', in *INFOCOM, 2011 Proceedings IEEE*, Shanghai, China, 10-15 April, Piscataway, New Jersey: IEEE, 3182-3190, available: http://dx.doi.org/10.1109/INFCOM.2011.5935166.

Parsons, J.D. (2000) *The Mobile Radio Propagation Channel*, 2nd ed, Chichester, New York: Wiley.

Patwari, N., Ash, J.N., Kyperountas, S., Hero, A.O., Moses, R.L. and Correal, N.S. (2005) 'Locating the nodes: cooperative localization in wireless sensor networks', *Signal Processing Magazine, IEEE*, 22(4), 54-69, available: http://dx.doi.org/10.1109/MSP.2005.1458287.

Piwek, L., Ellis, D.A., Andrews, S. and Joinson, A. (2016) 'The rise of consumer health wearables: promises and barriers', *PLoS Medicine*, 13(2), e1001953.

Pole Star (2016) *Pole Star, indoor positioning to anyone anywhere in the world − Polestar*, available: http://www.polestar.eu/en/ [accessed 29th March].

Postorino, M.N., Barrile, V. and Cotroneo, F. (2006) 'Surface movement ground control by means of a GPS–GIS system', *Journal of Air Transport Management*, 12(6), 375-381.

Priyantha, N.B., Chakraborty, A., Balakrishnan, H. (2000) ‘The Cricket Location-support System’, in *Proceedings of the 6th Annual International Conference on Mobile Computing and Networking, MobiCom ’00*, Boston, MA, USA, 6 – 11 Aug, New York, NY, USA: ACM, 32–43, available: http://doi.acm.org/10.1145/345910.345917.

Qiang, L. and Kaplan, L.M. (2010) 'Target localization using proximity binary sensors', in *Aerospace Conference, 2010 IEEE*, Big Sky MT, USA, 6 - 13 March, Piscataway, New Jersey: IEEE, 1-8, available: http://dx.doi.org/10.1109/AERO.2010.5446675.

Rahnema, M. (1993) 'Overview of the GSM system and protocol architecture', *IEEE Communications Magazine*, 31(4), 92-100, available: http://dx.doi.org/10.1109/35.210402.

Rantakokko, J., Rydell, J., Stromback, P., Handel, P., Callmer, J., Tornqvist, D., Gustafsson, F. and Grudén, M. (2011) 'Accurate and reliable soldier and first responder indoor positioning: multisensor systems and cooperative localization', *Wireless Communications, IEEE*, 18(2), 10-18.

Rappaport, T.S. (2002) Wireless Communications: Principles and Practice, 2nd ed, Upper Saddle River, NJ: Prentice Hall PTR.

Ren, Y., Lin, J., Zhu, J., Sun, B. and Ye, S. (2015) 'Coordinate transformation uncertainty analysis in large-scale metrology', *IEEE Transactions on Instrumentation and Measurement*, 64(9), 2380-2388.

Rosa, F.D., Li, X., Nurmi, J., Pelosi, M., Laoudias, C. and Terrezza, A. (2011) 'Hand-grip and body-loss impact on RSS measurements for localization of mass market devices', in *Localization and GNSS (ICL-GNSS), 2011 International Conference*, Tampere, Finland, 29 - 30 Jun, Piscataway, New Jersey: IEEE, 58-63, available: http://dx.doi.org/10.1109/ICL-GNSS.2011.5955274.

Rowe, A., Starr, Z. and Rajkumar, R. (2007) 'Using micro-climate sensing to enhance RF localization in assisted living environments', in *Systems, Man and Cybernetics, 2007. ISIC. IEEE International Conference*, Montreal, Que, Canada, 7 - 10 Oct, Piscataway, New Jersey: IEEE, 3668-3675, available: http://dx.doi.org/10.1109/ICSMC.2007.4414137.

Safavi, S., Khan, U.A., Kar, S. and Moura, J.M.F. (2018) 'Distributed Localization: A Linear Theory', *Proceedings of the IEEE*, 106(7), 1204 – 1223 available: http://dx.doi.org/10.1109/JPROC.2018.2823638.

Sai, R.P., Bapanapalle, S., Praveen, K. and Sunil, M.P. (2016) 'Pedometer and calorie calculator for fitness tracking using MEMS digital accelerometer', in *2016 International Conference on Inventive Computation Technologies (ICICT)*, Coimbatore, India, 26 - 27 Aug, Piscataway, New Jersey: IEEE, 1-6, available: http://dx.doi.org/10.1109/INVENTIVE.2016.7823237.

Sanpechuda, T. and Kovavisaruch, L. (2008) 'A review of RFID localization: Applications and techniques', in *Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology, 2008. ECTI-CON 2008. 5th International Conference*, Krabi, Thailand, 14 - 17 May, Piscataway, New Jersey: IEEE, 769-772, available: http://dx.doi.org/10.1109/ECTICON.2008.4600544.

Sato, T., Nakamura, S., Terabayashi, K., Sugimoto, M. and Hashizume, H. (2011) 'Design and implementation of a robust and real-time ultrasonic motion-capture system', in *2011 International Conference on Indoor Positioning and Indoor Navigation*, Guimaraes, Portugal, 21-23 Sep, Piscataway, New Jersey: IEEE, 1-6, available: http://dx.doi.org/10.1109/IPIN.2011.6071907.

Scholtz, R. (1968) 'Review of 'Detection, Estimation, and Modulation Theory, Part I' (Van Trees, H.; 1968)', *IEEE Transactions on Information Theory*, 14(4), 612-613, available: http://dx.doi.org/10.1109/TIT.1968.1054174.

Scopigno, R., Autolitano, A., Acarman, T., x00C, Yaman and Topsu, S. (2015) 'The potential benefits of on-board Li-Fi for the cooperation among vehicles', in *2015 17th International Conference on Transparent Optical Networks (ICTON)*, Budapest, Hungary, 5-9 Jul, Piscataway, New Jersey: IEEE, 1-6, available: http://dx.doi.org/10.1109/ICTON.2015.7193411.

Sharp, I., Yu, K. (2018) *Wireless Positioning: Principles and Practice*, New York, NY: Springer Berlin Heidelberg.

Shen, Y., Wymeersch, H. and Win, M.Z. (2010) 'Fundamental Limits of Wideband Localization; Part II: Cooperative Networks', *IEEE Transactions on Information Theory*, 56(10), 4981-5000, available: http://dx.doi.org/10.1109/TIT.2010.2059720.

Shih, C.Y., Marr, P.J. and x0F (2010) 'COLA: Complexity-Reduced Trilateration Approach for 3D Localization in Wireless Sensor Networks', in *Sensor Technologies and Applications (SENSORCOMM), 2010 Fourth International Conference* , Venice, Italy, 18-25 July, Piscataway, New Jersey: IEEE, 24-32, available: http://dx.doi.org/10.1109/SENSORCOMM.2010.11.

Siddiqui, F.A. (2004) 'A Hybrid Framework for Localization and Convergence in Indoor Environments', in *Engineering, Sciences and Technology, Student Conference*, Karachi, Pakistan, 30-31 Dec, Piscataway, New Jersey: IEEE, 12-18, available: http://dx.doi.org/10.1109/SCONES.2004.1564761.

SITA (2016) *Beacon Registry | SITA*, available: https://www.sita.aero/resources/type/white-papers/ibeacons [accessed 20/04/2016].

Sonitor (2018) *Sonitor*, available: http://www.sonitor.com [accessed 07/04/2018].

Spangenberg, M., Tourneret, J.Y., Calmettes, V. and Duchateau, G. (2008) 'Detection of variance changes and mean value jumps in measurement noise for multipath mitigation in urban navigation', in *Signals, Systems and Computers, 2008 42nd Asilomar Conference*, Pacific Grove, CA, USA, 26-29 Oct, Piscataway, New Jersey: IEEE, 1193-1197, available: http://dx.doi.org/10.1109/ACSSC.2008.5074604.

St-Pierre, M., Gingras, D. (2004) 'Comparison between the unscented Kalman filter and the extended Kalman filter for the position estimation module of an integrated navigation information system', in *IEEE Intelligent Vehicles Symposium, 2004*, Parma, Italy, 14 – 17 Jun, Piscataway, New Jersey: IEEE, 831–835, available: http://dx.doi.org/10.1109/IVS.2004.1336492.

Stojanović, D. and Stojanović, N. (2014) 'Indoor localization and tracking: Methods, technologies and research challenges', *Facta Universitatis, Series: Automatic Control and Robotics*, 13(1), 57-72.

Subhan, F., Hasbullah, H., Rozyyev, A., Bakhsh, S.T. (2011) 'Indoor positioning in Bluetooth networks using fingerprinting and lateration approach', in *2011 International Conference on Information Science and Applications*, Jeju Island, South Korea, 26 – 29 Apr, Piscataway, New Jersey: IEEE, 1–9, available: http://dx.doi.org/10.1109/ICISA.2011.5772436.

Takabayashi, Y., Matsuzaki, T., Kameda, H. and Ito, M. (2008) 'Target tracking using TDOA/FDOA measurements in the distributed sensor network', in *SICE Annual Conference, 2008*, Tokyo, Japan, 20-22 Aug, Piscataway, New Jersey: IEEE, 3441-3446, available: http://dx.doi.org/10.1109/SICE.2008.4655257.

Tang, Y. and Li, C. (2015) 'Wearable indoor position tracking using onboard K-band Doppler radar and digital gyroscope', in *2015 IEEE MTT-S 2015 International Microwave Workshop Series on RF and Wireless Technologies for Biomedical and Healthcare Applications (IMWS-BIO)*, Taipei, Taiwan, 21-23 Sept, Piscataway, New Jersey: IEEE, 76-77, available: http://dx.doi.org/10.1109/IMWS-BIO.2015.7303785.

Teizer, J. (2015) 'Status quo and open challenges in vision-based sensing and tracking of temporary resources on infrastructure construction sites', *Advanced Engineering Informatics*, 29(2), 225-238.

Tenmoku, R., Kanbara, M. and Yokoya, N. (2003) 'A wearable augmented reality system for navigation using positioning infrastructures and a pedometer', in *The Second IEEE and ACM International Symposium on Mixed and Augmented Reality, 2003. Proceedings.*, Tokyo, Japan, 10-10 Oct, Piscataway, New Jersey: IEEE, 344-345, available: http://dx.doi.org/10.1109/ISMAR.2003.1240752.

Tian, X., Miao, Y., Hu, T., Fan, B., Pan, J. and Xu, W. (2009) 'Maximum likelihood estimation based on time synchronization algorithm for wireless sensor networks', in *2009 ISECS International Colloquium on Computing, Communication, Control, and Management*, Sanya, China, 8-9 Aug, Piscataway, New Jersey: IEEE, 416-420, available: http://dx.doi.org/10.1109/CCCM.2009.5267612.

Tiemann, J., Schweikowski, F., Wietfeld, C. (2015) ‘Design of an UWB indoor-positioning system for UAV navigation in GNSS-denied environments’, in *2015 International Conference on Indoor Positioning and Indoor Navigation (IPIN),* Banff, AB, Canada, 13 – 16 Oct, Piscataway, New Jersey: IEEE, 1–7, available: http://dx.doi.org/10.1109/IPIN.2015.7346960.

Tsai, T.C. and Teng, W.T. (2012) 'A large scale cooperative localization method', in *2012 1st IEEE International Conference on Communications in China (ICCC),* Beijing, China, 15-17 Aug, Piscataway, New Jersey: IEEE, 722-727, available: http://dx.doi.org/10.1109/ICCChina.2012.6356978.

Van Sickle, J. (2010) *Basic GIS Coordinates,* Second Edition, 2nd ed, Boca Raton, FL: CRC Press.

Wang, Y., Yang, X., Zhao, Y., Liu, Y., Cuthbert, L. (2013) ‘Bluetooth positioning using RSSI and triangulation methods’, in *2013 IEEE 10th Consumer Communications and Networking Conference (CCNC),* Las Vegas, NV, USA, 11 – 14 Jan, Piscataway, New Jersey: IEEE, 837–842, available: http://dx.doi.org/10.1109/CCNC.2013.6488558.

Want, R. and Hopper, A. (1992) 'Active badges and personal interactive computing objects', *IEEE Transactions on Consumer Electronics*, 38(1), 10-20, available: http://dx.doi.org/10.1109/30.125076.

Welch, G. and Bishop, G. (2006) 'An introduction to the kalman filter. Department of Computer Science, University of North Carolina', *ed: Chapel Hill, NC, unpublished manuscript*.

Weyn, M. (2011) *Opportunstic Seamless Localization,* Morrisville, NC, USA: Lulu Press.

Wicaksono, H., Gunawan, Y. and Kristanto, C. (2015) 'A fast geometric Type2 Fuzzy controller using barometric sensor for altitude stabilization QuadRotor', in *2015 7th International Conference on Information Technology and Electrical Engineering (ICITEE),* Chiang Mai, Thailand, 29-30 Oct, Piscataway, New Jersey: IEEE, 520-524, available: http://dx.doi.org/10.1109/ICITEED.2015.7409002.

Wigren, T. (2007) 'Adaptive Enhanced Cell-ID Fingerprinting Localization by Clustering of Precise Position Measurements', *IEEE Transactions on Vehicular Technology*, 56(5), 3199-3209, available: http://dx.doi.org/10.1109/TVT.2007.900400.

Willim, R. (2007) 'Walking The Cognisphere: Navigation and Digital Media on The Go', in *Inter: A European Cultural Studies : Conference in Sweden,* Linköping, Sweden, 11 – 13 Jun, Linköping, Sweden: Linköping University Electronic Press, 667-676, available: http://www.ep.liu.se/ecp/025/ecp07025.pdf [accessed: 08 Mar 2018].

Win, M.Z., Conti, A., Mazuelas, S., Shen, Y., Gifford, W.M., Dardari, D. and Chiani, M. (2011) 'Network localization and navigation via cooperation', *IEEE Communications Magazine*, 49(5), 56-62, available: http://dx.doi.org/10.1109/MCOM.2011.5762798.

Wymeersch, H., Lien, J. and Win, M.Z. (2009) 'Cooperative Localization in Wireless Networks', *Proceedings of the IEEE,* 97(2), 427-450, available: http://dx.doi.org/10.1109/JPROC.2008.2008853.

Xiao, J., Liu, Z., Yang, Y., Liu, D., Han, X. (2011) ‘Comparison and analysis of indoor wireless positioning techniques’, in *2011 International Conference on Computer Science and Service System (CSSS),* Nanjing, China, 27 -29 Jun, Piscataway, New Jersey: IEEE, 293–296, available: http://dx.doi.org/10.1109/CSSS.2011.5972088.

Xie, B., Chen, K., Tan, G., Lu, M., Liu, Y., Wu, J. and He, T. (2016) 'LIPS: A Light Intensity--Based Positioning System for Indoor Environments', *ACM Transactions on Sensor Networks (TOSN)*, 12(4), 28.

Xie, P. and Petovello, M.G. (2015) 'Measuring GNSS Multipath Distributions in Urban Canyon Environments', *Instrumentation and Measurement, IEEE Transactions on*, 64(2), 366-377, available: http://dx.doi.org/10.1109/TIM.2014.2342452.

Yang, C., Nguyen, T. and Blasch, E. (2014) 'Mobile positioning via fusion of mixed signals of opportunity', *IEEE Aerospace and Electronic Systems Magazine*, 29(4), 34-46, available: http://dx.doi.org/10.1109/MAES.2013.130105.

Yang, C. and Shao, H.r. (2015) 'WiFi-based indoor positioning', *IEEE Communications Magazine*, 53(3), 150-157, available: http://dx.doi.org/10.1109/MCOM.2015.7060497.

Yang, Z., Sun, Z., Jiang, L., Xie, Y. and Kishida, H. (2009) 'An area zoning based WLAN location system', in *Wireless Mobile and Computing (CCWMC 2009), IET International Communication Conference*, Shanghai, China, 7-9 Dec Stevenage, UK: IET, 437-440.

Yassin, M. and Rachid, E. (2015) 'A survey of positioning techniques and location based services in wireless networks', in *2015 IEEE International Conference on Signal Processing, Informatics, Communication and Energy Systems (SPICES)*, Kozhikode, India, 19-21 Feb, Piscataway, New Jersey: IEEE, 1-5, available: http://dx.doi.org/10.1109/SPICES.2015.7091420.

Yilin, Z. (2002) 'Standardization of mobile phone positioning for 3G systems', *IEEE Communications Magazine*, 40(7), 108-116, available: http://dx.doi.org/10.1109/MCOM.2002.1018015.

Zaliva, V. and Franchetti, F. (2014) 'Barometric and GPS altitude sensor fusion', in *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Florence, Italy, 4-9 May, Piscataway, New Jersey: IEEE, 7525-7529, available: http://dx.doi.org/10.1109/ICASSP.2014.6855063.

Zhang, F. and Leonard, N.E. (2008) 'Cooperative Kalman filters for cooperative exploration', in *2008 American Control Conference*, Seattle, WA, USA, 11-13 Jun, Piscataway, New Jersey: IEEE, 2654-2659, available: http://dx.doi.org/10.1109/ACC.2008.4586893.

Zhang, W., Chowdhury, M.I.S. and Kavehrad, M. (2014) 'Asynchronous indoor positioning system based on visible light communications', *Optical Engineering*, 53(4), 045105.

Zhao, F. and Guibas, L.J. (2004) *Wireless sensor networks: an information processing approach*, Morgan Kaufmann.

Zhao, T. and Nehorai, A. (2007) 'Distributed Sequential Bayesian Estimation of a Diffusive Source in Wireless Sensor Networks', *IEEE Transactions on Signal Processing*, 55(4), 1511-1524, available: http://dx.doi.org/10.1109/TSP.2006.889975.

Zheng, S., Farley, R., Kaleas, T., Ellis, J. and Chikkappa, K. (2011) 'Cortina: Collaborative context-aware indoor positioning employing RSS and RToF techniques', in *Pervasive Computing and Communications Workshops (PERCOM Workshops), 2011 IEEE International Conference*, Seattle, WA, USA, 21-25 Mar, Piscataway, New Jersey: IEEE, 340-343, available: http://dx.doi.org/10.1109/PERCOMW.2011.5766901.

Zheng, X., Bao, G., Fu, R. and Pahlavan, K. (2012) 'The Performance of Simulated Annealing Algorithms for Wi-Fi Localization Using Google Indoor Map', in *2012 IEEE Vehicular*

Technology Conference (VTC Fall), Quebec City, QC, Canada, 3-6 Sep, Piscataway, New Jersey: IEEE, 1-5, available: http://dx.doi.org/10.1109/VTCFall.2012.6399302.

Zhou, Y. (2009) ‘An efficient least-squares trilateration algorithm for mobile robot localization’, in *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*, St. Louis, MO, USA, 10 – 15 Oct, Piscataway, New Jersey: IEEE, 3474–3479, available: http://dx.doi.org/10.1109/IROS.2009.5354370.

Zhuang, Y., Syed, Z., Georgy, J. and El-Sheimy, N. (2015) 'Autonomous smartphone-based WiFi positioning system by using access points localization and crowdsourcing', *Pervasive and mobile computing*, 18, 118-136.

Zhuang, Y., Syed, Z., Li, Y. and El-Sheimy, N. (2016) 'Evaluation of two WiFi positioning systems based on autonomous crowdsourcing of handheld devices for indoor navigation', *IEEE Transactions on Mobile Computing*, 15(8), 1982-1995.

Appendix 1 – Code

1.1 CAPTURE Code

```
package model;

public class Trilateration
{
   // Declare global variables
   private static double[] refPoint1Details = new double[3];
   private static double[] refPoint2Details = new double[3];
   private static double[] refPoint3Details = new double[3];
   private static double[] setDistance = new double[2];
   private static double[] calcedDistance = new double[2];

   private static double refP1_x;
   private static double refP1_y;
   private static double refP2_x;
   private static double refP2_y;
   private static double refP3_x;
   private static double refP3_y;

   /**
    * Method that sets the exact coordinates of the lost phone
    *
    * @param x_1
    * @param y_1
    * @param x_2
    * @param y_2
    * @param x_3
    * @param y_3
    * @param dist_1
    * @param dist_2
    * @param dist_3
   */
public static void fixedTrilateration(double x_1, double y_1, double x_2,
double y_2, double x_3, double y_3, double dist_1, double dist_2, double
dist_3)
   {
      refPoint1Details[0] = x_1;
      refPoint1Details[1] = y_1;
      refPoint1Details[2] = dist_1;
      refPoint2Details[0] = x_2;
      refPoint2Details[1] = y_2;
      refPoint2Details[2] = dist_2;

      refPoint3Details[0] = x_3;
      refPoint3Details[1] = y_3;
      refPoint3Details[2] = dist_3;

      double refP1_x = x_1;
      double refP1_y = y_1;
      double refP2_x = x_2;
      double refP2_y = y_2;
```

```
      double refP3_x = x_3;
      double refP3_y = y_3;

      double distanceRssiRefP_1 = dist_1;
      double distanceRssiRefP_2 = dist_2;
      double distanceRssiRefP_3 = dist_3;

double S = (Math.pow(refP3_x, 2.) - Math.pow(refP2_x, 2.) +
Math.pow(refP3_y, 2.) - Math.pow(refP2_y, 2.) +
Math.pow(distanceRssiRefP_2, 2.) - Math.pow(distanceRssiRefP_3, 2.)) / 2.0;

double T = (Math.pow(refP1_x, 2.) - Math.pow(refP2_x, 2.) +
Math.pow(refP1_y, 2.) - Math.pow(refP2_y, 2.) +
Math.pow(distanceRssiRefP_2, 2.) - Math.pow(distanceRssiRefP_1, 2.)) / 2.0;

double lostPhone_y = ((T * (refP2_x - refP3_x)) - (S * (refP2_x -
refP1_x))) / (((refP1_y - refP2_y) * (refP2_x - refP3_x)) - ((refP3_y -
refP2_y) * (refP2_x - refP1_x)));

double lostPhone_x = ((lostPhone_y * (refP1_y - refP2_y)) - T) / (refP2_x -
refP1_x);

      System.out.println("x = " + lostPhone_x);
      System.out.println("Y = " + lostPhone_y);

      setDistance[0] = (int)lostPhone_x;
      setDistance[1] = (int)lostPhone_y;
   }

   /**
    * Method that sets the coordinates from the given rssi of the lost
phone
    *
    * @param x_1
    * @param y_1
    * @param x_2
    * @param y_2
    * @param x_3
    * @param y_3
    * @param dist_1
    * @param dist_2
    * @param dist_3
    */

public static void calcedTrilateration(double x_1, double y_1, double x_2,
double y_2, double x_3, double y_3, double dist_1, double dist_2, double
dist_3)
   {
      // x and y coordinates
      refP1_x = x_1;
      refP1_y = y_1;
      refP2_x = x_2;
      refP2_y = y_2;
      refP3_x = x_3;
      refP3_y = y_3;
// RSS calculated distance from each ref point to the lost phone
      double distanceRssiRefP_1 = dist_1;
      double distanceRssiRefP_2 = dist_2;
      double distanceRssiRefP_3 = dist_3;
```

```
        // Use coordinates and distances to calculate variable S
        double S = (Math.pow(refP3_x, 2) - Math.pow(refP2_x, 2.) +
Math.pow(refP3_y, 2) - Math.pow(refP2_y, 2) + Math.pow(distanceRssiRefP_2,
2) - Math.pow(distanceRssiRefP_3, 2)) / 2;

        // Use coordinates and distances to calculate variable T
        double T = (Math.pow(refP1_x, 2) - Math.pow(refP2_x, 2.) +
Math.pow(refP1_y, 2) - Math.pow(refP2_y, 2) + Math.pow(distanceRssiRefP_2,
2) - Math.pow(distanceRssiRefP_1, 2)) / 2;

        // Use S and T along with coordinates and distances to calculate X
and Y
        double lostPhone_y = ((T * (refP2_x - refP3_x)) - (S * (refP2_x -
refP1_x))) / (((refP1_y - refP2_y) * (refP2_x - refP3_x)) - ((refP3_y -
refP2_y) * (refP2_x - refP1_x)));
        double lostPhone_x = ((lostPhone_y * (refP1_y - refP2_y)) - T) /
(refP2_x - refP1_x);

        // Print x and y to the console
        System.out.println("x = " + lostPhone_x);
        System.out.println("Y = " + lostPhone_y);

        // Store RSS calculated X and Y coordinates to the clacedDistance
array
        calcedDistance[0] = (int) lostPhone_x;
        calcedDistance[1] = (int) lostPhone_y;

    }

    /**
     * Method to return the info on ref Point 1
     *
     * @return double array of ref point 1 details
     */
    public static double[] getRefPoint1Details()
    {
        return refPoint1Details;
    }

    /**
     * Method to return the info on ref Point 2
     *
     * @return double array of ref point 2 details
     */
    public static double[] getRefPoint2Details()
    {
        return refPoint2Details;
    }

    /**
     * Method to return the info on ref Point 3
     * @return double array of ref point 3 details
     */
    public static double[] getRefPoint3Details()
    {
        return refPoint3Details;
    }

    /**
     * Method to return the info of set x and y
     * @return double array of set coordinates
```

```
     */
    public static double[] getsetDist()
    {
       return setDistance;
    }

    /**
     * Method to return the info of RSS set x and y
     *
     * @return double array of calculated distances by RSS
     */
    public static double[] getCalcedDist()
    {
       return calcedDistance;
    }
}
```

1.2 Kalman Filter Code

```
import org.apache.commons.math3.filter.DefaultMeasurementModel;
import org.apache.commons.math3.filter.DefaultProcessModel;
import org.apache.commons.math3.filter.KalmanFilter;
import org.apache.commons.math3.filter.MeasurementModel;
import org.apache.commons.math3.filter.ProcessModel;
import org.apache.commons.math3.linear.Array2DRowRealMatrix;
import org.apache.commons.math3.linear.ArrayRealVector;
import org.apache.commons.math3.linear.RealMatrix;
import org.apache.commons.math3.linear.RealVector;

/**
 * @author Gary Cullen
 *  Date:  18-Jul-2017
 */
public class KalmanFilterCartesian {

    // Position measurement noise (in meters)
    private final double MEAS_NOISE;
    // Process noise (in meters)
    private final double PROC_NOISE;
    // Error covariance
    private final double ERROR_COV;
    // Discrete time interval between steps
    private final double dt;

    // A - state transition matrix
    private RealMatrix A;
    // B - control input matrix
    private RealMatrix B;
    // H - measurement matrix
    private RealMatrix H;
    // Q - process noise covariance matrix (process error)
    private RealMatrix Q;
    // R - measurement noise covariance matrix (measurement error)
    private RealMatrix R;
    // P - error covariance matrix
    private RealMatrix P;
    // x - state
    private RealVector x;
```

```
    // Kalman Filter
    private KalmanFilter filter;

    /**
     * Constructs a default KalmanFilter
     */
    public KalmanFilterCartesian(){
        // Change first 3 parameters to change algorithm sensitivity
        // Last 2 parameters are the initial X and Y coordinates
        this(100d, 0.001d, 0.5d, 1e-6d, 0, 0);
    }

    /**
     * Constructs a KalmanFilter that takes initial system state
     * @param measNoise Measurement covariance
     * @param procNoise Process noise
     * @param error Error covariance
     * @param time Discrete time interval
     * @param X Initial X coordinate
     * @param Y Initial Y coordinate
     */
    public KalmanFilterCartesian(double measNoise, double procNoise, double
error, double time, double X, double Y) {
        // Set measurement and process error constants
        this.MEAS_NOISE = measNoise;
        this.PROC_NOISE = procNoise;
        this.ERROR_COV = error;
        // Set discrete time steps
        this.dt = time;
        // A =
        A = new Array2DRowRealMatrix(new double[][]{
            {1d, 0d, dt, 0d},
            {0d, 1d, 0d, dt},
            {0d, 0d, 1d, 0d},
            {0d, 0d, 0d, 1d}
        });
        // B =
        B = new Array2DRowRealMatrix(new double[][]{
            {Math.pow(dt, 2d) / 2d},
            {Math.pow(dt, 2d) / 2d},
            {dt},
            {dt}
        });
        //only observe first 2 values - the position coordinates
        H = new Array2DRowRealMatrix(new double[][]{
            {1d, 0d, 0d, 0d},
            {0d, 1d, 0d, 0d},
        });
        // System state with initial state included
        x = new ArrayRealVector(new double[] {X, Y, 0, 0});
        // Measurement noise covariance matrix
        R = new Array2DRowRealMatrix(new double[][] {
            { Math.pow(this.MEAS_NOISE, 2d), 0d },
            { 0d, Math.pow(this.MEAS_NOISE, 2d) }
        });
        // Process noise covariance matrix
        Q = new Array2DRowRealMatrix(new double[][]{
            {Math.pow(PROC_NOISE, 4d) / 4d, 0d, Math.pow(PROC_NOISE, 3d) /
2d, 0d},
            {0d, Math.pow(PROC_NOISE, 4d) / 4d, 0d, Math.pow(PROC_NOISE,
```

```
3d) / 2d},
            {Math.pow(PROC_NOISE, 3d) / 2d, 0d, Math.pow(PROC_NOISE, 2d),
0d},
            {0d, Math.pow(PROC_NOISE, 3d) / 2d, 0d, Math.pow(PROC_NOISE,
2d)}
        });
        // Error covariance matrix
        P = new Array2DRowRealMatrix(new double[][] {
            {ERROR_COV, 0d, 0d, 0d},
            {0d, ERROR_COV, 0d, 0d},
            {0d, 0d, ERROR_COV, 0d},
            {0d, 0d, 0d, ERROR_COV}
        });

        // Create process model, measurement model and kalman filter
        ProcessModel pm = new DefaultProcessModel(A, B, Q, x, P);
        MeasurementModel mm = new DefaultMeasurementModel(H, R);
        filter = new KalmanFilter(pm, mm);
    }

    /**
     * Method to estimate position using Kalman filter
     * @param xy measured position
     * @return estimated position
     */
    public double[] estimatePosition(double[] xy){
        filter.predict();
        filter.correct(xy);
        return filter.getStateEstimation();
    }

}
```

1.3 Pseudocode Description

Positioning Stanchions

```
// Get UWB Master Stanchion positions
For each UWB Ceiling Mounted Anchor (CMA)
Get CMA1 (x,y) coordinate //(pre-recorded stored positions)
// Get UWB estimates via DecaWave Time of Flight algorithm
    Get distance (d1) from CMA1 to Master Stanchion1 (MS1);
    Get distance (d2) from CMA2 to MS1;
    Get distance (d3) from CMA3 to MS1;

// estimate the coordinate position of the master stanchions
Calc MS (x,y) position via Trilateration Algorithm using:
        CMA1 position and d1;
        CMA2 position and d2;
        CMA3 position and d3;
    Store MS position

// Get UWB estimates via DecaWave Time of Flight algorithm
For each Anchor Stanchion (AS)
// Get (UWB) distances from AS's to the MS's
    Get d1 from MS1 to AS1;
    Get d2 from MS2 to AS1;
    Get d3 from MS3 to AS1;

// estimate the coordinate position of the ASs
Calc AS (x,y) position via Trilateration Algorithm using:
        MS1 position and d1;
        MS2 position and d2;
        MS3 position and d3;
    Store AS (x,y) coordinate
// Filter or clean stanchion positions
For each AS coordinate
    // Pass coordinate through a Discrete Kalman Filter
    Filter coordinate with Kalman Filter
    Store filtered coordinate and system time
```

Positioning Lost Devices

```
// Get lost device positions
For each mobileDevice (passenger held device)

// Get RSS (BLe\Wi-Fi) reads from stanchions to lost device
    Get rss (*100) from AS1 to mobileDevice;
    Get rss (*100) from AS2 to mobileDevice;
    Get rss (*100) from AS3 to mobileDevice;

        // Remove measurement noise (Basic Filter)
        Filter rss1 (*100);
        Filter rss2 (*100);
        Filter rss3 (*100);

// Pass rss values into path loss algorithm to determine range
            Calculate d1 from path loss algorithm using rss1;
            Calculate d2 from path loss algorithm using rss2;
            Calculate d3 from path loss algorithm using rss3;

// estimate the coordinate position of the lost device
Calc mobileDevice (x,y)coordinate via Trilateration using:
            AS1 position and d1;
            AS2 position and d2;
            AS3 position and d3;

// Filter or clean lost device positions
For each mobileDevice coordinate

// Pass coordinate through a Discrete Kalman Filter
    Filter coordinate with Kalman Filter
    Store filtered coordinate and system time
```

Calculate Distance - Path Loss Algorithm

```
     // rss = -(10n Log10 (d)+A)
     // n: Path Loss Exponent
     // d: Distance from transmitting device
     // A: rss at 1 metre distance
// Declare variables
Declare rss read at 1 metre
Declare pathLossExponent
Get rss read
    // Calculate distance
d = 10 to the power of ((rss_Read - 1_metreRead) / (-10
(pathLossExponent))
Return d
```

Basic Filter

```
// Declare rss noise to be filtered
Declare threshold
For 20 rss readings
    Calculate average
        if (rss > average + threshold)
            remove rss
        else if (rss < average - threshold)
            remove rss
        else
            return rss
```

Kalman Filter

```
//Declare process matrices
Declare state transition matrix //sampling rate is declared here
Declare control input matrix //sampling rate is declared here also
Declare process noise covariance matrix    //this   is   for   known
process errors
Declare error covariance matrix
Declare state matrix //this is used to hold the current state of the
system
// Create process model
Create process model using process matrices
//Declare measurement matrices
Declare measurement matrix //this holds current measurements of the
system
Declare  measurement  noise  covariance  matrix  //this  is  for  known
measurement errors
// Create measurement model
Create measurement model using measurement matrices
// Create Kalman Filter (KF)
Create KF using process and measurement models
// KF filtering process
For each coordinate to be filtered
    // Predict the system state based on previous system states
    Predict the state of the system using the KF
    // Correct the prediction with the measured state
    Correct the prediction using the coordinate and the KF
    // Get an estimation of the system state after correction
    Get an estimation of the new state using KF
```

Appendix 2 - Results

1.1 UWB Range results (partial)

ID	5m	10m	15m	20m	25m	30m	40m	50m	60m	70m	80m	90m
1	5.095	10.062	15.082	19.957	25.65	30.523	40.114	50.207	60.15	70.122	80.258	90.126
2	5.109	10.067	15.091	19.924	25.453	30.513	40.18	50.198	60.187	70.122	80.201	90.131
3	5.105	10.076	15.072	19.92	25.106	30.499	40.133	50.151	60.202	70.145	80.164	90.084
4	5.086	10.076	15.082	19.915	25.416	30.523	40.156	49.958	60.192	70.131	80.126	90.149
5	5.091	10.095	15.101	19.92	25.359	30.532	40.175	50.155	60.202	70.108	80.197	90.168
6	5.109	10.1	15.087	19.896	25.706	30.546	40.123	50.132	59.991	70.187	80.201	90.168
7	5.123	10.095	15.077	19.873	25.378	30.49	40.147	50.259	60.145	70.126	80.122	90.093
8	5.095	10.1	15.04	19.878	25.317	30.542	40.18	50.226	60.239	70.117	80.215	90.126
9	5.109	10.104	15.026	19.878	25.402	30.56	40.137	50.207	60.183	70.192	80.201	90.079
10	5.1	10.09	15.04	19.864	25.444	30.513	40.1	50.174	60.183	70.145	80.14	90.103
11	5.095	10.09	15.068	19.873	25.13	30.438	40.142	50.235	60.187	70.178	80.211	90.103
12	5.109	10.086	15.091	19.864	25.219	30.542	40.161	50.301	60.173	70.183	80.22	90.173
13	5.086	10.086	15.082	19.924	25.406	30.462	40.137	50.268	60.216	70.103	80.173	90.093
14	5.109	10.1	15.091	19.882	25.392	30.481	40.119	50.343	60.145	70.131	80.197	90.098
15	5.072	10.067	15.105	19.854	25.294	30.56	40.128	50.193	60.122	70.131	80.159	90.112
16	5.086	10.076	15.035	19.934	25.434	30.513	40.133	50.23	60.108	70.108	80.178	90.131
17	5.077	10.062	15.044	19.892	25.636	30.495	40.123	50.155	60.127	70.197	80.182	90.14
18	5.091	10.09	15.105	19.887	25.631	30.499	40.161	50.207	60.197	70.089	80.253	90.089
19	5.095	10.095	15.063	19.896	25.392	30.49	40.128	50.249	60.155	70.154	80.136	90.084
20	5.105	10.034	15.077	19.91	25.106	30.537	40.17	50.16	60.085	70.15	80.112	90.117

21	5.114	10.086	15.063	19.91	25.669	30.57	40.105	50.155	60.295	70.117	80.276	90.107
22	5.109	10.076	15.072	19.906	25.101	30.485	40.147	50.17	60.642	70.173	80.201	90.164
23	5.1	10.1	15.054	19.967	25.599	30.504	40.166	50.188	60.173	70.183	80.15	90.182
24	5.105	10.114	15.063	19.929	25.674	30.532	40.161	50.263	60.15	70.154	80.122	90.159
25	5.105	10.067	15.035	19.91	25.303	30.513	40.137	50.123	60.127	70.098	80.299	90.154
26	5.091	10.123	15.082	19.92	25.134	30.523	40.198	50.212	60.192	70.122	80.136	90.135
27	5.105	10.076	15.054	19.948	25.111	30.532	40.156	50.174	60.206	70.173	80.154	90.117
28	5.119	10.048	15.143	19.892	25.383	30.532	40.095	50.062	60.169	70.15	80.255	90.154
..												
…												
….												
……..												
…………..												
494	5.109	10.053	15.077	19.901	25.603	30.593	40.142	50.212	60.239	70.215	80.262	90.089
495	5.1	10.081	15.03	19.92	25.378	30.49	40.161	50.16	60.164	70.122	80.168	90.131
496	5.114	10.043	15.03	19.943	25.359	30.499	40.152	50.179	60.164	70.197	80.229	90.149
497	5.1	10.104	15.096	19.906	25.688	30.429	40.133	50.296	60.216	70.164	80.258	90.051
498	5.1	10.062	15.105	19.901	25.153	30.509	40.156	50.193	60.202	70.164	80.164	90.112
499	5.114	10.062	15.082	19.887	25.397	30.452	40.105	50.179	60.291	70.126	80.225	90.121
500	5.086	10.076	15.035	19.934	25.434	30.513	40.133	50.23	60.108	70.108	80.178	90.131
Average	5.10	10.08	15.07	19.90	25.44	30.52	40.14	50.21	60.22	70.15	80.19	90.12
Actual	5	10	15	20	25	30	40	50	60	70	80	90
Error Margin	0.10	0.08	0.07	-0.10	0.44	0.52	0.14	0.21	0.22	0.15	0.19	0.12

1.2 Wi-Fi metre readings

-44.69dBm	-44.21dBm	-45.8dBm	-46.54dBm	-45.7dBm	-45.91dBm	-44.83dBm	-44.35dBm	-44.93dBm	-44.86dBm
-44.68dBm	-46.49dBm	-44.17dBm	-45.32dBm	-45.94dBm	-46.96dBm	-44.35dBm	-45.69dBm	-45.49dBm	-45.27dB
-44.5dBm	-44.69dBm	-46.76dBm	-46.56dBm	-45.59dBm	-44.47dBm	-44.56dBm	-45.03dBm	-44.74dBm	-44.54dBm
-45.57dBm	-45.44dBm	-44.15dBm	-44.67dBm	-45.45dBm	-46.07dBm	-45.13dBm	-46.49dBm	-45.44dBm	-44.54dBm
-45.8dBm	-45.25dBm	-45.37dBm	-45.5dBm	-46.1dBm	-45.67dBm	-46.08dBm	-45.39dBm	-46.2dBm	-46.01dBm
-44.62dBm	-44.74dBm	-45.74dBm	-44.59dBm	-44.83dBm	-46.1dBm	-45.79dBm	-44.31dBm	-44.21dBm	-45.82dBm
-44.11dBm	-46.02dBm	-45.76dBm	-45.2dBm	-44.84dBm	-46.84dBm	-45.86dBm	-44.38dBm	-44.67dBm	-46.49dBm
-46.01dBm	-46.18dBm	-45.31dBm	-46.61dBm	-45.13dBm	-45.8dBm	-46.97dBm	-46.64dBm	-44.83dBm	-44.76dBm
-44.96dBm	-44.62dBm	-45.27dBm	-44.81dBm	-46.14dBm	-44.3dBm	-46.1dBm	-44.67dBm	-45.74dBm	-46.59dBm
-45.17dBm	-44.67dBm	-46.94dBm	-46.11dBm	-44.16dBm	-46.08dBm	-45.44dBm	-46.82dBm	-45.34dBm	-45.6dBm
-46.42dBm	-44.16dBm	-46.26dBm	-45.23dBm	-45.18dBm	-45.15dBm	-44.91dBm	-44.07dBm	-45.31dBm	-45.85dBm
-44.96dBm	-44.74dBm	-46.13dBm	-44.47dBm	-45.18dBm	-46.32dBm	-46.92dBm	-44.94dBm	-46.31dBm	-45.71dBm
-45.67dBm	-46.29dBm	-45.92dBm	-45.94dBm	-44.96dBm	-44.62dBm	-44.67dBm	-46.65dBm	-46.78dBm	-44.34dBm
-45.66dBm	-45.54dBm	-44.66dBm	-45.87dBm	-45.41dBm	-45.66dBm	-44.32dBm	-44.13dBm	-45.74dBm	-46.9dBm
-45.12dBm	-44.65dBm	-45.86dBm	-45.67dBm	-45.64dBm	-44.08dBm	-46.61dBm	-45.95dBm	-46.69dBm	-45.55dBm
-44.39dBm	-45.39dBm	-45.63dBm	-46.54dBm	-46.86dBm	-45.61dBm	-45.84dBm	-46.93dBm	-46.35dBm	-44.5dBm
-45.01dBm	-44.85dBm	-46.87dBm	-46.26dBm	-46.92dBm	-45.85dBm	-45.21dBm	-44.1dBm	-45.7dBm	-44.2dBm
-45.12dBm	-46.49dBm	-45.57dBm	-46.07dBm	-45.3dBm	-45.45dBm	-44.39dBm	-46.04dBm	-45.49dBm	-45.21dBm
-44.87dBm	-44.17dBm	-45.91dBm	-44.62dBm	-46.69dBm	-46.28dBm	-44.13dBm	-46.46dBm	-45.4dBm	-44.37dBm
.. … ……									
-44.42dBm	-45.41dBm	-44.68dBm	-44.41dBm	-45.12dBm	-46.1dBm	-46.04dBm	-45.63dBm	-46.46dBm	-46.63dBm
-45.3dBm	-46.39dBm	-46.38dBm	-45.81dBm	-46.16dBm	-46.55dBm	-44.24dBm	-46.31dBm	-44.4dBm	-45.35dBm
-45.6dBm	-45.78dBm	-44.84dBm	-45.3dBm	-46.13dBm	-46.84dBm	-46.84dBm	-46.55dBm	-44.93dBm	-44.3dB
-44.52dBm	-45.6dBm	-44.16dBm	-46.2dBm	-44.29dBm	-46.48dBm	-44.44dBm	-45.33dBm	-46.84dBm	-44.69d
-44.79dBm	-448dBm	-44.53dBm	-44.98dBm	-45.59dBm	-45.94dBm	-45.04dBm	-44.19dBm	-46.91dBm	-44.52dBm

1.3 Bluetooth metre readings

-54.12dBm	-56.03dBm	-58.93dBm	-55.11dBm	-56.61dBm	-54.49dBm	-58.15dBm	-55.8dBm	-58.99dBm	-55.83dBm
-57.13dBm	-57.28dBm	-57.43dBm	-54.42dBm	-58.96dBm	-57.28dBm	-56.77dBm	-57.65dBm	-55.22dBm	-58.47dBm
-57.92dBm	-55.21dBm	-55.48dBm	-55.61dBm	-56.29dBm	-56.06dBm	-56.74dBm	-56.87dBm	-57.41dBm	-56.62dBm
-55.77dBm	-55.9dBm	-55.9dBm	-58.45dBm	-57.72dBm	-57.25dBm	-55.59dBm	-57.77dBm	-58.93dBm	-55.39dBm
-57.71dBm	-56.29dBm	-56.25dBm	-55.36dBm	-54.46dBm	-57.73dBm	-58.87dBm	-57.01dBm	-58.88dBm	-58.4dBm
-56.94dBm	-54.32dBm	-56.21dBm	-56.78dBm	-54.19dBm	-56.8dBm	-54.36dBm	-57.37dBm	-54.09dBm	-55.78dBm
-54.91dBm	-57.36dBm	-55.9dBm	-55.96dBm	-57.15dBm	-56.46dBm	-58.55dBm	-54.52dBm	-55.81dBm	-55.2dBm
-56.14dBm	-54.36dBm	-58.08dBm	-55.31dBm	-54.37dBm	-56.73dBm	-57.75dBm	-57.19dBm	-57.19dBm	-58.9dBm
-58.57dBm	-54.54dBm	-57.72dBm	-58.26dBm	-54.89dBm	-54.09dBm	-56.22dBm	-55.98dBm	-55.99dBm	-55.01dBm
-56.82dBm	-55.39dBm	-55.88dBm	-57.01dBm	-57.79dBm	-54.09dBm	-57.42dBm	-54.21dBm	-57.68dBm	-57.05dBm
-54.08dBm	-58.24dBm	-57.04dBm	-58.22dBm	-54.03dBm	-58.15dBm	-59.07dBm	-58.55dBm	-54.41dBm	-58.02dBm
-57.89dBm	-54.45dBm	-54.45dBm	-58.73dBm	-54.89dBm	-58.17dBm	-58.1dBm	-55.16dBm	-56.87dBm	-54.17dBm
-56.69dBm	-57.42dBm	-54.86dBm	-54.22dBm	-58.32dBm	-55.7dBm	-54.36dBm	-58.7dBm	-54.58dBm	-57.73dBm
-58.36dBm	-56.35dBm	-55.4dBm	-54.97dBm	-56.3dBm	-56.13dBm	-55.75dBm	-54.83dBm	-57.62dBm	-56.34dBm
-57.23dBm	-54.8dBm	-55.76dBm	-58.83dBm	-54.67dBm	-57.24dBm	-55.72dBm	-54.59dBm	-56.04dBm	-58.64dBm
-54.77dBm	-55.85dBm	-55.24dBm	-56.53dBm	-57.06dBm	-54.99dBm	-54.55dBm	-58.97dBm	-58.46dBm	-56.17dBm
-58.89dBm	-57.42dBm	-58.33dBm	-56.95dBm	-55.29dBm	-57.15dBm	-54.34dBm	-54.6dBm	-55.31dBm	-56.64dBm
… …..									
-55.18dBm	-57.36dBm	-54.64dBm	-54.71dBm	-57.64dBm	-55.66dBm	-54.71dBm	-56.83dBm	-58.79dBm	-55.46dBm
-55.27dBm	-57.8dBm	-55.03dBm	-55.4dBm	-54.71dBm	-55.19dBm	-54.34dBm	-56.15dBm	-56.9dBm	-54.36dBm
-54.65dBm	-55.48dBm	-54.03dBm	-58.54dBm	-54.3dBm	-54.42dBm	-57.11dBm	-57.95dBm	-58.67dBm	-58.55dBm
-54.54dBm	-54.24dBm	-57.22dBm	-58.63dBm	-57.92dBm	-56.22dBm	-58.61dBm	-55.56dBm	-55.73dBm	-56.06dBm
-58.8dBm	-56.27dBm	-58.54dBm	-56.49dBm	-57.52dBm	-54.62dBm	-54.82dBm	-54.29dBm	-57.75dBm	-54.44dBm
-58.72dBm	-58.08dBm	-55.38dBm	-56.0dBm	-55.24dBm	-54.96dBm	-58.66dBm	-56.84dBm	-55.0dBm	-54.9dBm
-58.63dBm	-58.29dBm	-58.83dBm	-54.52dBm	-57.96dBm	-55.71dBm	-57.97dBm	-58.14dBm	-56.59dBm	-57.12dBm

1.4 Kalman Filter results

ID	Measurement Noise	Process Noise	Error Rate	Discrete Time	Estimated Range Error 10 Reads)	Filtered Range Error 10 Reads)	Improved By ???	Estimated Range Error (100 Reads)	Filtered Range Error (100 Reads)	Improved By ???
Preliminary Tests										
0	1	1	1.000	1	0.096	0.09010713	0.005893	0.3223	0.32289281	-0.000593
1	1	1	1.000	0.1	0.096	0.06922799	0.026772	0.3223	0.32573284	-0.003433
2	1	1	1.000	0.01	0.096	0.06580281	0.030197	0.3223	0.30654234	0.015758
3	1	1	1.000	0.001000	0.096	0.06576283	0.030237	0.3223	0.22349894	0.098801
4	1	1	1.000	0.000100	0.096	0.06576244	0.030238	0.3223	0.22008035	0.102220
5	1	1	0.100	1.000000	0.096	0.08830196	0.007698	0.3223	0.32271243	-0.000412
6	1	1	0.010	1.000000	0.096	0.08790276	0.008097	0.3223	0.32267254	-0.000373
7	1	1	0.001	1.000000	0.096	0.08785897	0.008141	0.3223	0.32266816	-0.000368
8	1	1	0.000	1.000000	0.096	0.08785456	0.008145	0.3223	0.32266772	-0.000368
9	1	0.1	1.000	1.000000	0.096	0.09010713	0.005893	0.3223	0.32289281	-0.000593
10	1	0.01	1.000	1.000000	0.096	0.09010713	0.005893	0.3223	0.32289281	-0.000593
11	1	10	1.000	1.000000	0.096	0.09010713	0.005893	0.3223	0.32289281	-0.000593
12	1	100	1.000	1.000000	0.096	0.09010713	0.005893	0.3223	0.32289281	-0.000593
13	0.1	1	1.000	1.000000	0.096	0.09616892	-0.000169	0.3223	0.32545468	-0.003155
14	0.01	1	1.000	1.000000	0.096	0.09723134	-0.001231	0.3223	0.32627408	-0.003974
15	10	1	1.000	1.000000	0.096	0.07410306	0.021897	0.3223	0.32178039	0.000520
16	100	1	1.000	1.000000	0.096	0.05868132	0.037319	0.3223	0.31554397	0.006756
Custom Tests										
17	100	1	0.001	0.000100	0.096	0.05860034	0.037400	0.3223	0.05859973	0.263700
18	100	100	0.100	0.000100	0.096	0.05860054	0.037399	0.3223	0.05853939	0.263761
19	100	1	0.500	0.000001	0.096	0.05860136	0.037399	0.3223	0.05830104	0.263999
20	1000	1	0.000	0.000010	0.096	0.05860034	0.037400	0.3223	0.05860034	0.263700

1.5 Library Results

ID	x	y	Timestamp	ID	x	y	Timestamp	ID	x	y	Timestamp
1	4.716145	0.637811	05/07/2017 10:26	19	4.753851	0.605334	05/07/2017 10:28	37	4.713394	0.606656	05/07/2017 10:29
2	4.768034	0.652767	05/07/2017 10:26	20	4.712454	0.623673	05/07/2017 10:28	38	4.722148	0.671789	05/07/2017 10:29
3	4.726517	0.683012	05/07/2017 10:26	21	4.729707	0.661853	05/07/2017 10:28	39	4.716876	0.661204	05/07/2017 10:29
4	4.735326	0.669471	05/07/2017 10:26	22	4.739011	0.674512	05/07/2017 10:28	40	4.716876	0.636986	05/07/2017 10:29
5	4.73977	0.626269	05/07/2017 10:26	23	4.765655	0.637893	05/07/2017 10:28	41	4.739627	0.630427	05/07/2017 10:29
6	4.725157	0.675461	05/07/2017 10:26	24	4.747832	0.636986	05/07/2017 10:28	42	4.718689	0.628852	05/07/2017 10:29
7	4.755326	0.620634	05/07/2017 10:26	25	4.75753	0.66191	05/07/2017 10:28	43	4.736912	0.637685	05/07/2017 10:29
8	4.705926	0.615912	05/07/2017 10:26	26	4.728788	0.629407	05/07/2017 10:28	44	4.725	0.63617	05/07/2017 10:29
9	4.710967	0.655351	05/07/2017 10:26	27	4.769312	0.648938	05/07/2017 10:28	45	4.750085	0.659596	05/07/2017 10:29
10	4.742184	0.653336	05/07/2017 10:26	28	4.745132	0.630108	05/07/2017 10:28	46	4.73977	0.659596	05/07/2017 10:29
11	4.746637	0.653552	05/07/2017 10:26	29	4.743411	0.661015	05/07/2017 10:28	47	4.739011	0.650305	05/07/2017 10:29
12	4.725753	0.66464	05/07/2017 10:26	30	4.728788	0.643545	05/07/2017 10:28	48	4.722895	0.656866	05/07/2017 10:29
13	4.730267	0.630054	05/07/2017 10:26	31	4.724895	0.659509	05/07/2017 10:28	49	4.713309	0.63914	05/07/2017 10:29
14	4.736786	0.637811	05/07/2017 10:26	32	4.745007	0.673163	05/07/2017 10:28	50	4.746637	0.643454	05/07/2017 10:29
15	4.741958	0.669471	05/07/2017 10:26	33	4.767247	0.648503	05/07/2017 10:28	51	4.721309	0.622024	05/07/2017 10:29
16	4.737674	0.671202	05/07/2017 10:26	34	4.75753	0.637685	05/07/2017 10:28	52	4.704546	0.612363	05/07/2017 10:29
17	4.755944	0.61798	05/07/2017 10:26	35	4.725753	0.636374	05/07/2017 10:28	53	4.72079	0.658382	05/07/2017 10:29
18	4.7251	0.647582	05/07/2017 10:26	36	4.733225	0.642735	05/07/2017 10:28	54	4.731804	0.660329	05/07/2017 10:29

55	4.74564	0.63213	05/07/2017 10:26	64	4.740467	0.656982	05/07/2017 10:28	73	4.759009	0.648938	05/07/2017 10:30
56	4.734813	0.681574	05/07/2017 10:26	65	4.727206	0.646072	05/07/2017 10:28	74	4.736276	0.688806	05/07/2017 10:30
57	4.740597	0.666953	05/07/2017 10:26	66	4.716145	0.637811	05/07/2017 10:28	75	4.753851	0.605334	05/07/2017 10:30
58	4.706534	0.656162	05/07/2017 10:26	67	4.768034	0.652767	05/07/2017 10:28	76	4.712454	0.623673	05/07/2017 10:30
59	4.737743	0.640009	05/07/2017 10:26	68	4.726517	0.683012	05/07/2017 10:28	77	4.729707	0.661853	05/07/2017 10:30
60	4.759621	0.660395	05/07/2017 10:26	69	4.735326	0.669471	05/07/2017 10:28	78	4.739011	0.674512	05/07/2017 10:30
61	4.717617	0.64122	05/07/2017 10:26	70	4.73977	0.626269	05/07/2017 10:28	79	4.765655	0.637893	05/07/2017 10:30
62	4.723562	0.663852	05/07/2017 10:26	71	4.725157	0.675461	05/07/2017 10:28	80	4.747832	0.636986	05/07/2017 10:30
63	4.755944	0.63213	05/07/2017 10:26	72	4.755326	0.620634	05/07/2017 10:28	81	4.75753	0.66191	05/07/2017 10:30

..
....
....

471	4.739011	0.650305	05/07/2017 10:27	481	4.705814	0.64972	05/07/2017 10:29	491	4.732626	0.643454	05/07/2017 10:31
472	4.722895	0.656866	05/07/2017 10:27	482	4.736912	0.670986	05/07/2017 10:29	492	4.71414	0.658382	05/07/2017 10:31
473	4.713309	0.63914	05/07/2017 10:27	483	4.753706	0.604467	05/07/2017 10:29	493	4.7583	0.680275	05/07/2017 10:31
474	4.746637	0.643454	05/07/2017 10:27	484	4.715412	0.650513	05/07/2017 10:29	494	4.740042	0.647718	05/07/2017 10:31
475	4.721309	0.622024	05/07/2017 10:27	485	4.735326	0.650305	05/07/2017 10:29	495	4.763895	0.621334	05/07/2017 10:31
476	4.704546	0.612363	05/07/2017 10:27	486	4.759009	0.673163	05/07/2017 10:29	496	4.715295	0.635477	05/07/2017 10:31
477	4.72079	0.658382	05/07/2017 10:27	487	4.761978	0.675235	05/07/2017 10:29	497	4.715412	0.669683	05/07/2017 10:31
478	4.731804	0.660329	05/07/2017 10:27	488	4.747226	0.647783	05/07/2017 10:29	498	4.734058	0.640009	05/07/2017 10:31
479	4.759009	0.648938	05/07/2017 10:28	489	4.756948	0.629308	05/07/2017 10:29	499	4.72858	0.640343	05/07/2017 10:31
480	4.736276	0.688806	05/07/2017 10:28	490	4.736912	0.676027	05/07/2017 10:29	500	4.750997	0.65414	05/07/2017 10:31

1.6 Library UWB LoS Results

id	fixed_x	fixed_y	est_x	est_y	diff	timestamp	id	fixed_x	fixed_y	est_x	est_y	diff	timestamp
1	5.061	0.458	4.717	0.638	0.389	4/11/17 - 20:39:00	251	5.061	0.458	4.747	0.654	0.371	4/11/17 - 20:43:10
2	5.061	0.458	4.769	0.653	0.352	4/11/17 - 20:39:01	252	5.061	0.458	4.726	0.665	0.394	4/11/17 - 20:43:11
3	5.061	0.458	4.727	0.684	0.404	4/11/17 - 20:39:02	253	5.061	0.458	4.731	0.631	0.373	4/11/17 - 20:43:12
4	5.061	0.458	4.736	0.67	0.389	4/11/17 - 20:39:03	254	5.061	0.458	4.737	0.638	0.371	4/11/17 - 20:43:13
5	5.061	0.458	4.74	0.627	0.363	4/11/17 - 20:39:04	255	5.061	0.458	4.742	0.67	0.384	4/11/17 - 20:43:14
6	5.061	0.458	4.726	0.676	0.4	4/11/17 - 20:39:05	256	5.061	0.458	4.738	0.672	0.388	4/11/17 - 20:43:15
7	5.061	0.458	4.756	0.621	0.346	4/11/17 - 20:39:06	257	5.061	0.458	4.756	0.618	0.345	4/11/17 - 20:43:20
8	5.061	0.458	4.706	0.616	0.389	4/11/17 - 20:39:07	258	5.061	0.458	4.726	0.648	0.386	4/11/17 - 20:43:17
9	5.061	0.458	4.711	0.656	0.403	4/11/17 - 20:39:08	259	5.061	0.458	4.746	0.633	0.361	4/11/17 - 20:43:18
10	5.061	0.458	4.743	0.654	0.374	4/11/17 - 20:39:09	260	5.061	0.458	4.735	0.682	0.396	4/11/17 - 20:43:19
11	5.061	0.458	4.747	0.654	0.371	4/11/17 - 20:39:10	261	5.061	0.458	4.741	0.667	0.383	4/11/17 - 20:43:20
12	5.061	0.458	4.726	0.665	0.394	4/11/17 - 20:39:11	262	5.061	0.458	4.707	0.657	0.407	4/11/17 - 20:43:21
13	5.061	0.458	4.731	0.631	0.373	4/11/17 - 20:39:12	263	5.061	0.458	4.738	0.641	0.372	4/11/17 - 20:43:22
14	5.061	0.458	4.737	0.638	0.371	4/11/17 - 20:39:13	264	5.061	0.458	4.76	0.661	0.364	4/11/17 - 20:43:23
15	5.061	0.458	4.742	0.67	0.384	4/11/17 - 20:39:14	265	5.061	0.458	4.718	0.642	0.39	4/11/17 - 20:43:24
16	5.061	0.458	4.738	0.672	0.388	4/11/17 - 20:39:15	266	5.061	0.458	4.724	0.664	0.395	4/11/17 - 20:43:25
17	5.061	0.458	4.756	0.618	0.345	4/11/17 - 20:39:20	267	5.061	0.458	4.756	0.633	0.352	4/11/17 - 20:43:26
18	5.061	0.458	4.726	0.648	0.386	4/11/17 - 20:39:17	268	5.061	0.458	4.761	0.65	0.357	4/11/17 - 20:43:27
19	5.061	0.458	4.746	0.633	0.361	4/11/17 - 20:39:18	269	5.061	0.458	4.74	0.679	0.39	4/11/17 - 20:43:28
20	5.061	0.458	4.735	0.682	0.396	4/11/17 - 20:39:19	270	5.061	0.458	4.702	0.667	0.416	4/11/17 - 20:43:29
21	5.061	0.458	4.741	0.667	0.383	4/11/17 - 20:39:20	271	5.061	0.458	4.735	0.668	0.388	4/11/17 - 20:43:30
22	5.061	0.458	4.707	0.657	0.407	4/11/17 - 20:39:21	272	5.061	0.458	4.728	0.676	0.399	4/11/17 - 20:43:31
23	5.061	0.458	4.738	0.641	0.372	4/11/17 - 20:39:22	273	5.061	0.458	4.748	0.666	0.376	4/11/17 - 20:43:32
24	5.061	0.458	4.76	0.661	0.364	4/11/17 - 20:39:23	274	5.061	0.458	4.74	0.617	0.359	4/11/17 - 20:43:33
25	5.061	0.458	4.718	0.642	0.39	4/11/17 - 20:39:24	275	5.061	0.458	4.724	0.618	0.374	4/11/17 - 20:43:34
26	5.061	0.458	4.724	0.664	0.395	4/11/17 - 20:39:25	276	5.061	0.458	4.743	0.64	0.367	4/11/17 - 20:43:35
27	5.061	0.458	4.756	0.633	0.352	4/11/17 - 20:39:26	277	5.061	0.458	4.737	0.641	0.373	4/11/17 - 20:43:36
28	5.061	0.458	4.761	0.65	0.357	4/11/17 - 20:39:27	278	5.061	0.458	4.713	0.638	0.392	4/11/17 - 20:43:37
29	5.061	0.458	4.74	0.679	0.39	4/11/17 - 20:39:28	279	5.061	0.458	4.751	0.617	0.349	4/11/17 - 20:43:38
30	5.061	0.458	4.702	0.667	0.416	4/11/17 - 20:39:29	280	5.061	0.458	4.726	0.667	0.395	4/11/17 - 20:43:39
31	5.061	0.458	4.735	0.668	0.388	4/11/17 - 20:39:30	281	5.061	0.458	4.74	0.677	0.389	4/11/17 - 20:43:40

32	5.061	0.458	4.728	0.676	0.399	4/11/17 - 20:39:31	282	5.061	0.458	4.706	0.613	0.388	4/11/17 - 20:43:41
33	5.061	0.458	4.748	0.666	0.376	4/11/17 - 20:39:32	283	5.061	0.458	4.753	0.654	0.366	4/11/17 - 20:43:42
34	5.061	0.458	4.74	0.617	0.359	4/11/17 - 20:39:33	284	5.061	0.458	4.745	0.659	0.375	4/11/17 - 20:43:43
35	5.061	0.458	4.724	0.618	0.374	4/11/17 - 20:39:34	285	5.061	0.458	4.752	0.62	0.349	4/11/17 - 20:43:44
36	5.061	0.458	4.743	0.64	0.367	4/11/17 - 20:39:35	286	5.061	0.458	4.743	0.654	0.374	4/11/17 - 20:43:45
37	5.061	0.458	4.737	0.641	0.373	4/11/17 - 20:39:36	287	5.061	0.458	4.754	0.668	0.372	4/11/17 - 20:43:46
38	5.061	0.458	4.713	0.638	0.392	4/11/17 - 20:39:37	288	5.061	0.458	4.754	0.634	0.354	4/11/17 - 20:43:47
39	5.061	0.458	4.751	0.617	0.349	4/11/17 - 20:39:38	289	5.061	0.458	4.758	0.652	0.36	4/11/17 - 20:43:48
40	5.061	0.458	4.726	0.667	0.395	4/11/17 - 20:39:39	290	5.061	0.458	4.742	0.628	0.362	4/11/17 - 20:43:49
41	5.061	0.458	4.74	0.677	0.389	4/11/17 - 20:39:40	291	5.061	0.458	4.733	0.644	0.378	4/11/17 - 20:43:50
42	5.061	0.458	4.706	0.613	0.388	4/11/17 - 20:39:41	292	5.061	0.458	4.715	0.659	0.401	4/11/17 - 20:43:51
43	5.061	0.458	4.753	0.654	0.366	4/11/17 - 20:39:42	293	5.061	0.458	4.759	0.681	0.376	4/11/17 - 20:43:52
44	5.061	0.458	4.745	0.659	0.375	4/11/17 - 20:39:43	294	5.061	0.458	4.741	0.648	0.373	4/11/17 - 20:43:53
....													
....													
....													
236	5.061	0.458	4.758	0.638	0.353	4/11/17 - 20:42:57	486	5.061	0.458	4.726	0.676	0.4	4/11/17 - 20:47:05
237	5.061	0.458	4.726	0.637	0.38	4/11/17 - 20:42:57	487	5.061	0.458	4.756	0.621	0.346	4/11/17 - 20:47:06
238	5.061	0.458	4.734	0.643	0.376	4/11/17 - 20:42:57	488	5.061	0.458	4.706	0.616	0.389	4/11/17 - 20:47:07
239	5.061	0.458	4.741	0.657	0.377	4/11/17 - 20:42:58	489	5.061	0.458	4.711	0.656	0.403	4/11/17 - 20:47:08
240	5.061	0.458	4.728	0.647	0.383	4/11/17 - 20:42:59	490	5.061	0.458	4.743	0.654	0.374	4/11/17 - 20:47:09
241	5.061	0.458	4.717	0.638	0.389	4/11/17 - 20:43:00	491	5.061	0.458	4.747	0.654	0.371	4/11/17 - 20:47:10
242	5.061	0.458	4.769	0.653	0.352	4/11/17 - 20:43:01	492	5.061	0.458	4.726	0.665	0.394	4/11/17 - 20:47:11
243	5.061	0.458	4.727	0.684	0.404	4/11/17 - 20:43:02	493	5.061	0.458	4.731	0.631	0.373	4/11/17 - 20:47:12
244	5.061	0.458	4.736	0.67	0.389	4/11/17 - 20:43:04	494	5.061	0.458	4.737	0.638	0.371	4/11/17 - 20:47:13
245	5.061	0.458	4.74	0.627	0.363	4/11/17 - 20:43:04	495	5.061	0.458	4.742	0.67	0.384	4/11/17 - 20:47:14
246	5.061	0.458	4.726	0.676	0.4	4/11/17 - 20:43:05	496	5.061	0.458	4.738	0.672	0.388	4/11/17 - 20:47:15
247	5.061	0.458	4.756	0.621	0.346	4/11/17 - 20:43:06	497	5.061	0.458	4.756	0.618	0.345	4/11/17 - 20:47:20
248	5.061	0.458	4.706	0.616	0.389	4/11/17 - 20:43:07	498	5.061	0.458	4.726	0.648	0.386	4/11/17 - 20:47:17
249	5.061	0.458	4.711	0.656	0.403	4/11/17 - 20:43:08	499	5.061	0.458	4.746	0.633	0.361	4/11/17 - 20:47:18
250	5.061	0.458	4.743	0.654	0.374	4/11/17 - 20:43:09	500	5.061	0.458	4.735	0.682	0.396	4/11/17 - 20:47:19

1.7 Library UWB NLoS Results

id	fixed_x	fixed_y	est_x	est_y	diff	timestamp	id	fixed_x	fixed_y	est_x	est_y	diff	timestamp
1	5.061	0.458	5.017	0.36	0.108	4/11/17 - 16:58:25	251	5.061	0.458	5.013	0.426	0.058	4/11/17 - 17:02:35
2	5.061	0.458	4.997	0.35	0.126	4/11/17 - 16:58:26	252	5.061	0.458	4.909	0.37	0.176	4/11/17 - 17:02:36
3	5.061	0.458	5.035	0.35	0.112	4/11/17 - 16:58:27	253	5.061	0.458	4.732	0.398	0.335	4/11/17 - 17:02:37
4	5.061	0.458	4.995	0.317	0.156	4/11/17 - 16:58:28	254	5.061	0.458	4.801	0.372	0.274	4/11/17 - 17:02:38
5	5.061	0.458	5.009	0.304	0.163	4/11/17 - 16:58:29	255	5.061	0.458	4.891	0.346	0.204	4/11/17 - 17:02:39
6	5.061	0.458	5.009	0.369	0.104	4/11/17 - 16:58:30	256	5.061	0.458	4.921	0.347	0.179	4/11/17 - 17:02:40
7	5.061	0.458	5.014	0.381	0.091	4/11/17 - 16:58:31	257	5.061	0.458	4.914	0.388	0.163	4/11/17 - 17:02:41
8	5.061	0.458	4.969	0.349	0.143	4/11/17 - 16:58:32	258	5.061	0.458	4.948	0.328	0.173	4/11/17 - 17:02:42
9	5.061	0.458	4.991	0.36	0.121	4/11/17 - 16:58:33	259	5.061	0.458	4.938	0.371	0.151	4/11/17 - 17:02:43
10	5.061	0.458	4.986	0.347	0.134	4/11/17 - 16:58:34	260	5.061	0.458	4.94	0.343	0.167	4/11/17 - 17:02:44
11	5.061	0.458	5.023	0.37	0.096	4/11/17 - 16:58:35	261	5.061	0.458	4.956	0.375	0.134	4/11/17 - 17:02:45
12	5.061	0.458	4.988	0.328	0.15	4/11/17 - 16:58:36	262	5.061	0.458	4.946	0.368	0.147	4/11/17 - 17:02:46
13	5.061	0.458	4.976	0.399	0.104	4/11/17 - 16:58:37	263	5.061	0.458	4.982	0.397	0.1	4/11/17 - 17:02:47
14	5.061	0.458	4.986	0.346	0.135	4/11/17 - 16:58:38	264	5.061	0.458	5.021	0.376	0.092	4/11/17 - 17:02:48
15	5.061	0.458	5.019	0.363	0.104	4/11/17 - 16:58:39	265	5.061	0.458	4.986	0.372	0.115	4/11/17 - 17:02:49
16	5.061	0.458	4.982	0.354	0.131	4/11/17 - 16:58:40	266	5.061	0.458	5.017	0.314	0.151	4/11/17 - 17:02:50
17	5.061	0.458	4.977	0.324	0.159	4/11/17 - 16:58:41	267	5.061	0.458	5.011	0.335	0.133	4/11/17 - 17:02:51
18	5.061	0.458	5.006	0.375	0.1	4/11/17 - 16:58:42	268	5.061	0.458	4.989	0.359	0.123	4/11/17 - 17:02:52
19	5.061	0.458	5.023	0.416	0.057	4/11/17 - 16:58:43	269	5.061	0.458	4.99	0.324	0.152	4/11/17 - 17:02:53
20	5.061	0.458	5.074	0.403	0.057	4/11/17 - 16:58:44	270	5.061	0.458	4.996	0.375	0.106	4/11/17 - 17:02:54
21	5.061	0.458	5.033	0.392	0.072	4/11/17 - 16:58:45	271	5.061	0.458	5.016	0.368	0.101	4/11/17 - 17:02:57
22	5.061	0.458	5.041	0.345	0.115	4/11/17 - 16:58:46	272	5.061	0.458	4.999	0.344	0.13	4/11/17 - 17:02:57
23	5.061	0.458	5.019	0.359	0.108	4/11/17 - 16:58:47	273	5.061	0.458	5.032	0.422	0.047	4/11/17 - 17:02:57
24	5.061	0.458	5.007	0.417	0.068	4/11/17 - 16:58:48	274	5.061	0.458	5.001	0.349	0.125	4/11/17 - 17:02:58
25	5.061	0.458	4.974	0.358	0.133	4/11/17 - 16:58:49	275	5.061	0.458	4.987	0.408	0.09	4/11/17 - 17:02:59
26	5.061	0.458	4.993	0.338	0.138	4/11/17 - 16:58:50	276	5.061	0.458	4.986	0.345	0.136	4/11/17 - 17:03:00

27	5.061	0.458	4.991	0.302	0.171	4/11/17 - 16:58:51	277	5.061	0.458	5.001	0.384	0.096	4/11/17 - 17:03:01
28	5.061	0.458	4.972	0.369	0.126	4/11/17 - 16:58:52	278	5.061	0.458	5.021	0.398	0.073	4/11/17 - 17:03:02
29	5.061	0.458	4.99	0.304	0.17	4/11/17 - 16:58:53	279	5.061	0.458	5.013	0.378	0.094	4/11/17 - 17:03:03
30	5.061	0.458	5.006	0.373	0.102	4/11/17 - 16:58:54	280	5.061	0.458	5.013	0.389	0.085	4/11/17 - 17:03:04
31	5.061	0.458	5.016	0.322	0.144	4/11/17 - 16:58:55	281	5.061	0.458	4.979	0.374	0.118	4/11/17 - 17:03:05
32	5.061	0.458	5.004	0.353	0.12	4/11/17 - 16:58:56	282	5.061	0.458	5	0.333	0.14	4/11/17 - 17:03:06
33	5.061	0.458	4.983	0.312	0.166	4/11/17 - 16:58:57	283	5.061	0.458	5.008	0.376	0.098	4/11/17 - 17:03:07
34	5.061	0.458	5.006	0.346	0.125	4/11/17 - 16:58:58	284	5.061	0.458	5.059	0.331	0.128	4/11/17 - 17:03:08
35	5.061	0.458	5.019	0.334	0.131	4/11/17 - 16:58:59	285	5.061	0.458	4.892	0.295	0.235	4/11/17 - 17:03:09
…													
…..													
……..													
238	5.061	0.458	5.018	0.347	0.12	4/11/17 - 17:02:22	488	5.061	0.458	5.005	0.349	0.123	4/11/17 - 17:06:32
239	5.061	0.458	5.041	0.36	0.101	4/11/17 - 17:02:23	489	5.061	0.458	4.974	0.364	0.129	4/11/17 - 17:06:33
240	5.061	0.458	5.025	0.386	0.081	4/11/17 - 17:02:24	490	5.061	0.458	4.974	0.343	0.145	4/11/17 - 17:06:34
241	5.061	0.458	4.987	0.283	0.191	4/11/17 - 17:02:25	491	5.061	0.458	5.001	0.347	0.127	4/11/17 - 17:06:35
242	5.061	0.458	4.974	0.332	0.154	4/11/17 - 17:02:26	492	5.061	0.458	4.979	0.349	0.137	4/11/17 - 17:06:36
243	5.061	0.458	4.964	0.333	0.159	4/11/17 - 17:02:27	493	5.061	0.458	4.99	0.389	0.1	4/11/17 - 17:06:37
244	5.061	0.458	4.898	0.348	0.197	4/11/17 - 17:02:28	494	5.061	0.458	4.982	0.378	0.113	4/11/17 - 17:06:38
245	5.061	0.458	4.877	0.337	0.221	4/11/17 - 17:02:29	495	5.061	0.458	5	0.358	0.118	4/11/17 - 17:06:39
246	5.061	0.458	4.88	0.359	0.207	4/11/17 - 17:02:30	496	5.061	0.458	5.018	0.422	0.057	4/11/17 - 17:06:40
247	5.061	0.458	4.897	0.328	0.21	4/11/17 - 17:02:31	497	5.061	0.458	5.015	0.388	0.084	4/11/17 - 17:06:41
248	5.061	0.458	4.893	0.317	0.22	4/11/17 - 17:02:32	498	5.061	0.458	4.983	0.358	0.127	4/11/17 - 17:06:42
249	5.061	0.458	4.904	0.34	0.197	4/11/17 - 17:02:33	499	5.061	0.458	4.984	0.355	0.129	4/11/17 - 17:06:43
250	5.061	0.458	4.672	0.366	0.4	4/11/17 - 17:02:34	500	5.061	0.458	4.999	0.363	0.114	4/11/17 - 17:06:44

Appendix 3 – Schematics

The following appendix details some of the configurations that were used during the evaluation of CAPTURE.

3.1 Sample Configurations for Canteen Experiments

The following experiments were carried out in the canteen, the results for these can be viewed in [3]

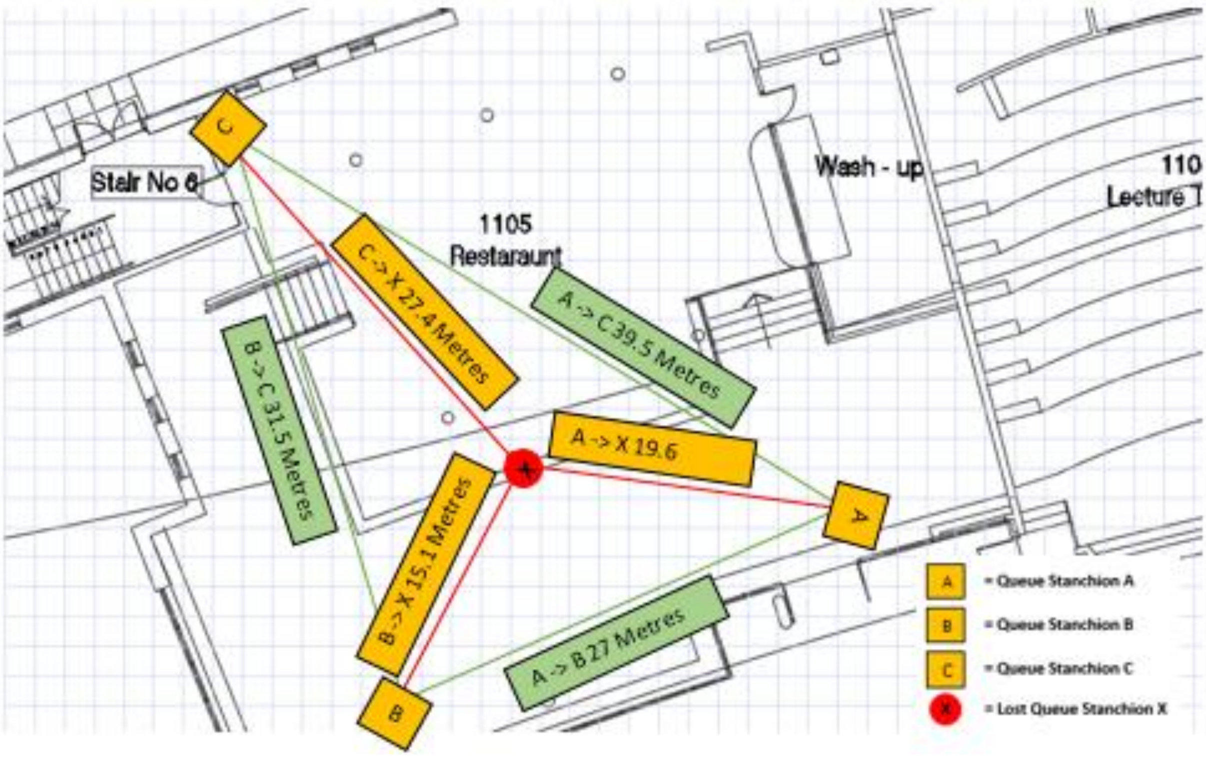


Figure A3–1: Canteen test configuration 1

[3] https://captureips.com/results/Canteen_Results/

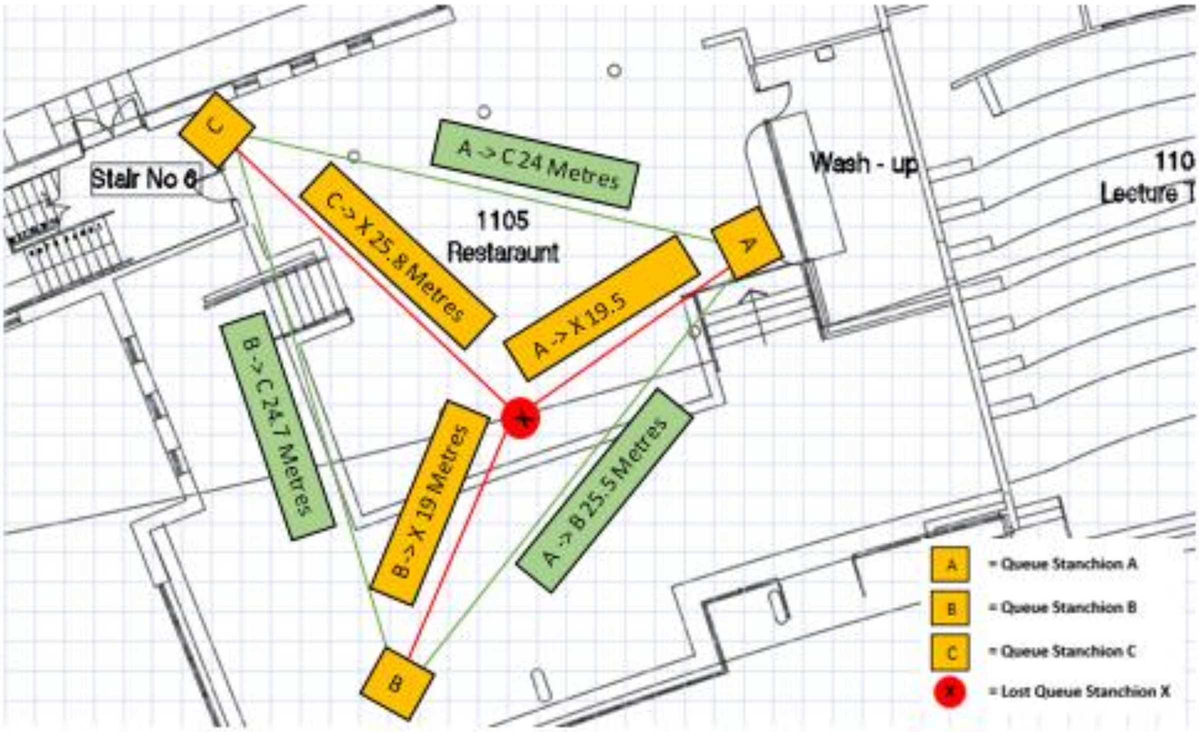


Figure A3–2: Canteen test configuration 3

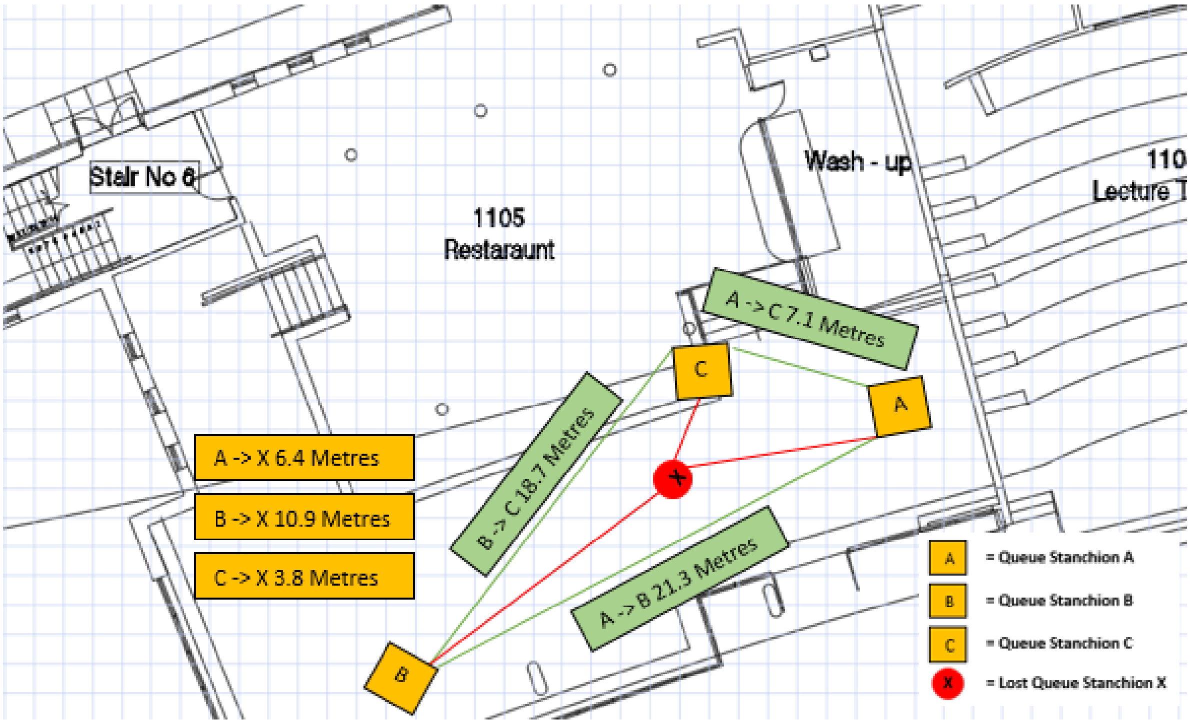


Figure A3–3: Canteen test configuration 4

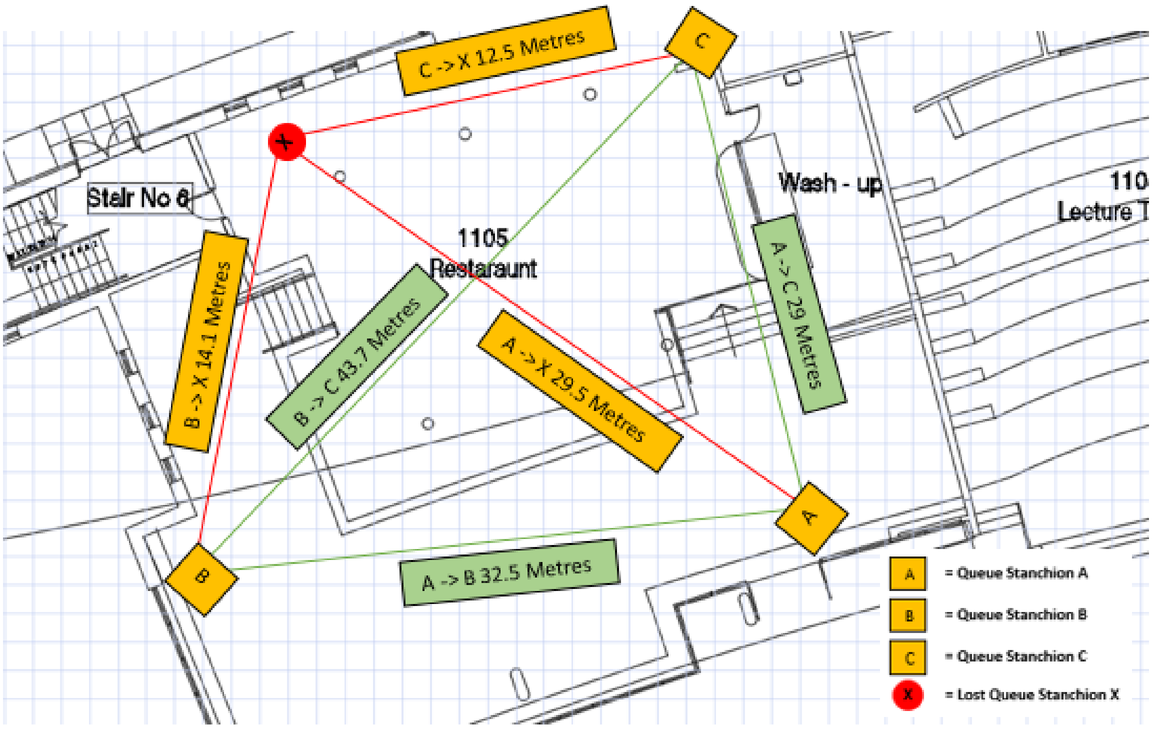


Figure A3–4: Canteen test configuration 5

3.2 Sample Configurations for Library Experiments

The following experiments were carried out in the Library, the results for these can be viewed in [4]

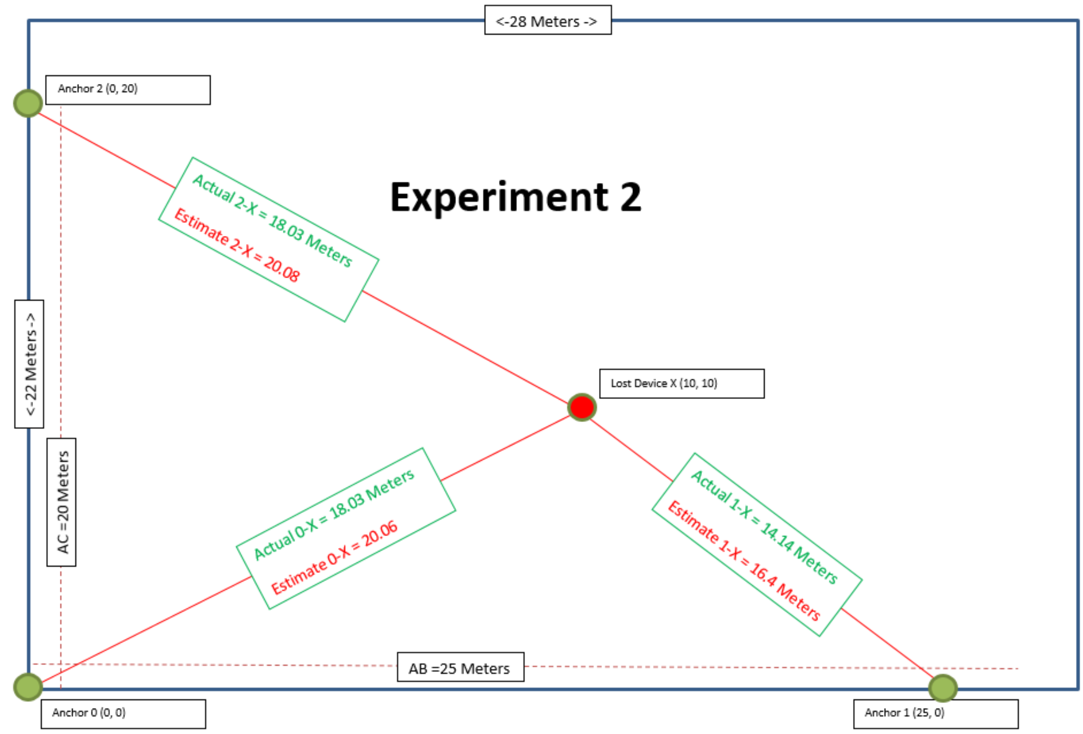


Figure A3–5: Library test configuration 2

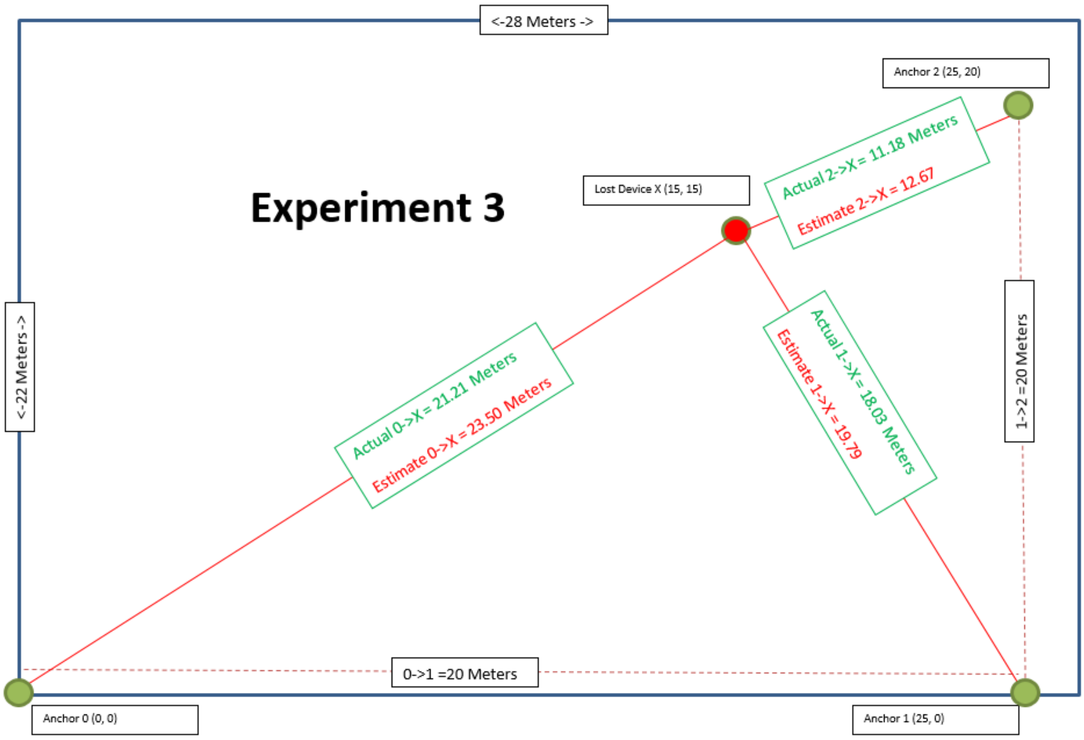


Figure A3–6: Library test configuration 3

[4] https://captureips.com/results/Library_Results/

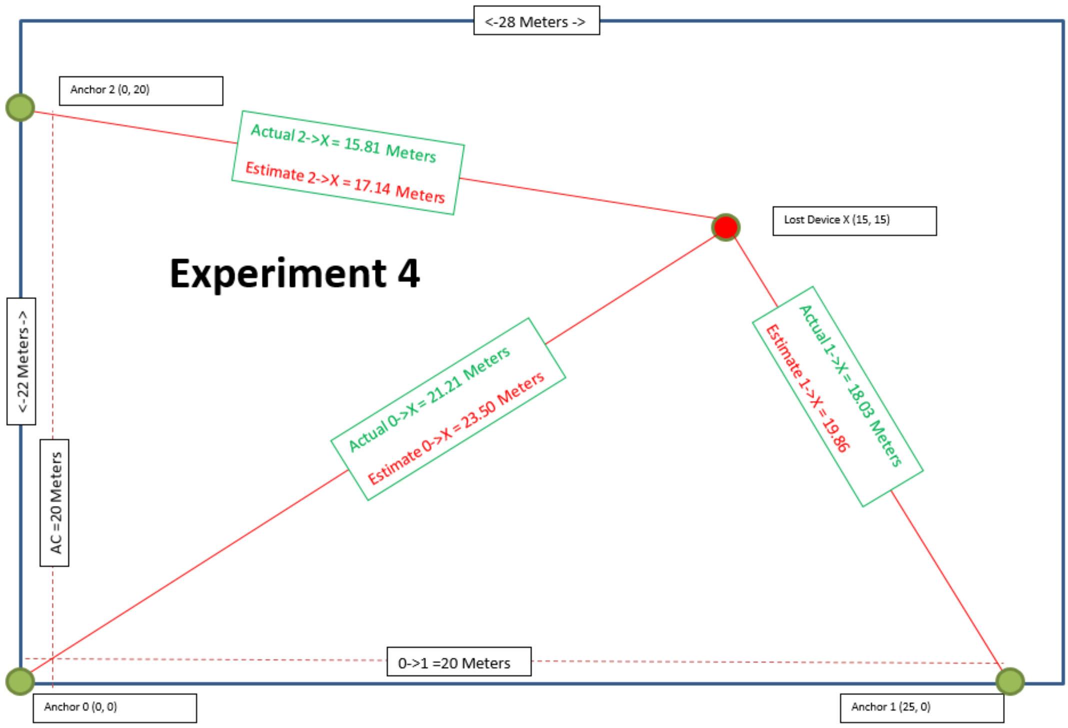


Figure A3–7: Library test configuration 4

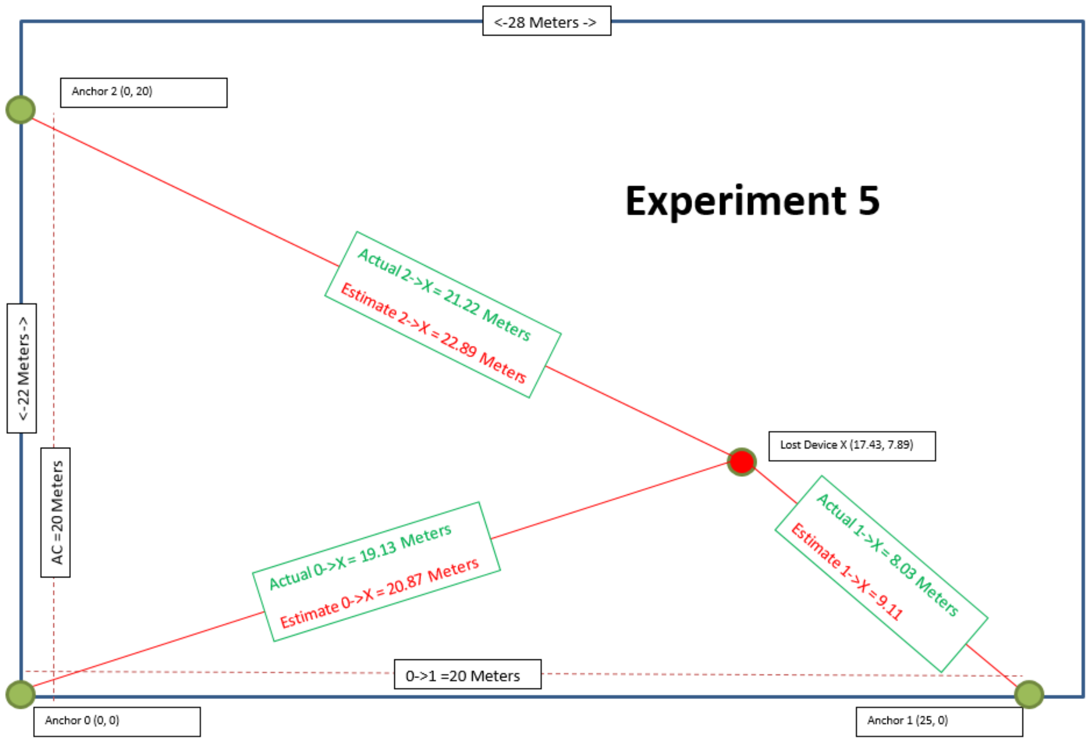


Figure A3–8: Library test configuration 5