Indoor Location Determination: Taking A Step Back

by

Christopher Pearson
B.Sc., University of Victoria, 2009

A Thesis Submitted in Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

in the Department of Computer Science

Indoor Location Determination: Taking A Step Back

by

Christopher Pearson
B.Sc., University of Victoria, 2009

Supervisory Committee

Dr. Yvonne Coady, Co-Supervisor
(Department of Computer Science)

Dr. Michael McGuire, Co-Supervisor
(Department of Electrical & Computer Engineering)

Dr. Rick McGeer, Department Member
(Department of Computer Science)

Supervisory Committee

Dr. Yvonne Coady, Co-Supervisor
(Department of Computer Science)

Dr. Michael McGuire, Co-Supervisor
(Department of Electrical & Computer Engineering)

Dr. Rick McGeer, Department Member
(Department of Computer Science)

ABSTRACT

Along with the huge growth of mobile devices in recent years we have seen a matching growth in interest for mobile applications, with location-aware applications experiencing rapid growth for mobile devices. Radiolocation from measurements of radio received signal strength has demonstrated excellent precision, although despite a decade of research there have been no wide-spread deployments of indoor location systems. The majority of the existing research has been focused towards producing improved precision at the cost of increased time requirements for system configuration and maintenance. This thesis proposes taking a step back from increasing complexity by giving up precision in exchange for simplicity and speed of deployment, while still providing sufficient accuracy for many indoor location tasks. This is accomplished by putting aside the standard x, y, z coordinate systems and by using a method based on defined areas. Carefully choosing the defined areas to include Wi-Fi access points and to have signal attenuating walls separating the area from the next, this work demonstrates locational accuracy of over 90% in most cases. While this method is not applicable to wide open areas that lack signal attenuating features, it is highly applicable to many indoor environments.

Contents

List of Tables

List of Figures

ACKNOWLEDGEMENTS

First and foremost, I would like to express my gratitude to Dr. Yvonne Coady for her drive and her patience — it's been a longer road than we had hoped. Dr. Michael McGuire for his insight into location-related work, and his patience in explaining the various maths that were involved. Dr. Stephen Neville for the help he provided along the way, especially when it came to advice for teaching. Dr. Rick McGeer, who came into this halfway through, but whose strong belief in my abilities and whose frank and to-the-point discussions helped out more than he could know.

My parents, Tom and Katy Pearson, so supported me in so many ways during my transition from working to returning to school. This wouldn't have happened without them.

Ashley Gasten Shaw who, besides being a good friend, helped to motivate me to go to grad school. Our long MSN chats seemed to help motivate both of us towards furthering our educations. I also cannot forget my friend Kerby, who taught me a great deal about life, and whom I still miss.

I'd also like to thank Cara Pearson and Maria Blanchard for their help editing this document. I'm not a writer, even if I'm occasionally forced to write.

Finally, I'd like to thank Nokia for their generosity over the years. Without their initial grants of devices to us, I doubt I would have taken this path.

DEDICATION

This thesis is dedicated to my loving wife Cara, who joined me when I was starting back into computer science, and who has believed in me the whole way through. Cara, you have my greatest thanks and my undying love.

Chapter 1

Introduction

Mobile devices have led us through an incredible shift in the use of information technology over the past five years, and this has been primarily due to the mass-market adoption of the smartphone. The previous growth of the Internet and its related information technologies over the past two decades has provided us amazing services, but our connections to it had remained tied down by some form of network cable. The past decade has brought us wireless local networking and the rapid adoption of laptops with wireless capabilities, but it has only been since the birth of Apple's iPhone that the idea of truly mobile networking has become part of the social consciousness in North America. The numbers are impressive, with smartphones accounting for 45% of the mobile phones in the hands of people in Canada [1] and 50% in the United States [2] in early 2012. These devices are not just an alternate and mobile means of connecting to the Internet: recent research has shown that more than 47% of young Canadians use mobile devices as their primary connection to the Internet [3].

This rapid shift in technology has presented a challenge that requires developers and manufacturers to be very quick to respond. For example, Nokia and devices using its Symbian operating system were the world market leader only three years ago, until it was dethroned by Google's Android in late 2010 [4]. Google's Android operating system itself was launched on only one device in February 2009, but by June 2012 there were 400 million activated Android devices in the world and there were one million new Android devices being activated each day [5]. Simply looking at the past two years shows how unpredictable this market has been, with well respected market analysis organizations such as Gartner Inc. giving a market share estimate (October 6, 2009) [6] for 2012 showing Symbian leading at 39%, followed by Android at 14.5%, iPhone at 13.5%, Windows Mobile at 12.8%, BlackBerry at 12.5%, and Palm at 2.1%. However, reality has proven much different [7], with Android leading the first quarter of 2012 with 59.0% of the market, followed by iPhone (iOS) at 23.0%, Symbian at 6.8%, BlackBerry at 6.4%, Linux at 2.3%, Windows Phone 7 (Windows Mobile) at 2.2%, and Palm / others at 0.3%.

During this same period of time, a growing trend of providing information services that are tailored for each individual user emerged. While targeted advertising may have been the initial driving factor for this, the side benefit is an increasingly personalized experience for anyone using the Internet. While Internet services have always had the ability to collect data regarding their individual users, through their IP addresses and by “cookie” data stored by their browsers, knowing the location of a user had become increasingly more accurate over the past few years as databases matching IP addresses to individual cities have grown and improved [8]. This has led to the development of improved contextual information services, such as the ability to simply type “pizza” into a web search engine and receive a list of restaurants in the user’s local area.

However, if a smartphone is being used, knowing the IP address of a Internet user does not translate to knowing that user’s location. This has rapidly changed as web browsers have recently gained the ability to provide a website with its user’s location [9]. This may be of limited use in an indoor setting, but its full potential can be seen with mobile smartphones that have many sources of data for outdoor locations, such as GPS, the location of the connected cell tower, and Wi-Fi base station ID look-up.

Throughout this large market shift, location technologies for outdoor use have become ubiquitous among the available smartphones, but the lack of a wide-spread indoor location determination system has remained. There are many reasons for this and Chapter 2 will overview the previous work to solve this problem.

Most of the previous work focuses on using Wi-Fi radio signals, and the unique IDs associated with each transmitter, due to their ubiquitous nature: these signals are literally everywhere, and all access points broadcast those unique IDs to all receivers, regardless of whether or not a network connection requires a password. While it may be tempting to use these ubiquitous unique IDs, there are some large difficulties and physical limitations involved in working with radio signals. Chapter 3 will examine some of these problems and demonstrate how indoor environments make the difficulties even larger.

Even with this difficulties there have been some impressive accuracy results with indoor Wi-Fi location determination systems, as the overview of previous work will show. Improving a result always comes with some form of cost or trade-off, and in this case it is in the form of very large time requirements for both the initial configuration and longer term maintenance.

With trade-offs and compromises in mind, Chapter 4 suggests taking a step back from existing methods of ever-improving precision, and to look at solving an immediate problem: even with the large amount of existing research there is, with a few sparse exceptions, a lack of deployed indoor location methods. The alternative suggested by this chapter assumes that high levels of positional precision are not needed for many indoor location applications, such as indoor navigation. As such, it trades that positional precision for fast configuration and low maintenance, all while using the difficulties of the indoor radio environment to its advantage.

The claims made by the discussion of this simple method obviously require proof of its effectiveness, and Chapter 5 provides this by detailing the testing applications that were written to validate the method and their results. This chapter also points to interesting results related to power consumption that suggest that this location determination method could be used continuously on a smartphone with little impact to battery life.

In the end, this entire work has spawned more thoughts and ideas than could possibly fit into one thesis. Chapter 6 brings some order to this by suggesting many avenues of potential future work.

Chapter 2

Locating Mobile Devices

As we will see throughout this chapter, locating mobile devices is not a trivial problem. The combination of the incredible growth in cellular phone use and government regulations stimulated this field of research, however, as described in Section 2.1. We will discuss the more modern uses of indoor location for smart devices in Section 2.2, followed by an in-depth look at current techniques and research in Section 2.3.

2.1 Cellular Phones

With the expansion in use of cellular phones in the 1990's, it soon became obvious that some form of location information service would be required for reasons of safety. Emergency 9-1-1 (E-911) services, which give the name and address of the caller to emergency personnel, had become a common and relied-upon service in the late 1980's and early 1990's. Such a service requires subscriber home address information from the phone company, which works well for static landline phones but not for mobiles. As such, the U.S. Federal Communications Commission (FCC) introduced regulations in 1996 that required all service providers to report the location of E-911 callers with an accuracy of 125m, 65% of the time, by October 1, 2002 [10]. This event is referred to by many authors ([11], [12], [13], [10], to list just a few) as the catalyst of research into mobile device location technologies.

The Global Positioning System of satellites, which is well known simply as GPS, may appear to have been an obvious solution to the need to provide location services to emergency responders. However, at that time, adding the relatively expensive GPS technology to mobile phones would have increased their price significantly [10]. Perhaps more importantly, the radio signals broadcast by the GPS satellites are relatively low power and determining a device's location in a dense urban area that lacks direct line-of-sight with the GPS satellites can be very difficult [12]. In an indoor setting receiving any GPS signal at all is nearly impossible [14], which would leave little or no coverage where most people spend the majority of their time [11]. Studies to investigate this were conducted at the University of Washington's Place Lab [15] and it was found that the average person would be able to receive a GPS location determination (or *GPS fix*) for only 4.5% of their day, with an average time of 105 minutes between GPS fixes.

Alongside the work on GPS coverage, the Place Lab study looked at both cellular phone GSM[1] coverage and IEEE 802.11 (Wi-Fi) coverage. Their results [15] showed that an average person is a location with GSM coverage for 99.6% of their day with Wi-Fi signals for 94.5% of the day. It should be noted that this study was conducted in 2005, which was still the early days of wireless computing. Given that 67.8% of Canadian households now have wireless routers [17], the average time spent in areas with Wi-Fi signal coverage will now be even higher.

Providing E-911 location services without replacing or modifying the existing mobile handsets required a solution that could be implemented using the service providers' equipment. One of the first methods used the *Received Signal Strength* (RSS) from the mobile handset. In simple terms, as radio signal power decreases with distance from the transmitter, the RSS value provides a rough estimation of the distance between the *base station* (typically located on a transmission tower) and the mobile handset. However, in the real world there are many factors that can attenuate the radio signal, and excellent work was done to estimate this effect and account for it [13]. With a reasonable estimation of the distance from several base stations, it is then possible to use triangulation / multilateration techniques to estimate the location of the handset.

[1] Global System for Mobile communication, which is a world-wide standard for cellular communications [16]

Other techniques involved base station equipment capable of detecting both the *angle of arrival* (AOA) and the *time of arrival* (TOA) of a handset's radio signal [18]. With information on the radio signal's travel time, along with the angle from the base station, the location of a handset could then be estimated by that one base station.

2.2 Locations Beyond E-911

As mobile phones and other mobile devices became more and more powerful, other applications for device location determination began to appear. Research focusing on location determination has been steadily increasing over the past two decades [19].

A working indoor navigation system would have many potential uses. As an extension to the walking directions provided by modern smartphones, one could imagine how a seamless transition to indoor mapping could be very useful. Shopping malls, conference centers, university buildings, museums, and many other large facilities would be perfect candidates for such a system.

Beyond direction finding, smartphone users have many other uses for personal location information. Finding friends at large events, or finding colleagues at conferences, could be a very useful time saving tool. Mobile phone applications exist that will notify you if your friends have checked in to locations that are near to you, but adding a more precise knowledge of everyone's location can help to bring those friends together.

The geolocation of images has been a feature of many photograph album software packages over the past few years, and more recently services such as Facebook and Google+ have added options for attaching the user's location to their posted messages. Many web browsers now include functionality for determining the user's location and providing that information to web site, and most modern smartphones will automatically add the current GPS location data to photographs.

A common use of GPS location is seen in the tracking of cargo trucks and other large equipment [20], where the owners of fleets of vehicles can track the location of their property. Disturbingly, however, there have been recent news reports of GPS being intentionally jammed, either to hide location of a stolen vehicle with a GPS locator, or for the more mundane reason of preventing a company head office from tracking every movement of an employee [21]. The information required for this is readily available through research into the methods of jamming GPS [22], so it should be expected that more such incidents will be seen in the future.

Besides being a fun and novelty feature, location verification can be important for some applications. An excellent example of this is the Foursquare[2] service, which is a tool that allows the user to “check in” to the current location and to share their location and activities with friends. Foursquare monetizes their operation by selling advertising to businesses in the form of discounts and coupons for Foursquare users that visit those businesses. Foursquare also highlights these special offers to its users, showing lists of the available deals near their current location. These discounts are typically available to users who have visited a location more than once, or for the user with the most check-ins over the course of a month. In Foursquare terms, the visitor with the most check-ins is known as the “mayor” of the location and, since some discounts are only available to the location's mayor, the competition for this title can be fierce. This would suggest that Foursquare has a strong interest in verifying that the user checking in at a business is truly at that location.

Naturally there are many privacy concerns that come with knowing the locations of others, and many publications discuss this fact, but that topic is outside the scope of this work. However, it is interesting to read that many of the same potential uses and the same potential problems for mobile device location that are discussed today were discussed as far back as 1992 [23].

2.3 Methods for Determining a Location Indoors

Determining the location of a device indoors is something that, to many people, may appear to be a trivial problem [24]. It is, in fact, a very challenging task as many authors are quick to admit [25, 26, 27, 28, 29, 30]. To solve this problem, some form of analysable data from the environment is needed that can be used to uniquely recognize

[2]Foursquare Labs, Inc. `http://foursquare.com/`

a location. There are many potential sources of such data and, as one author aptly describes it, "a plethora of indoor positioning systems have been proposed [12]".

While the core of this thesis is work related to using 802.11 Wi-Fi radio signals for indoor location determination, there are other methods that have been used for the same purpose. Looking back over the past two decades we can see that indoor location has been of continuous interest to researchers, and their work demonstrates the available technologies of the time. The remainder of this chapter looks at some of these methods and some of the work that has been done with them.

2.3.1 Infrared

Starting in 1992 we can find examples of location determination using infrared light, in a similar manner to that used by television remote controls. In *The Active Badge Location System* [23] we find a location system based on an *Active Badge* that would be worn by the participants. This badge would broadcast a unique code every 15 seconds using infrared light. This burst of invisible light would be received by sensors strategically placed throughout a room and a central computer system would log where a particular code was last seen. The signal from the badges would reach up to 6 meters and while successful reception would typically require line-of-slight (LoS) between badge and receiver, reflected signals could be received in some circumstances. This technology was demonstrated on a particular problem of the day: knowing which room a person was in so that their telephone calls could be forwarded to them. Performing a task such as this with location technology seems quaint in comparison to how location data is used today, but it is worth considering how primitive indoor location technology still is and therefore the fact that it may have many more new application in the future.

This work with Active Badges was quickly improved as shown in a *A Distributed Location System for the Active Office* [31] from 1994. In this experiment the badges were improved to include buttons for immediately sending signals, as well as a speaker and infrared receiving capability for creating a simple paging system. While this was an impressive improvement over [23], this work is all the more interesting for describing a feature that is very similar to more recent recent work [32] (see Section 2.3.3)) that combines Radio Frequency Identification (RFID) and Wi-Fi technologies. For "desk-scale location", a low power radio transmitter would be placed where fine grain location services are required. A passive receiver in the badge would detect an identification code from that radio signal and the badge would rebroadcast that same code as an infrared message. As the radio transmitter's signal had a very short range, the badge would be transmitting a very precise location to the infrared receivers.

Another article of interest is *The Design Of A Handheld, Location-Aware Guide For Indoor Environments* [33] which was published in the early days of Wi-Fi wireless networking. In the context of 2003, and with the goal of creating a mobile information system for a museum, the authors make a comparison between three wireless technologies that could give location information while transmitting data: 802.11b Wi-Fi, Bluetooth 1.x, and the Infrared Data Association's IrDA infrared wireless data standard [34]. Their goal was to provide museum guests with handheld computing devices (Compaq iPAQ personal digital assistant (PDA) [35]) that would provide contextual information regarding nearby works of art, and that could be used as a map for navigating the museum. It was found that the IrDA infrared was the best solution for a number of reasons:

- An IrDA infrared receiver was built into the PDA devices, while Bluetooth or Wi-Fi receivers would need to be added on at additional expense.
- Both IrDA and Wi-Fi had "immediate" connection speeds while Bluetooth required 5 to 10 seconds to discover local Bluetooth devices
- IrDA and Wi-Fi had the fastest data throughput speeds at approximately 4 Mbps, as seen in real world practice, while Bluetooth tested at approximately 0.7 Mbps.
- IrDA beacons were inexpensive, while both Bluetooth and Wi-Fi were relatively new and their access points were expensive.

The system created for the museum worked differently from the other two infrared systems discussed here. In this case, while this system had the ability to push data to the PDA, the PDA located itself in its surroundings based on the last IrDA beacon it had connected to. This is similar to the simple Wi-Fi method that will be discussed in Section 4.1.

2.3.2 Ultrasonic

Another potential source of location data is ultrasonic sound. In an aptly-named system called Cricket [28], ultrasonic beacons are placed strategically throughout a building. The system is a decentralized one, with the beacons communicating with each other to determine their distance from each other by measuring the travel time of the sound waves. Several such distance measurements from other beacons used for triangulation[3] provides the device's overall position relative to the others. A mobile device can then discover its current position using the same method. The idea is quite ingenious as it provides a system that requires minimal setup and maintenance while being fault tolerant.

In the initial experiment [28] the devices could locate themselves to an precision of one square meter. However, this was soon improved on, and that follow-on work provided an improved precision of 5cm [36]. These improved Crickets have since been used to assist in other work such as [14] and [37] which will be discussed in Section 2.3.4.

2.3.3 Radio Frequency Identification

A current trend in mobile devices is the inclusion of Near Field Communication (NFC) hardware. NFC is an expansion on the older Radio Frequency Identification (RFID) technology which has been in common use in various forms since the 1970's in such applications as electronic door opening and merchandise theft detection. It has only been in the past two decades that RFID methods have been standardized to allow for interoperability between devices [38].

RFID devices come in two types: those that are connected to a power supply and those that are not. The devices without their own power sources are referred to as *tags*, and they are activated by the radio energy transmitted from a powered device and they use that power to transmit their data. Powered devices are commonly referred to as *RFID readers* but are technically *transponders* as they both transmit

[3] Since more than three devices would typically be involved, this is actually multilateration. However, triangulation is the well-known common term.

and respond. When scanned by a transponder a tag is *read*; its circuitry is powered up by the radio energy, it can receive and process messages from the transponder, and it can transmit messages to the transponder. Some tags are read-only, in that the transponder cannot change any of the data stored in the tag, while some tags can have their data written once or rewritten many times [38].

Most of the work with RFID technology for location determination investigates how fixed tags can be used at short ranges to pass along information. A good example can be found in Using Active And Passive RFID Technology To Support Indoor Location-Aware Systems [32] where the authors look at using hand held devices in museum situations, with Wi-Fi methods for location determination being used primarily by the devices, but with RFID tags providing exact location information at places of interest: when a museum visitor sees an object of interest, placing the hand held device within 5 to 8 cm from the marked tag will provide the device with precise location information while triggering its software to display more information about the object.

However, the idea of using RFID tags for location determination can be taken too far. In Information Sharing by Evacuee Collaboration [39], the authors examine disaster evacuation scenarios where mains power has been lost, but where up-to-date evacuation information would be very useful. Their proposal is for the placement of many passive RFID tags lining the hallways and stairwells of a building, along with equipping every evacuee with handheld transponders. The RFID tags would be embedded in glow-in-the-dark type materials so as to be visible in a darkened building and evacuees would be expected to scan as many tags as possible along their escape routes. This scanning stores a message that the evacuee was there and what other tags they have scanned, while at the same time collecting lists of the other evacuees that have scanned the tag and what other tags they have scanned. The hand held device would process this data and provide the evacuee with the best known escape route from the current location, taking into account that blocked escape routes can be detected by other evacuees having travelled one route and doubled back. Unfortunately this proposal has obvious problems, not the least of which is the concept of evacuees dutifully scanning RFID tags during the chaos of an evacuation, and this problem might be more properly addressed through the use of the Wi-Fi abilities built into everyone's smart phones.

It is possible to use RFID technology for location determination in a way that does not require active scanning by the user. In Indoor Location Estimation Technique Using UHF Band RFID [29] we find a workable method where RFID tags attached to the ceiling of a room in a grid pattern with a 50 cm separation between tags. A hand held device with a relatively powerful RFID transponder continuously scans its surroundings, detecting RFID tags up to approximately 3 meters distance. Software processes the list of currently scanned tags to determine the most probable location for the device. The authors report that by using a simple method to calculate that position they can achieve an estimated location to within 90 cm of the true location. They make note of a tag scanning problem related to the RFID frequency having a wavelength of 30 cm, but unfortunately what the exact problem was is not well described, although it is related to multipath reflection (see Section 3.2). It appears that this difficulty is caused by multipath fading making it impossible to scan some nearby tags. One potential difficulty with this system, however, is its use of power by the transmitter. The authors initially set their RFID transponder to 27dBm (500mW), which if used in a mobile phone could double the device's power use (See Section 5.3). The authors conclude by stating that the optimum power use would be 18dBm (63mW), which would be acceptable for a mobile phone, however that value is the result of simulation and not experimentation.

2.3.4 IEEE 802.11 Wi-Fi

Wireless Internet access has become commonplace over the past decade thanks to the IEEE 802.11 Wi-Fi standards [40]. While the Wi-Fi standard has had support for the 2.4 GHz and 5 GHz radio bands from its early days [41], despite its limitations [27] the 2.4 GHz band is the one most commonly used today. As demand for wireless Internet has increased, so has the number of base stations (commonly referred to as *access points* or APs) deployed in the environment. A quarter of households worldwide, and 67.8% of the households in Canada, now have Wi-Fi home networks [17]. Given that most smartphones have built-in support for Wi-Fi wireless Internet, and that we're almost always surrounded by Wi-Fi signals, using Wi-Fi as a data source seems like an obvious choice. It is, at the very least, a very active area of research [42].

One possible method of indoor location determination with Wi-Fi signals is to use a *time of arrival* (TOA) and *angle of arrival* (AOA) method similar to that used by cellular service operators in locating handsets [13]. (See Section 2.1) This method is well described in *Super-Resolution TOA Estimation With Diversity for Indoor Geolocation* [25]. As well, the authors point to a correlation between the error in location estimates from their method and the bandwidth of the radio signal used. This suggests that an interesting Wi-Fi location determination accuracy experiment could be performed using 5 GHz 802.11n access points as they are capable of switching between 20 MHz and 40 MHz bandwidths. This idea, along with other future work, will be discussed in Chapter 6.

For a location determination method to be in widespread use outside the experimental laboratory, a method must be found that will work with common devices. As noted in [43], commodity devices such as smartphones lack features such as TOA and AOA, and the only measurement of Wi-Fi radio signals available on such devices is the *received signal strength* (RSS[4]). For the purposes of Wi-Fi location determination, RSS measurements are a good fit as they are always associated with the unique *base station identifier* (BSSID[5]) of the broadcasting Wi-Fi device [47]. As well, unless configured otherwise, Wi-Fi APs continuously announce their presence by broadcasting their BSSIDs, which is ideal for passively listening devices (see Section 5.3 for an example). As the power of transmitted radio energy decreases with distance from the transmitter, the RSS observed by a receiver is (in a simplistic sense) a function of the distance from the transmitting AP. Together this BSSID and RSS form a *signature tuple* [45] that can be used to judge the distance from an AP. The signature tuples are generally collected together as an *RSS vector*, and a *location fingerprint* is created when an RSS vector is paired with an identifier for a location. This entire process is referred to as *RSS fingerprinting* [27].

Unfortunately, as will be discussed in Chapter 3, the physics of electromagnetic waves is extremely complex and their interaction with the typical indoor environment makes this a difficult method to work with. But, as the existing literature on the topic will attest, indoor location determinations can be achieved using Wi-Fi RSS measurements with excellent accuracy.

---

[4]Different authors may use different terms for the received signal strength, such as received signal strength indicator (RSSI) [44, 45] or observed signal strengths (OSS) [46], but the meaning is the same.

[5]A Wi-Fi AP uses an IEEE Medium Access Control (MAC) address as the value for the BSSID [47], and the BSSID is commonly referred to as the MAC address.

To achieve that excellent accuracy, most RSS location determination methods consists of two stages: [42, 45, 48, 49]

1. A first stage where a database of location fingerprint data is collected. This is commonly referred to as the *offline phase*. As a rule of thumb, the higher the density of location fingerprints taken in a given area, the more accurate the location determinations will be [27].

2. A second stage where the local Wi-Fi RSS is sampled by a device and the location determined based on the database of location fingerprint data. This is commonly referred to as the *online phase*.

Examples of this method can be found dating back over a decade to the emergence of 801.11 Wi-Fi. In what may be the most heavily cited Wi-Fi location determination paper *RADAR: An In-Building RF-based User Location and Tracking System* [49] from the year 2000, the authors initially looked at using signal propagation models to calculate indoor location to reduce the dependence on the empirical measurements of RSS fingerprinting methods. While their modeling was successful to a degree, due to ‘‘the hostile nature of the radio channels’’ their system was much more accurate using the empirical RSS fingerprinting method. While other works tend to agree with the poor performance of propagation modeling [13, 50], this paper remains interesting as using signal propagation modeling could be used to improve some RSS fingerprinting methods. See Future Work, Chapter 6, for a discussion of this idea.

There is good reason to wish to limit the need for RSS fingerprinting during the offline phase: it can be extremely time consuming [14]. One author writes that ‘‘one floor of an average-sized office building (2000m^2) is surveyed in eight hours by a single technician” [14]. Another example is provided in *Convert Wi-Fi Signals for Fingerprint Localization Algorithm* [46] where the authors describe how collecting fingerprint data for 200 individual locations will take 14 hours. This paper does make an excellent comparison between mobile devices of different types, as 16 different laptops and smartphones were used in the experiment, but at the cost of 224 total hours of scanning by more than 60 student volunteers. These results show clear differences in the RSS readings from differing devices, which is an effect that will be discussed in Section 3.6.

To avoid the need to duplicate RSS fingerprinting work by scanning each location with each type of device that is to be located, *Received Signal Strength Calibration for Handset Localization in WLAN* [37] presents a calibration method for adjusting the RSS values collected by device in the online phase to a level comparable to the original RSS values collected during the offline phase. This method works by using the new device to collect RSS data at a few known locations from the original RSS fingerprinting survey. The automated calibration method described in this paper is then able to calculate effective parameters to be used in an affine transformation of the original RSS fingerprinting data set. Using this method the new devices have a localization error of less than 2 meters.

When collecting a location fingerprint and its two components, the location and the RSS vector, it is important to know the RSS scan location as precisely as possible. Any error in the knowledge of that location becomes part of the error in determining the location of a device in the online stage. While some methods have used measured markings on floors or walls to ensure repeatable experiments [27], the paper *RadLoco: A Rapid and Low Cost Indoor Location-Sensing System* [14] presents a method that uses the Cricket devices previously described in Section 2.3.2. These Crickets were an updated model [51] and were shown by the authors to have a mean accuracy to within 14 cm of true location. However, these Crickets also came at a price of $250 each, which is twenty-five times the $10 per unit goal described in the earlier works on Cricket [28]. The Crickets were used in the offline location fingerprint collection phase, and they simplified the process by automatically providing the location half of the location fingerprint tuple. To accomplish this, the authors would place all but one of the Crickets along the hallways to be scanned, with the remaining unit being co-located with the Wi-Fi scanning laptop device on a push cart. Rather than rely on measured and marked locations, this method allows the data collection technician to push the cart the approximate distance to the next scanning location while the Crickets determine the laptop's Cricket location, and therefore the scanning location, to within 14 cm of its true location. For the online phase the Crickets have been removed and the mobile device calculates its location strictly from the location fingerprint database generated during the offline phase. Location determinations made by this system would be within 3.5m of the mobile device's true location more than 80% of the time.

While some methods, including the method described in Chapter 4 of this thesis, are intentionally designed to avoid the cost of the offline phase RSS fingerprinting, others take the challenge on through automation. In their paper *Robust Navigation Indoor Using WiFi Localization* [52], the authors use robots to perform the RSS fingerprinting. During the offline phase a robot equipped with sensors for autonomous building navigation, as well as a Wi-Fi receiver for RSS fingerprinting, is placed at a known starting point and instructed to begin. While travelling down hallways it collects the RSS fingerprinting data while generating a map of its surroundings from ultrasonic range finding and inertial dead reckoning sensors. While the paper does not state the positional accuracy of the robot, conversations with the authors indicated a very high level of precision as the combination of ultrasonic range finding and inertial dead reckoning sensors provided a mechanism for self-correcting any errors. A later paper by the same authors [53] indicates an online phase Wi-Fi location determination of 2.57 meters.

It is also possible to collect too much data as was shown in *Real-time Indoor Positioning System* [54] where the authors tested the hypothesis that a very dense collection of RSS fingerprint data would provide highly accurate results. A short hallway was chosen and scanning locations were set at two foot intervals with a total of 200 individual locations. The authors had noticed that the orientation of the device had an impact on the scan results (this problem is discussed in Section 3.6), and to test this effect they took ten individual scans at each location, with the device aimed at the eight compass points, and with two extra scans with the device aimed in arbitrary directions. The effort that was put into this work cannot be understated as a RSS fingerprint database of approximately 8000 scans was built over a total of approximately 30 hours. They then proceeded to scan other hallways in the building using the simpler methodology of taking four RSS fingerprint scans every five feet, with the device directed towards the four primary compass points at each location. The results of their work nullified their dense scanning hypothesis, as their final location determination algorithm shows that the two data sets each would correctly identify the location 80% of the time. This was acheived using a relatively simple method, similar to the one that will be discussed in Chapter 5, where n signature tuples with the strongest RSS values . The results did differ in the remaining 20%, with the first data set always generating a location determination even though it was an incorrect one, while two thirds of the failed location determination attempts from the second data set were due to the current RSS fingerprint sample not being matched any known location. However, it is important to point out that, due to the unusually large database size of the first sample set, the algorithms used to make these online location determinations varied somewhat depending on whether the first or the second data set was being used. Regardless, the results of their experiment clearly show that there is a point where collecting more ever more RSS fingerprint location data is not necessary and is a waste of time and resources.

While the authors of [54] used a relatively simple method that would generate location determinations showing the nearest RSS fingerprint scan location that matches the current RSS sample, many other research efforts have used statistical methods find a position by calculating which location has the highest probability given the current RSS fingerprint. The use of Gaussian distributions [46] have proven successful in both cell phone [55] and Wi-Fi [26,27,56] location determinations. Machine learning and Bayesian networks [57] also show promise, and there are many examples of how these methods can produce excellent results [12,43,50,58,59,60].

2.3.5 Bluetooth

As most mobile devices today support the Bluetooth [61] wireless standard, location determination methods using this technology can be considered complementary to method using Wi-Fi. Similar to the BSSID of Wi-Fi devices, all Bluetooth devices have unique Bluetooth Device Addresses (BD_ADDR, also commonly referred to as MAC addresses) that can be used for identification [62]. Bluetooth has and added advantage of being a short range radio technology, with typical devices having a range of 30 feet, and this provides the potential for using these devices as low cost radio beacons [24] that give a more precise location determination by cover smaller regions than Wi-Fi APs [63]. An example of work that combines both Wi-Fi and Bluetooth technologies can be found in *Fusion of WI-FI and Bluetooth for Indoor Localization* [58] which shows promising results.

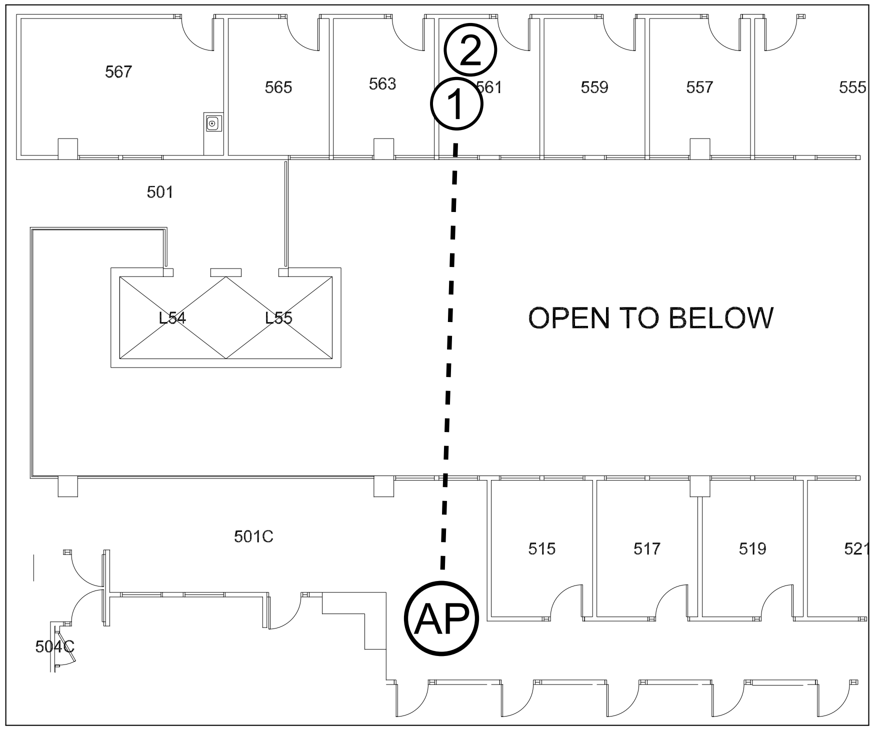
Chapter 3

Why The Complexity?

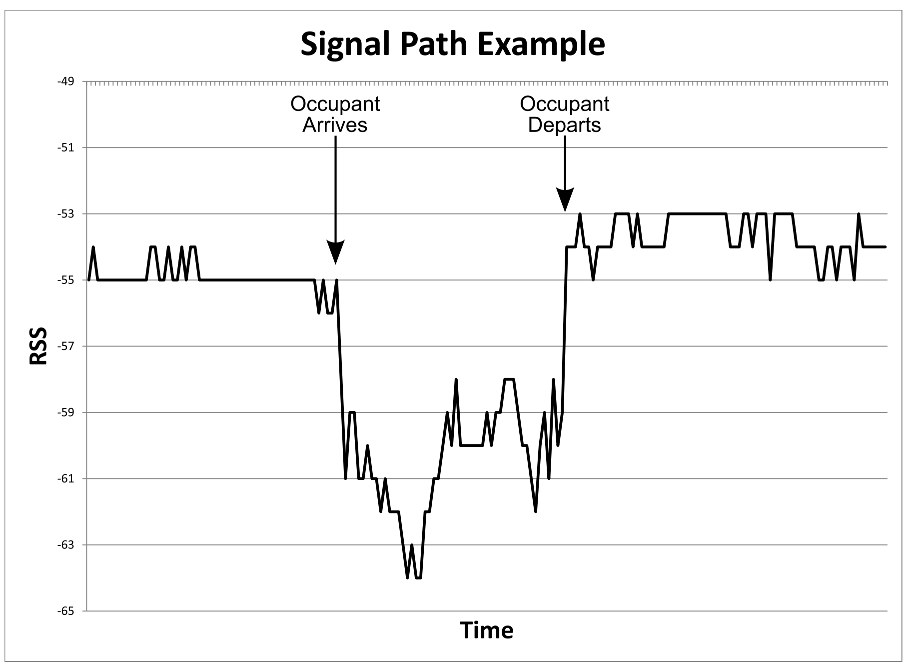
To examine the feasibility of any indoor location determination method we must first have an understanding of the complexities of indoor Wi-Fi radiolocation, and those complexities are the combined total of many limiting problems. In this section we will discuss some of these issues, including multipath fading (Section 3.2) and the related topic of paths taken by radio signals (Section 3.1), the effect seen from human activity and human presence (Section 3.3), and the variation in received signal strength that may be due to changing weather patterns (Section 3.5). Furthermore, differences between individual devices of different models and, in some cases, even those of the same model, have an important effect on the ability to locate a device (Section 3.6). Finally we will examine the roles played by the builders of modern structures and how the materials they use in construction can attenuate radio waves (Section 3.7).

3.1 Signal Propagation

Like the higher frequency electromagnetic waves we see as light, radio waves can pass through some materials (while losing some energy in the process through attenuation) while being reflected or absorbed by others. We naturally understand how light waves propagate through our environment from a lifetime of experience, but the invisibility of radio waves makes their propagation difficult to intuitively understand.



(a) A map of the location that interferes with Wi-Fi reception.



(b) RSS change when seated vs when out of the room

Figure 3.1 – An example of an unexpected radio wave path. The received signal strength from the access point (marked AP) at the mobile device (marked 1) would be weakened when an office occupant sat in the chair (marked 2).

An excellent example of this comes from a simple experiment in a university office. ECS 561 is a typical inner-ring office in the ECS building, with windows that face in to a multi-story open atrium. Visible through the window and across the atrium is a Wi-Fi access point antenna, and one would naturally (though incorrectly) assume that the best radio signal would be in a straight line from this AP to a point in the office. The map shown in Figure 3.1a gives the layout of this scenario, with a direct line-of-sight between the mobile device (marked ①) and the access point (marked AP). An odd effect was noticed when the device's RSS data was examined: when an office occupant that was seated in a certain chair (marked ②) there was a noticeable decrease in the signal strength from the AP. If the occupant was to leave the office the RSS from this AP would increase. Even though the chair is on the opposite side of the line of sight between the AP and the device, having someone sit in that chair would have a detrimental effect on the signal received at that device. While the actual path taken by the radio waves in this case are unknown, the case itself is an excellent example of how a seemingly simple environment can be far more complex for radio propagation than we would expect.

One of the effects that can cause this kind of complexity is the *reflection* which occurs when the radio waves hit a smooth surface that is much larger than the wavelength of the radio signal [64]. In the same way that the waves seen in a lake or a bathtub will come together to form higher waves or smaller waves, radio waves will come together as *constructive interference* to create a stronger signal, or together as *destructive interference* to create a weaker signal [65].

Other effects can come into play as well, especially in the crowded indoor environment. When a wave encounters a dense object that is larger than its wavelength, waves appear to bend or spread out on the other side of the object in a phenomena called *diffraction*. If a wave encounters a rough surface with features that are of similar size or smaller to its wavelength, the wave will *scatter* unpredictably in all directions [64]. Certain materials will also *absorb* some of the the radio energy, through the process of *attenuation* [66], making it unavailable for reception.

In some cases reflection, diffraction, and scattering can be useful for sending the radio signal to areas where it might not otherwise be available [64]. However, for the purposes of indoor Wi-Fi location determination, these effects simply add a great deal of complexity to the problem.

3.2 Fading

Radio transmissions can experience degradation due to multipath propagation, which occurs when radio signals reflect off multiple surfaces and arrive at the receiver via paths of differing length and delay. This is especially problematic for the indoor scenarios we are concerned with, given the myriad surfaces found inside buildings. These reflections lead to the effect known as multipath fading: when multiple signals from a single source arrive at a receiver at slightly different phases, they will cause the received signal to increase or decrease in power [67]. This fading effect causes the power of a radio signal to change dramatically when receiver displacements are on the order of half the radio signal wavelength. The wavelength of 2.4GHz Wi-Fi IEEE 802.11b/g signals is 12.5cm (see Appendix A) and so it can be expected that different RSS levels due to fading would be seen over spatial displacements as small as 6.25cm [53].

To counteract multipath fading, most devices that are larger than a hand-held phone (such as laptop computers) will have multiple antennas with a minimum separation of 12.5cm. This provides *selection diversity* [68, 69] as the radio receiver would only experience a deep fade in the rare event that the signal was weak at both antennas. However, multiple antennas are not an option for handsets due to their small geometric size; hand held mobile devices are physically not large enough to place multiple antennas into different fade areas.

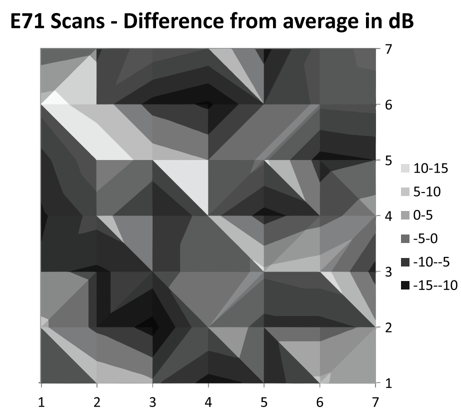
To examine the difference between single and dual antenna devices, an initial experiment was performed using two Nokia E71-1 devices (single antenna), and one Lenovo X200 laptop (dual antenna) with a factory installed Intel Wi-Fi Link 5300. A 7x7 grid with an edge length of 6.25cm (half the wavelength of 2.4GHz radio) was set up, and RSS measurements for a single AP were taken by all three devices at each of the 49 vertices.

Device	Mean (dB)	Stdev
E71 #1	-74.0	5.09
E71 #2	-76.0	5.68
X200	-35.9	3.38

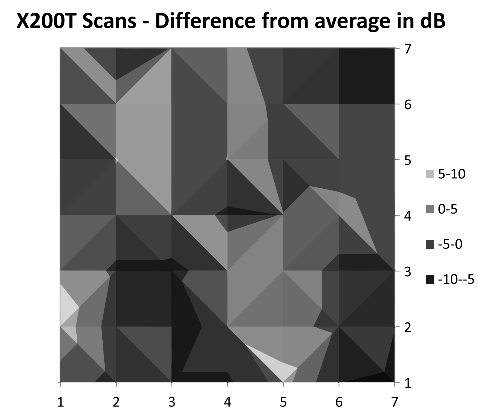
Table 3.1 – Initial Fading Experiment Results

The expected outcome of this experiment would be for a dual antenna laptop to have experienced less fading than either of the two single antenna phones, and Table 3.1 suggests that this was the case. Over the 49 test points the laptop showed both a higher mean RSS and less deviation in that RSS value.

These results are also displayed as a surface plot in Figure 3.2, where significant changes in reception strength over very short distances are seen for the single antenna mobile phone (Figure 3.2a), while the antenna configuration of the laptop avoided the fading effect (Figure 3.2b).



(a) Nokia E71 (Single antenna)

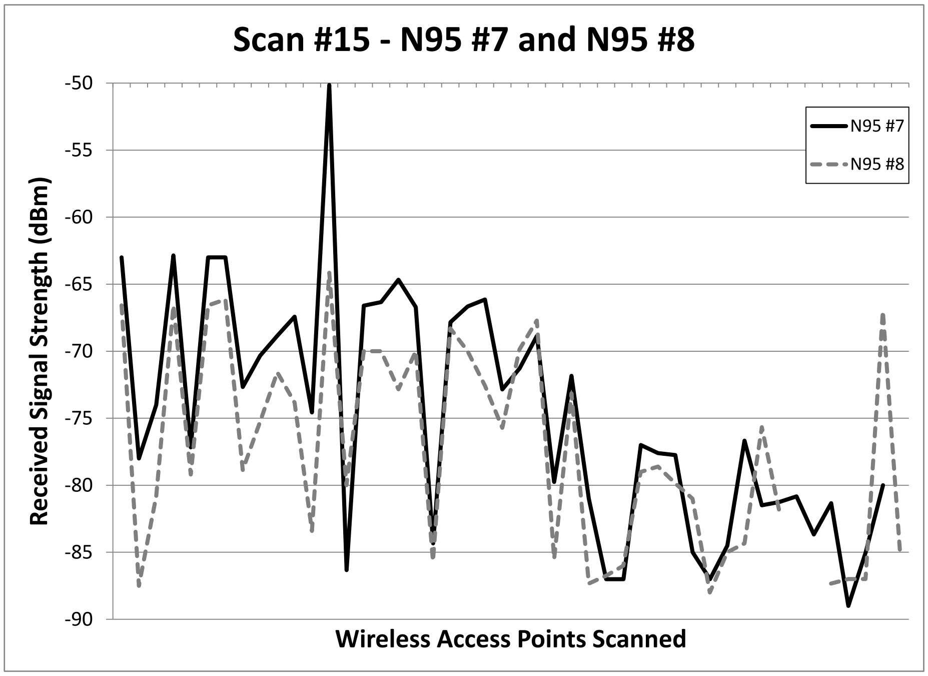


(b) Lenovo X200T (Dual antennas)

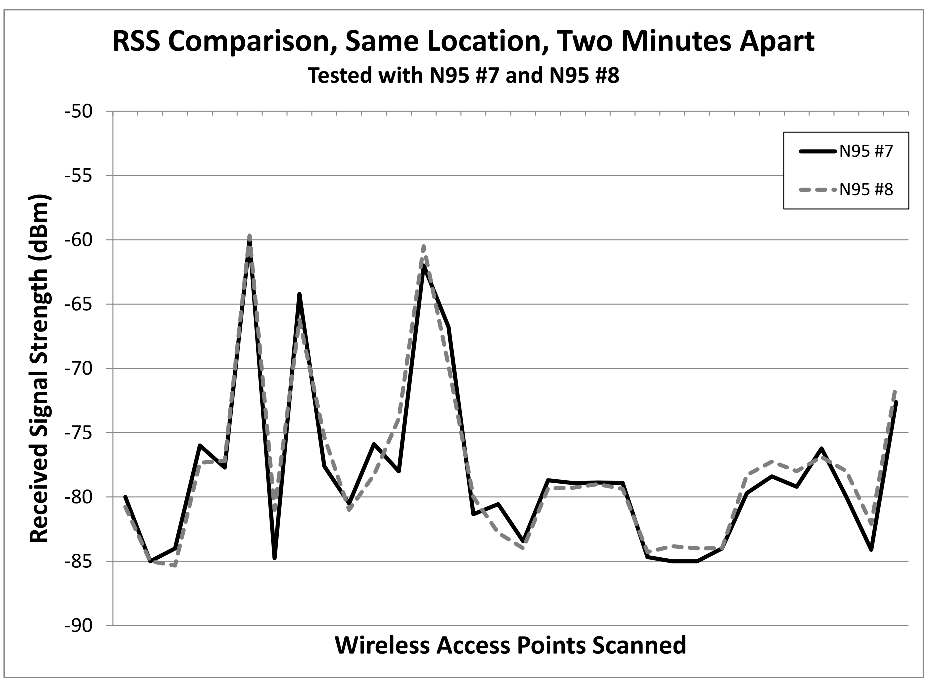
Figure 3.2 – Fading comparisons between a single antenna mobile phone and a dual antenna laptop.

To investigate the effects of multipath fading, an experiment was conducted involving two Nokia N95-3 mobile phones that were positioned on a survey cart with a 30cm separation between the phones. A typical result from this experiment is shown in Figure 3.3a, where the difference in RSS for a given AP, as recorded by the two devices, is interpreted as the result of multipath fading.

As a control to ensure that these results were not an artifact of the differences between the two N95-3 phones, these devices were tested sequentially in the same location. As seen in Figure 3.3b, while differences were observed in their RSS measurements, their readings were generally consistent and did not show the larger differences that are attributed to multipath fading previous in Figure 3.3a.



(a) Multipath fading example where two N95-3 devices were scanning simultaneously while placed 30cm apart



(b) The control test where the same two N95-3 devices scanned from the same location, two minutes apart.

Figure 3.3 – An experiment to demonstrate the multipath fading effect.

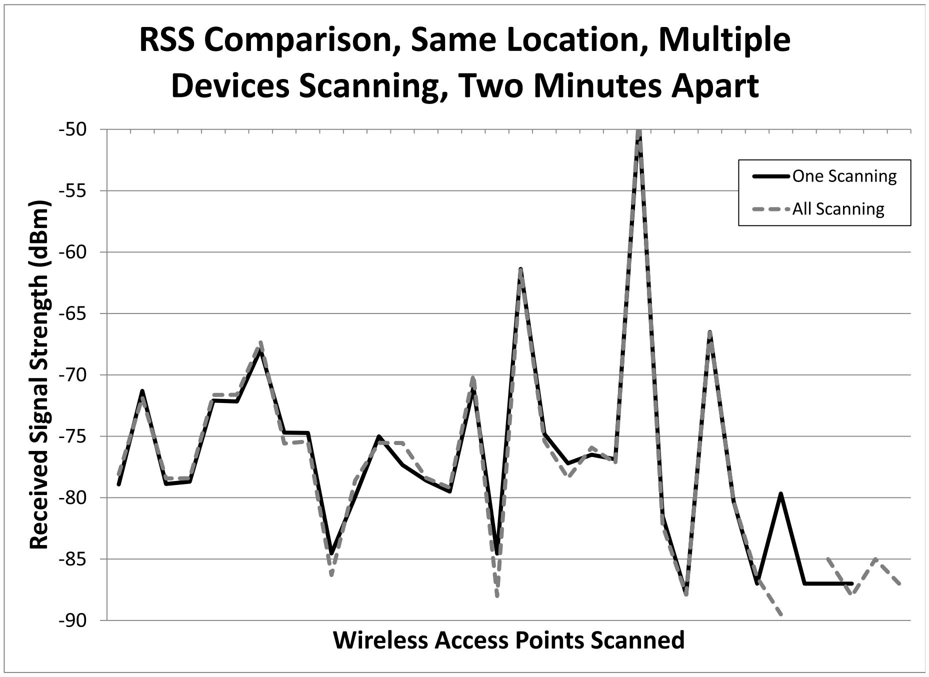


Figure 3.4 – The results of an experiment to test whether the scanning of Wi-Fi access points results in differences in received signal strength. The N95 #8 device was placed near six other Wi-Fi devices and two sets of scan data were collected: one with and one without the other devices scanning.

As the Symbian devices appeared to be actively scanning for APs, another control experiment was conducted to determine whether multiple scanning phones would interfere with each other. Seven phones were positioned next to each other and two tests were run: one with a single device scanning and another with all seven devices scanning. To minimize any environmental changes to the RSS for this comparison, the scans were run within two minutes of each other. No substantial differences between these data sets were observed, as shown in Figure 3.4.

3.3 Human Presence and Activity

A *busy environment* -- an environment with significant human activity that may alter our results -- can add many complications to indoor Wi-Fi radiolocation. The 2.4GHz radio spectrum used by 802.11 Wi-Fi is "crowded", in that many devices share these frequencies, such as cordless phones, baby monitors, wireless security cameras, and microwave ovens. However, the most important source of interference in a busy environment may be the physical reason why microwave ovens are included in this list: radio waves in the 2.4GHz frequency range are easily absorbed by water [70]. As the average human body is comprised of approximately 70% water by weight [71], a busy environment therefore contains many moving sources of signal attenuation.

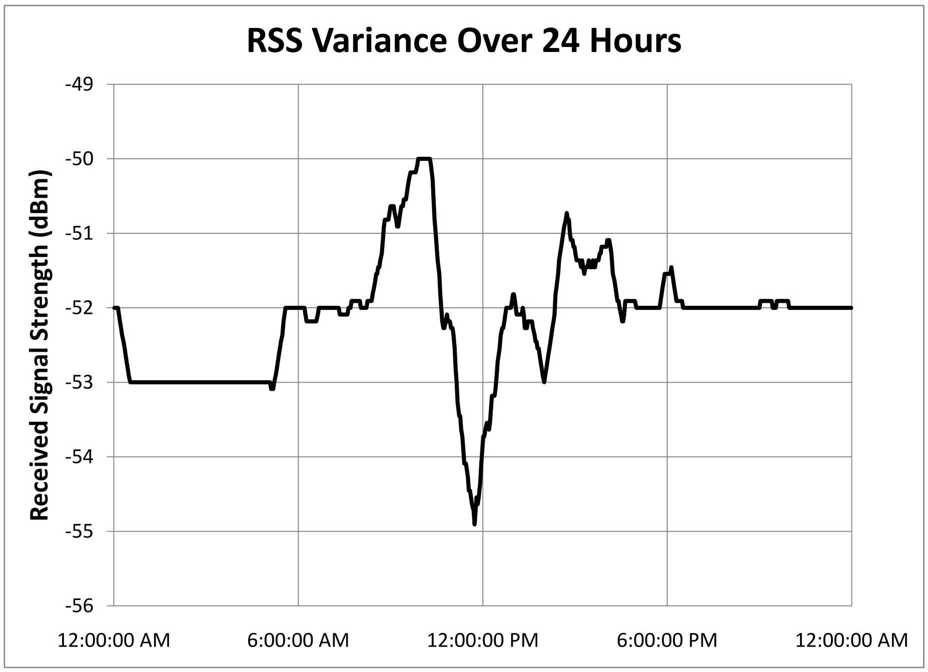


Figure 3.5 – And example of the variability of a Wi-Fi signal in a busy environment over the course of one day.

This effect can be easily demonstrated by configuring a mobile device to collect Wi-Fi RSS data over the course of a work day. In this experiment a Nokia N95 was placed in an office to record data over a 24 hour period. The data collection was started after regular office hours and the resulting data for the four strongest APs was averaged. As the graph of this data in Figure 3.5 demonstrates, the averaged RSS data from these APs remained relatively constant during the evening hours but deviated when the building was occupied.

3.4 Moving Access Points

All Wi-Fi location methods rely on the fact that access points are not regularly moved. In the case of outdoor radiolocation using Wi-Fi, such as the services supplied by

Google, one could expect that the scanned APs would not typically move from building to building, and any change in location within a building would not necessarily have an impact on the system as a whole. However, when one considers finer grained indoor location finding, it is obvious that moving an AP from one part of a building to another would have a serious impact on the accuracy of the system.

Communication between the operators of a Wi-Fi location system and the operators of the Wi-Fi network itself is critical to avoid any unexpected interruptions in location services. This exact problem was seen during this research when the ECS building's wireless network was re-engineered; new access points were first added, then the old access points were either moved or disconnected. With many new BSSIDs showing up as the strongest RSS for their areas, the existing location test software (described later in Section 5.1) would report back that the device was in an unknown location.

Any Wi-Fi location system must be designed to be watchful of such changes. The software must be wary of BSSIDs that are not part of the expected set for a given area, and action must be taken to avoid the inaccurate results that would be the by-product of a relocated AP. Flagging a BSSID as suspicious in the database would be a first step followed by attempts to confirm where this BSSID is actually located.

3.5 Variation in a Quiet Environment

With the busy environment data in hand, it makes sense to see what RSS variations might be found in a *quiet environment* -- an environment where nearby human activity does not significantly alter our results. To test this the same Nokia N95 from the busy environment test (see Section 3.3) was situated two metres from an AP in an empty building. This device was left to scan continuously for four days. The results of this experiment are shown in Figure 3.6, where we can see a slowly occurring variation in the RSS data. Attempts were made to discover the reason for this variation, such as possible connections to local weather conditions, but its source remains unknown.

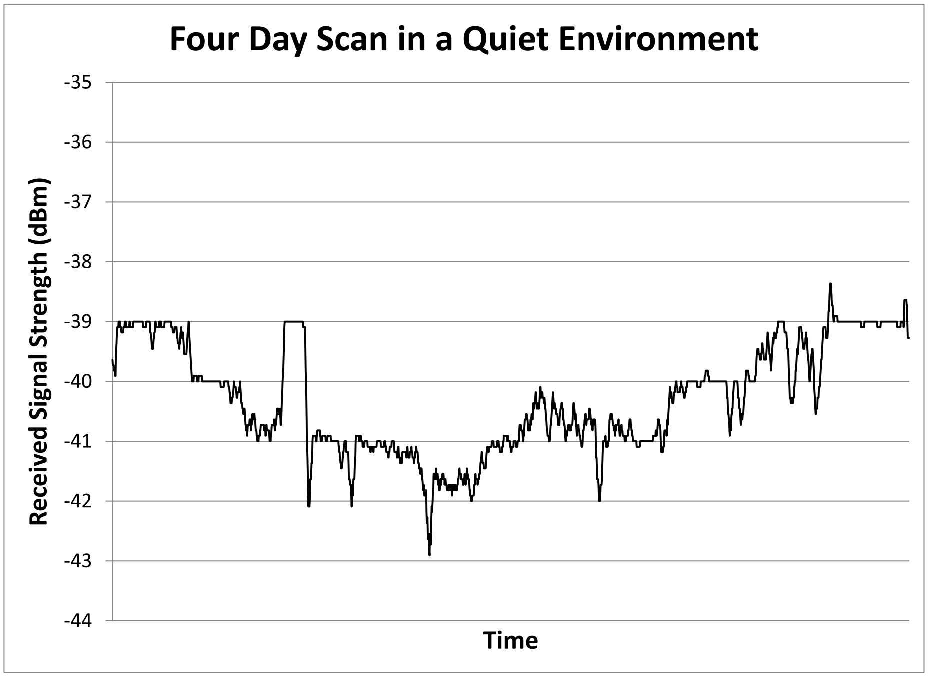


Figure 3.6 – The variability of a Wi-Fi signal in a quiet environment.

3.6 Differences in Devices

It's clear that different device models from different manufacturers are different in appearance and, as one would expect, they are also different in internal design. One significant internal difference that is important to Wi-Fi radiolocation is the position and direction of the Wi-Fi antenna. In the case of mobile phones the placement of these antennas is secondary to the placement of the cellular antennas, and different devices will have their Wi-Fi antennas in different positions. These differences in direction lead to variations in RSS measurements.

An interesting source of information on antenna placement is the Federal Communications Commission in the United States. All transmitting radio frequency devices that are sold in the USA must first pass FCC inspection, and part of an FCC submission includes internal photographs of the device. While these photographs are commonly kept secret until after the device is released, they can be used to compare devices that are more than a year or two old. For example, FCC documentation shows that the Wi-Fi antenna for the Nokia N96 faces out the back near the top [72], for the Nokia N95 the Wi-Fi antenna faces out the right side near the bottom [73],

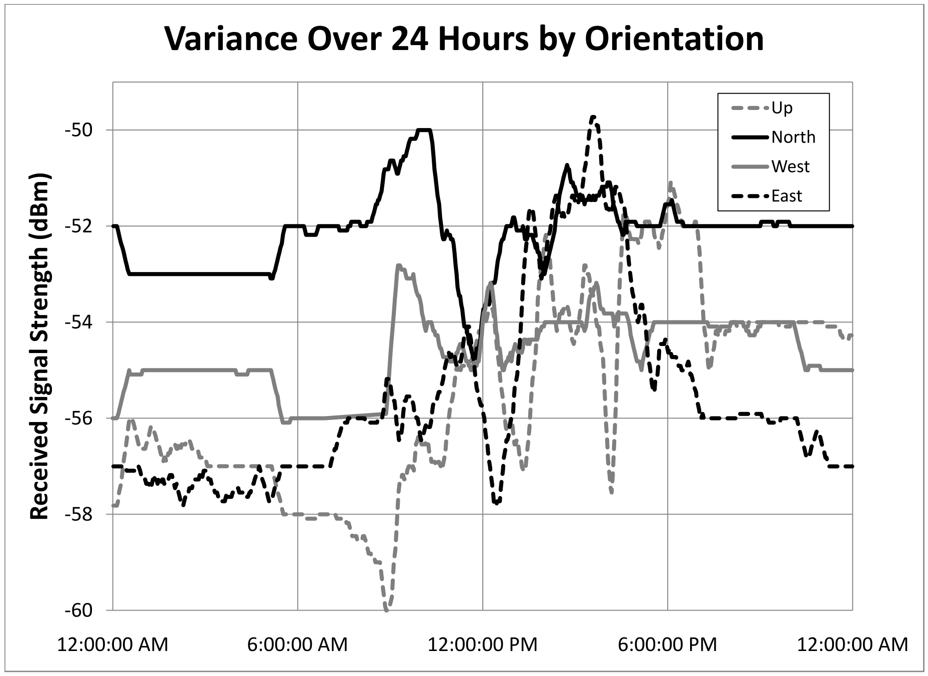


Figure 3.7 – The variability of a Wi-Fi signal due to mobile device orientation. This data was collected by a Nokia N95 on four separate days.

the Wi-Fi antenna for the Nokia E71 faces out the top and back [74], and for the HTC Nexus One the Wi-Fi antenna faces out back at top left [75].

To investigate RSS variation due to the position of antennas and device orientation, an experiment was set up to measure the effects of changing the orientation of a Nokia N95. Controlling variables in this experiment was a difficult problem as the phone must be rotated in place to avoid any effects from fading. At the same time a full day's worth of data was to be collected in each direction, and so the data collection was made over four days.

The same averaging method that was used for the busy environment experiment (see Section 3.3) was used to produce the the results shown in Figure 3.7. From this data a difference related to the direction of the handset can be seen, although it is not necessarily a large difference in terms of relative signal strength.

3.7 Building Materials and Attenuation

Another challenge to radio signals in general is the materials used in the construction of the buildings we use. Simple things that one might not consider, such as the metal mesh screens (similar to chicken wire) that are used for reinforcing plaster or for holding insulation in place, can create interference. The spacing of the holes in chicken wire are close enough to create a Faraday Cage for 2.4GHz transmissions [76], which will absorb those radio waves.

While it is understandable that buildings built before the wireless innovations of the past two decades may have such problems, this is also the case for modern buildings. An example close to home is the coating on the exterior windows of the University of Victoria's Engineering and Computer Science (ECS) building. ECS was completed in June 2006 with modern energy-efficient windows designed to reflect infrared radiation, but these also have the side effect of blocking radio signals. This can be tested with a simple GPS device; held next to a closed ECS window the device will not receive any signals from the GPS satellites, but if the window is opened the device will immediately begin to receive those signals.

Windows are not the only problematic building material, however. Modern materials used for insulation, such as Protect TF200 Thermo[1], have a metallic layer that may be perfect for blocking wireless signals [77]. While such materials may not typically be installed in indoor walls, such problems should be taken into account when constructing any modern building.

Most building materials do not completely block radio signals, however, but instead attenuate them to some degree. In *3Com® Wireless Antennas Product Guide* [78], and reproduced here in Table 3.2, are examples of the attenuation from common building features on 2.4 GHz radio. These attenuations are listed in *dB*, which is the logarithmic decibel unit used to describe ratios of power or intensity, where 3 dB represents (approximately) a factor of 2 change in power and 10 dB represents a factor of 10 change in power.

As we will see in Section 4.2, it is possible to take these signal attenuation problems and use them to our advantage.

[1] `http://www.glidevale.com/downloads/protect_tf200_thermo.pdf`

Building Material	2.4 GHz Attenuation
Solid Wood Door 1.75”	6 dB
Hollow Wood Door 1.75”	4 dB
Interior Office Door w/Window 1.75”/0.5”	4 dB
Steel Fire/Exit Door 1.75”	13 dB
Steel Fire/Exit Door 2.5”	19 dB
Steel Rollup Door 1.5”	11 dB
Brick 3.5”	6 dB
Concrete Wall 18”	18 dB
Cubical Wall (Fabric) 2.25”	18 dB
Exterior Concrete Wall 27”	53 dB
Glass Divider 0.5”	12 dB
Interior Hollow Wall 4”	5 dB
Interior Hollow Wall 6”	9 dB
Interior Solid Wall 5”	14 dB
Marble 2”	6 dB
Bullet-Proof Glass 1”	10 dB
Exterior Double Pane Coated Glass 1”	13 dB
Exterior Single Pane Window 0.5”	7 dB
Interior Office Window 1”	3 dB
Safety Glass-Wire 0.25”	3 dB
Safety Glass-Wire 1.0”	13 dB

Table 3.2 – Attenuation Properties of Common Building Materials, from the *3Com® Wireless Antennas Product Guide* [78]

Chapter 4

The Simple Method

As discussed in Chapter 2, there are excellent examples of remarkable accuracy in locating hand-held devices using 2.4GHz 802.11 Wi-Fi signals. However, the need for preciseness in any human endeavour is application dependant. This section presents the argument that indoor location determination of a reasonable preciseness for many uses, such as indoor navigation, can be achieved at low cost and with very simple setup requirements.

Taking a step back from a problem and looking at it from a different perspective is always a useful exercise. Most of the location methods reviewed in Section 2.3 are driven by how accurate and precise their location determinations can be on a given x, y, z coordinate system. There is nothing wrong with such goals, of course, and some of the results are very impressive. However, even with all of the work that has been done on indoor Wi-Fi radio location research, there are very few deployed indoor location systems.

Reaching an ideal ubiquitous indoor location system requires a balance of three properties:

1. The minimization of the cost of deployment and maintenance, ideally by using infrastructure that is already in place

2. The need for wide-spread compatibility with existing mobile devices

3. The choice of a reasonable level of accuracy and precision that fits am application while balancing #1 and #2

Indoor navigation is case that demonstrates a useful location application and a situation where a more relaxed location determinations would be acceptable. When observing people as they navigate through the world, it is clear that we will look around ourselves for landmarks. In certain types of indoor environments, such as that seen at a typical university with regularly numbered doors, this can be interpreted as an argument that fine grained location resolution is not required for human navigation; it would be expected that while searching for the destination, a visitor to such an environment would only require assistance in finding the correct section of the building. Once in the correct section the visitor would then proceed to read the numbers on the doors until the destination is found. Rather than relying on a map to arrive within feet of the destination, it could be said that finding the correct section, wing, or floor of the building is ‘‘good enough’’.

Navigation isn’t the only application that can be achieved with this type of semi-fine-grained locational resolution[1]. A system for notifying a user when friends are nearby would not need a high level of precision; the important goal in this case is to simply alert the user that a friend is in the general area. The process of meeting up can then be conducted by some form of direct communication. The same can be argued for a conference setting when an attendee is looking for a colleague and the knowledge of which room to look in is the level of positional resolution that is necessary to complete the task.

An important factor when considering an indoor location system is the time and expense that is required to collect the data set needed for the creation of a location fingerprint database. Looking at the work described in Chapter 2, it is apparent that increases in locational precision are dependant on the time spent calibrating the system. Using the typical university as an example, the time and effort required to deploy an indoor navigation system would be extremely prohibitive. When considering

[1] The term ‘‘semi-fine-grained location resolution” is meant to describe a resolution that is much closer to the fine-grained indoor resolutions seen in Chapter 2 than to the coarse-grained resolutions seen from the Wi-Fi BSSID method employed by Google Maps. Google’s data is collected by their Street View cars driving through the streets of a city [79] and can only provide an approximate street location to an indoor user.

an ad-hoc setting where wireless networks are configured for certain events, such as at technical conferences where temporary Wi-Fi access points are required, the dozens of hours required to configure a highly calibrated system would not be available.

The usability of a completed indoor location system is, of course, of great importance. To see widespread use it can be assumed that such a system would need to be simple, fast, reliable, and compatible with the average smartphone. Moreover, if the indoor location system were to use a simple method of collecting the required location data, one could imagine the average user of the system contributing location data back to the system in ways similar to crowdsourced Internet projects. Mitigating the expense and maintenance of an indoor location system in a way such as this would be very attractive to the facility's administrators.

4.1 A Simple Method

The literature on indoor radiolocation using 2.4GHz 802.11b/g Wi-Fi signals typically focuses on the difficulties inherent in the indoor environment, such as radio signal multipathing, multipath that makes automated calculation of expected RSS values very complex [56, 80]. As these methods aim to determine a device's exact x, y, z location as accurately as possible, they ignore the simpler solution of defining broader areas and determining which area the device is located in.

To even consider such a simple method often requires a significant shift in thinking: moving from the typical concept of absolute location determination, where the goal is to determine a device's exact x, y, z location as accurately as possible, to a concept of determining what region or areas encompasses the device's location. It is important to realize that this is not the same as simply creating a larger error bounds on an absolute location determination[2] and thereby not knowing exactly which area a device is located in. Instead, this is a method that locates a device within a given pre-defined area with a high accuracy.

[2]Simply creating a larger error bounds on an absolute location determination would be, in essence, drawing a bigger circle around the calculated location on a map

To make such a simple system feasible requires two important features in the environment to be mapped:

1. There must be relatively strong signal attenuating features separating the regions that will be considered defined areas for the purposes of location determination.
2. A defined area must contain at least one AP (and, therefore, at lease one unique BSSID being broadcast) to clearly separate that area from the others. Ideally the environment would have multiple APs in the area as the spacial resolution of such a system is clearly limited by the distance between the access points.

The first requirement can be read as ‘‘signals from one defined area must lose strength when penetrating into other defined areas’’. For the simplest case where only the BSSID with the highest RSS is considered for location purposes, the attenuation of the signal from more distant APs is required to ensure that local APs are found to be the maximums. The importance of signal attenuation will be discussed in Section 4.2, but this requirement argues for the method's usefulness in the buildings of a university, where there are typically many hallways, or in the rooms of a conference center where there are walls separating the areas of interest for mapping.

The second requirement relates to the fact that the spacial resolution of such a system is clearly limited by the distance between the access points. While this requirement puts a significant limitation on the applicability of the method to the average indoor environment, it also argues for the method's usefulness in the buildings of a university or a conference center where the density of access points is comparatively high. Exploration of a typical university building will show a minimum of one access point antenna in any given hallway, and heavily used areas may contain multiple access points. In the event that there are sections of buildings that lack the required number of access points, the system can be easily augmented, and accuracy improved, with inexpensive consumer-grade wireless routers.

Configuration of the system can be as simple as walking the hallways of a building and recording where each Wi-Fi access point's received signal strength is at its maximum. This matching of BSSID/RSS maximum data to the sections of buildings may already be maintained by a university's wireless network operators in the form of the floor plans marking their access points and the BSSIDs of the equipment in use, although relying solely on this data would not make use of other APs that are in the area. However, as will be shown later in Section 5.8.1, collecting the required data can be as simple as one walk through the area.

That simplicity of configuration is the most important aspect of this system. With a simple and inexpensive system up and running, other parts of the system can then be refined or, for an area where this method is not applicable, one of the more expensive methods described in Chapter 2 could be used for determining location. However, as a whole, the simple method described here can be used to very quickly prototype an indoor location determination system that can be then modified and improved as needed.

4.1.1 The Algorithm

To demonstrate the effectiveness of this idea, the simplest possible Wi-Fi location method was used; when performing a location determination, the device performs a Wi-Fi scan to determine which BSSID currently has the strongest RSS, followed by a database look-up to determine which area that BSSID is associated with. There is no doubt that this part of the system can be improved, such as by using methods based on multiple local RSS values and Bayesian statistical methods, and this will be discussed in Chapter 6. However, doing so for this work would have defeated the purpose of demonstrating the simplicity of performing location determinations using areas defined by signal attenuating features.

Formally written, the two main algorithms of this system are quite simple. Algorithm 1 describes the method used during the initial Phase 1 data collection survey. While collecting data for a location, this algorithm is used each time the system returns with a new set of Wi-Fi scan data. It performs two tasks:

1. Update the location information for BSSIDs when they are seen with a new maximum RSS, setting the BSSID's location to the current location.
2. Add new BSSIDs to the database with their current RSS and the current location.

```
Input : results → the results of the previous Wi-Fi scan
Data  : db → the mapping of BSSIDs to locations with a maximum reported RSS
Data  : locationID → the ID of the area for which data is being collected

foreach result in results do
    if db[result.bssid].exists then
        if db[result.bssid].rss < result.rss then
            db[result.bssid].rss ← result.rss
            db[result.bssid].location ← locationID
        end
    else
        db.NewAP(result.bssid)
        db[result.bssid].rss ← result.rss
        db[result.bssid].location ← locationID
    end
end
```

Algorithm 1: During Phase 1 data collection, this algorithm is used when a new Wi-Fi scan data set is available.

Algorithm 2 describes the method used during the Phase 2 location determinations. When a new set of Wi-Fi scan data is returned from the system, this algorithm sorts the data from strongest RSS to weakest RSS, then iterates through the data until a BSSID match with the database is found. The location associated with that BSSID is then returned as the current location.

4.2 Using Attenuation

The most interesting revelation during this work is that the effects of attenuation, which are normally detrimental to indoor wireless activities, can be exploited for an indoor location method that uses defined areas instead of absolute locations. Collecting data on this effect in the real world is challenging given all of the complexities of radio, as described in Chapter 3, and modeling the potential attenuation effects in an environment is extremely complex, as shown in [81]. However, we can gain an understanding of the phenomena through the use of a very simple simulation of 2.4GHz radio propagation.

Input : $results \rightarrow$ the results of the previous Wi-Fi scan
Data : $db \rightarrow$ the mapping of BSSIDs to locations with a maximum reported RSS
Output : $locationID \rightarrow$ the ID of the area for which data is being collected

```
SortByRssDescending(results)          /* Sorted strongest RSS first */
while result → results.next() do
    if db[result.bssid].exists then
        locationID ← db[result.bssid].location
        break
    end
end
```

Algorithm 2: During Phase 2 location determination, this algorithm is used when a new Wi-Fi scan data set is available.

The simulation that was created began with a probabilistic free-space propagation MatLab simulation created by Dr. Michael McGuire. This software would simulate a two-dimensional region of empty space by the following steps:

1. Randomly distributing 25 APs throughout the space
2. Dividing the space into four equally sized quadrants
3. Calculating the RSS from each AP at 250 random locations in each quadrant, or 1000 locations in total.
4. In a manner similar to the algorithm described in Section 4.1.1, estimate the quadrant location of a given AP by where the maximum RSS from that AP was measured
5. Using a second data set of 250 random locations in each quadrant, or 1000 locations in total, estimate the quadrant of the location by matching the maximum observed RSS with the AP quadrant estimations
6. Calculate the average percentage of correct matches between the second data set locations and the estimate of their quadrants

This simulation was run 5000 times and showed that, on average, correct matches were made 81.4% of the time. Software was then created to generate visualizations

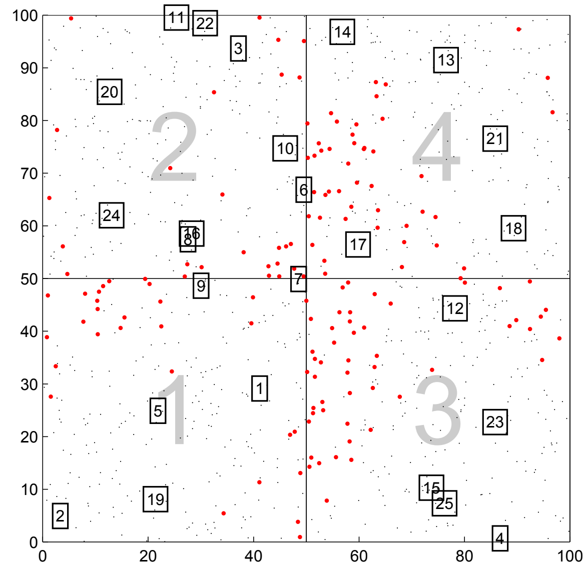


Figure 4.1 – An example of the AP simulation where 85.0% are correct matches (small points) and 15.0% are incorrect (larger dots)

of the results, such as the one shown in Figure 4.1. Here we see the four quadrants of the space with the distribution of 25 APs represented by boxed numbers. Correct matches are represented by small grey points, while incorrect matches are represented by larger red dots. While this method successfully highlights the areas where incorrect matches were made, the larger red dots may be visually misleading and suggestful of a higher rate of incorrect matches than were actually measured. For instance, in the example shown in Figure 4.1, 85.0% of the matches were correct. However, the ability to easily spot the incorrect location determinations is useful throughout the remainder of this chapter.

To examine these simulations analytically, software was written to calculate the probability of an incorrect location determination within each of the four quadrants. Using Equation 4.1, contour plots such as Figure 4.3 were generated to demonstrate how these probabilities are distributed throughout each quadrant.

$$P\left\{Y_1 \text{ has highest RSS}\right\} = \int_{-\infty}^{\infty} f_{Y_1}\left(y_1\right) \prod_{k=2}^{N} P\left\{Y_k \leq y_1\right\} \mathrm{d}y_1 \tag{4.1}$$

Attenuation Factor	0.0 dB	2.5 dB	5.0 dB	7.5 dB	10.0 dB	12.5 dB	15.0 dB	17.5 dB	20.0 dB
Percent Correct	85.0%	91.3%	95.0%	97.8%	98.7%	99.2%	99.4%	99.7%	99.8%

Table 4.1 – The percent of correct location determinations from simulation #43.

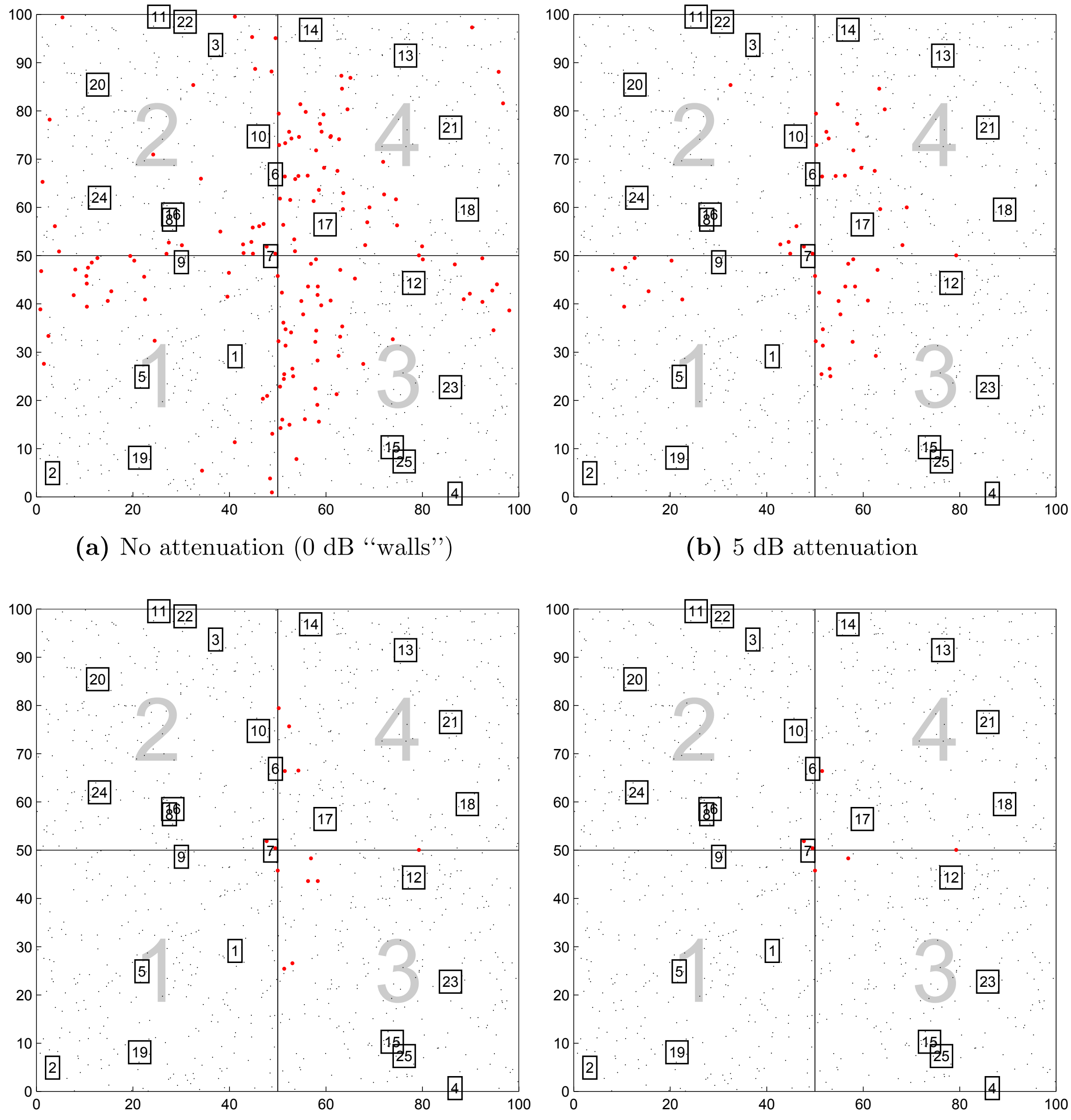
4.2.1 Randomly Placed APs with Attenuation

To produce a simple visual example of how objects in the environment can attenuate radio signals, the simulation was extended to allow for the creation of virtual walls; an attenuation factor would be applied to any signal that crossed the boundary between quadrants, and applied twice for signals that crossed two quadrant boundaries[3]. A typical indoor wall may attenuate a signal by 10 dB [78], and so various attenuation factors between 0 dB and 25 dB were tested in this simulation. Figure 4.2 shows a typical result of this simulation: a clear decrease in the number of incorrect matches as the wall attenuation factor is increased from 0 dB in Figure 4.2a, through 5 dB in Figure 4.2b and 10 dB in Figure 4.2c, to 15 dB in Figure 4.2d. For this example, these graphs represent correct match percentages of 85.0%, 95.0%, 98.7%, and 99.4%, respectively, and the full set set of data can be seen in Table 4.1.

To gain a clear understanding of the attenuation effect, a large set of simulations needed to be run. Figure 4.4 is the graphed results of these simulation, which shows the cumulative results of simulations involving 50,000 different AP distributions testing wall attenuation factors for every integer value between 1 and 25. The resulting graph is of a simple inverse curve that places the probability of a successful location determination using the expected attenuation from an indoor wall (approximately 5 dB to 12 dB) at over 0.92.

Even with some knowledge of the average attenuation effect a wall might have on a radio signal, some of the random scenarios generated by the simulation were still surprising in their accuracy. Simulation #54, graphed in Figure 4.5, is an excellent example, showing area 4 with only one AP that is very close to the boundary with area 2. The distribution in area 1 is also unusual, and the combined effect is for a significant number of incorrect location determinations in those two areas. Table 4.2 shows us how unusual these results are, with the zero attenuation (ie: no walls) scenario

[3]Note that this simulation was intended to be very simple and to avoid any attempt at ray-tracing. Regardless of the incidence angle of the radio wave, or of any other potential factors, the same attenuation factor is applied at each boundary.



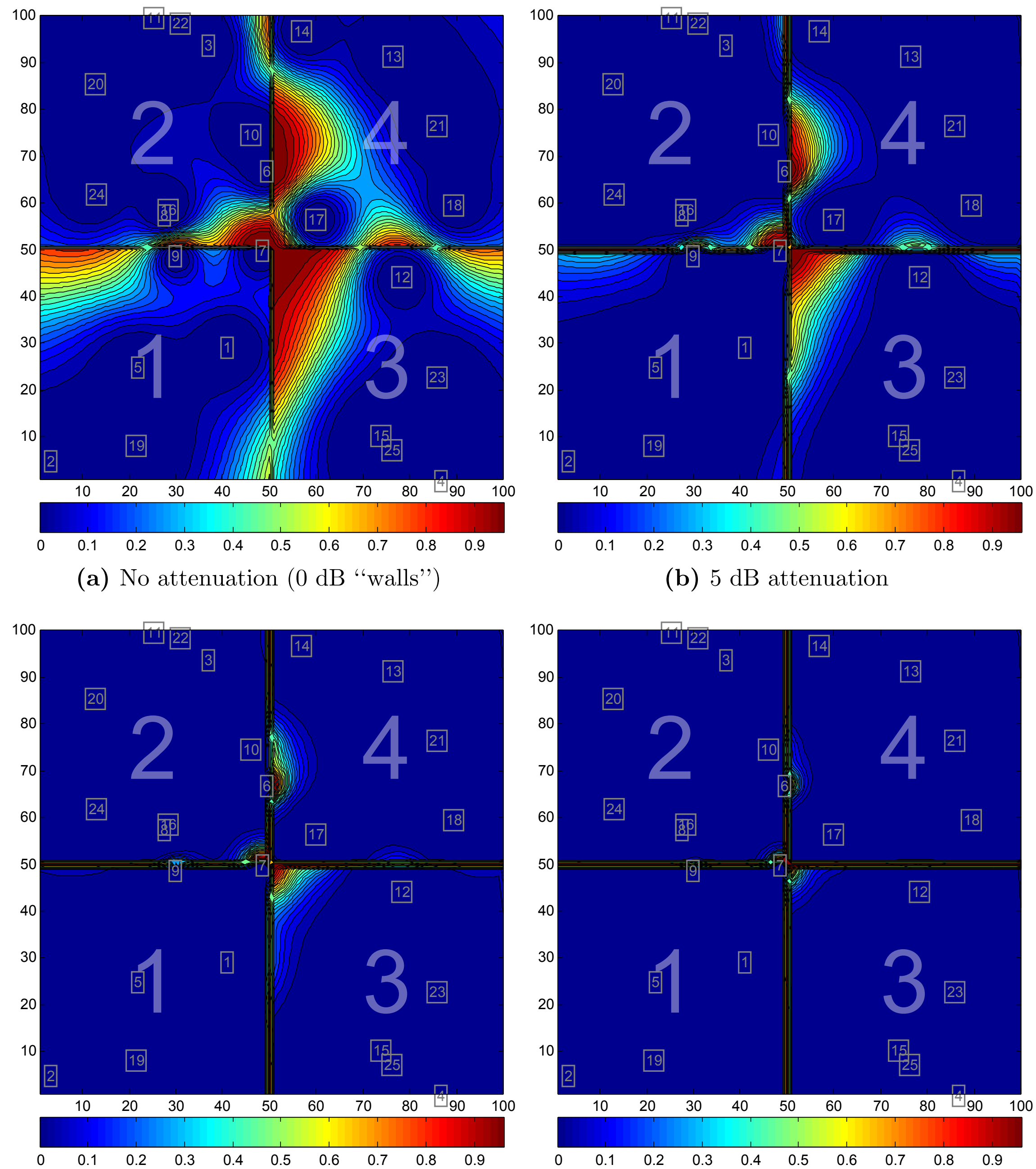
(a) No attenuation (0 dB "walls")

(b) 5 dB attenuation

(c) 10 dB attenuation

(d) 15 dB attenuation

Figure 4.2 – A simulation (#43) of the attenuating effect of walls on the simple Wi-Fi location method. This is an example of a balanced random distribution of APs.



(a) No attenuation (0 dB "walls")

(b) 5 dB attenuation

(c) 10 dB attenuation

(d) 15 dB attenuation

Figure 4.3 – Using the AP locations from the simulation (#43) shown in Figure 4.2, and calculated using Equation 4.1, these diagrams highlight the probability of an incorrect location determination throughout the simulated space.

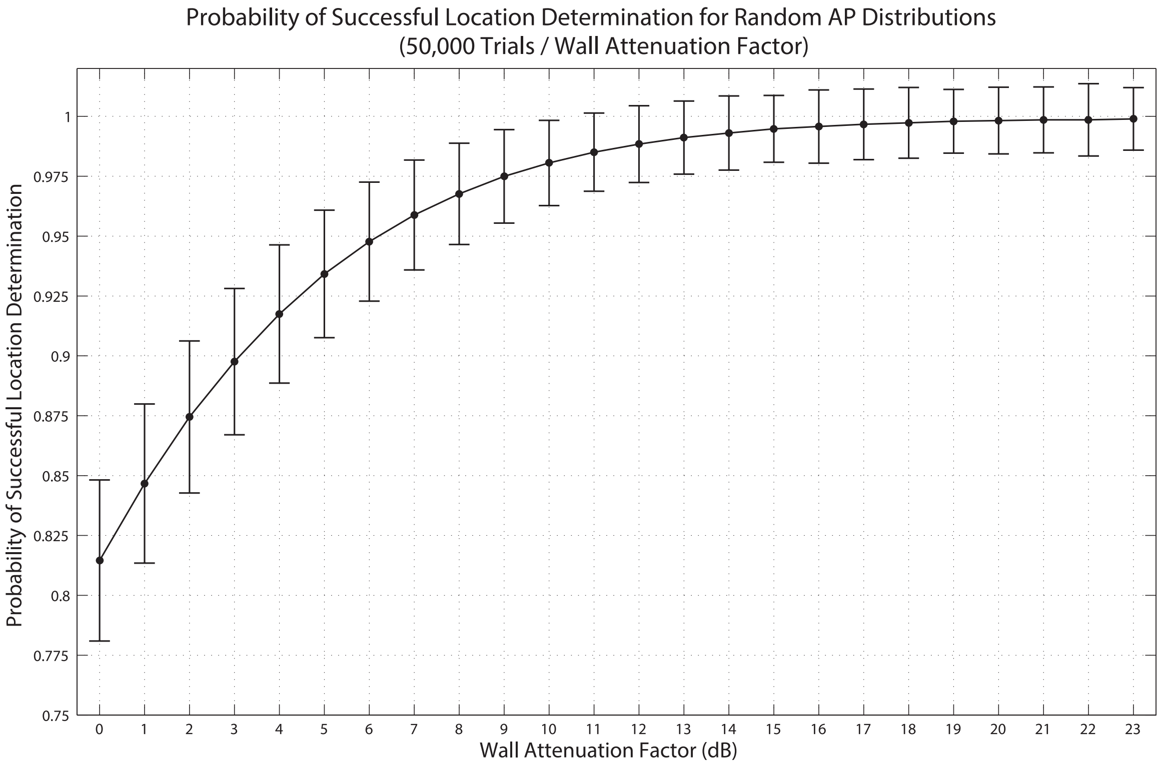


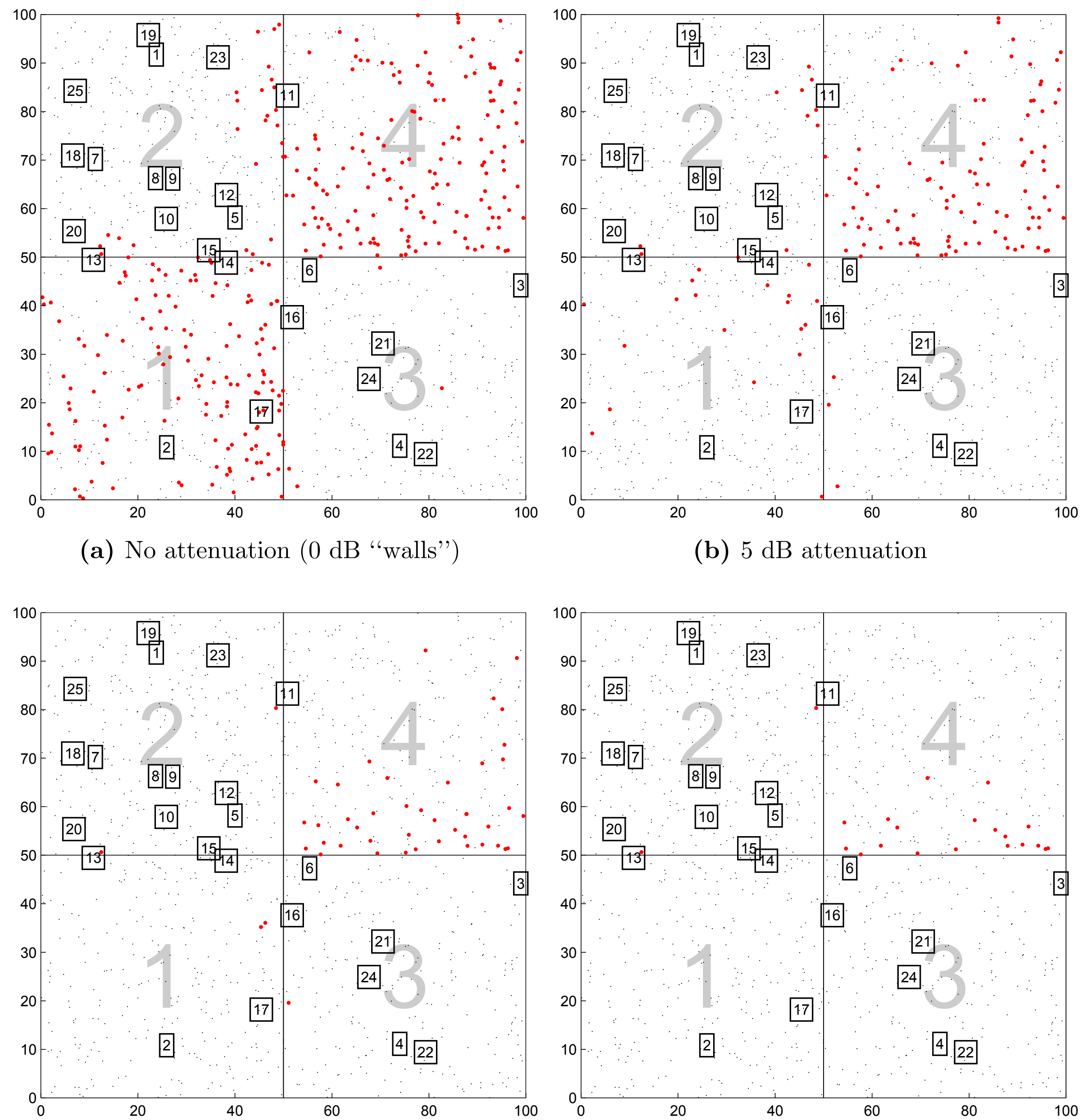
Figure 4.4 – The cumulative results wall attenuation simulations with randomly distributed APs and 50,000 trials per wall attenuation factor. The mean value is plotted and the error bars represent the standard deviation.

Attenuation Factor	0.0 dB	2.5 dB	5.0 dB	7.5 dB	10.0 dB	12.5 dB	15.0 dB	17.5 dB	20.0 dB
Percent Correct	66.5%	79.9%	86.4%	92.1%	95.3%	96.9%	97.9%	99.2%	99.6%

Table 4.2 – The percent of correct location determinations from simulation #54.

providing correct location determinations only 66.5% of the time, as compared to the average of 81.4% seen over 50,000 trials at zero attenuation.

The importance of this example is shown when the attenuation factor is in the range of an average indoor wall. Between the range of 7.5 dB to 12.5 dB correct location determinations are made between 92.1% and 96.9% of the time. This is visible in the graphs, with most of the incorrect location determinations outside of area 4 having vanished at an attuation factor of 10 dB (Figure 4.5c). There are also a few points in this graph where APs are close enough to the quadrant boundary to cause incorrect determinations on the other side, with one incorrect seen in area 2 due to AP 13 and another due to AP 11, two in area 1 due to AP 16, and one more in area 3 due to AP 17. Once the wall attenuation has been raised to 15 dB (Figure 4.5d), all



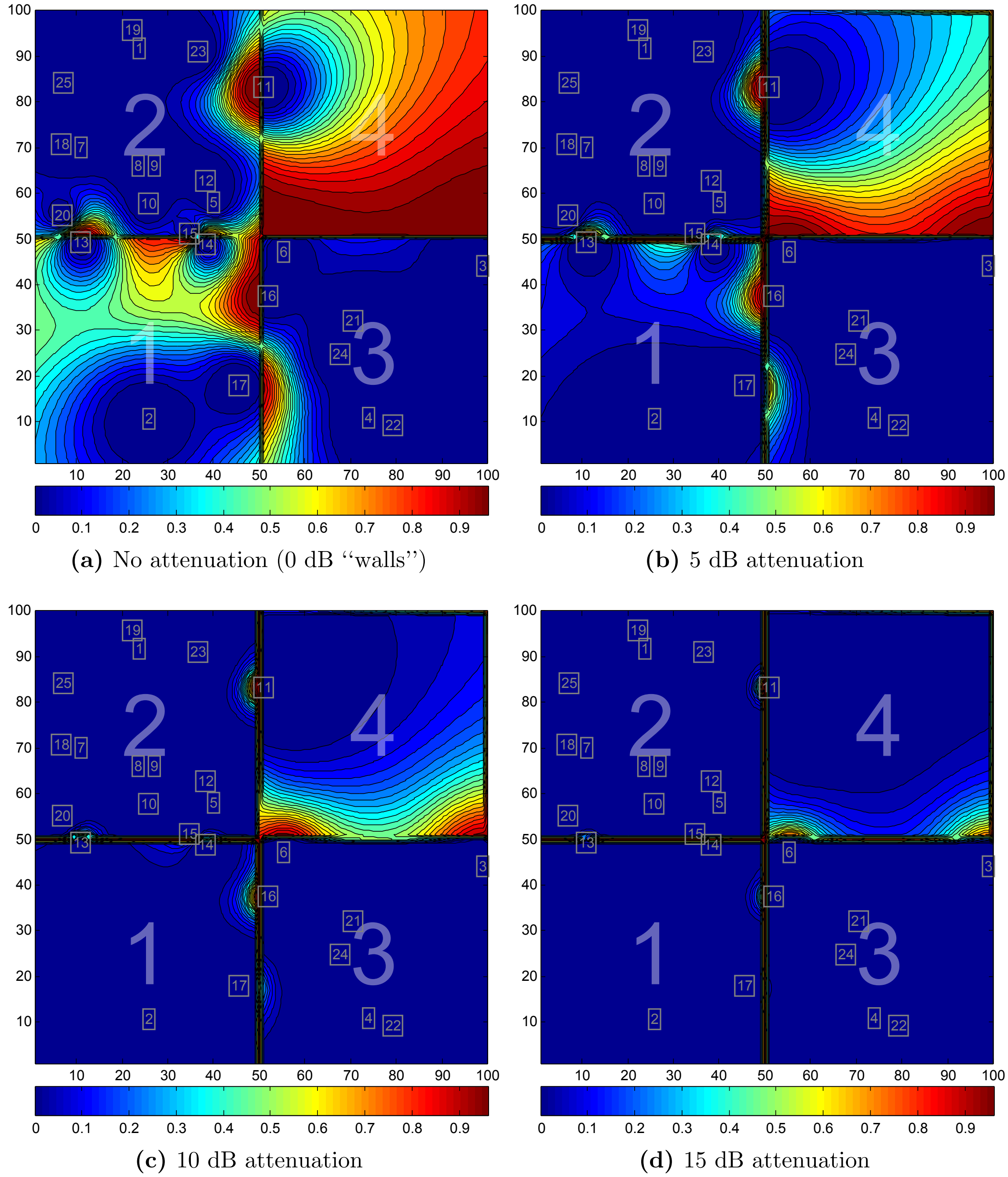
(a) No attenuation (0 dB "walls")

(b) 5 dB attenuation

(c) 10 dB attenuation

(d) 15 dB attenuation

Figure 4.5 – A simulation (#54) of the attenuating effect of walls on the simple Wi-Fi location method. This example is very imbalanced, with only one AP located in area 4.



(a) No attenuation (0 dB "walls")

(b) 5 dB attenuation

(c) 10 dB attenuation

(d) 15 dB attenuation

Figure 4.6 – Using the AP locations from the simulation (#54) shown in Figure 4.5, and calculated using Equation 4.1, these diagrams highlight the probability of an incorrect location determination throughout the simulated space.

Attenuation Factor	0.0 dB	2.5 dB	5.0 dB	7.5 dB	10.0 dB	12.5 dB	15.0 dB	17.5 dB	20.0 dB
Percent Correct	80.6%	89.7%	94.7%	97.8%	99.0%	99.5%	99.9%	100%	100%

Table 4.3 – The percent of correct location determinations when one AP was centered in each quadrant.

but two of the remaining incorrect location determinations are located within area 4.

4.2.2 Intentionally Placed APs with Attenuation

To examine what effect carefully placed APs would have on the probability of correct location determinations, the simulation was modified to place APs in specific locations, rather than the previous random placement, while retaining the random survey and random placement of location determinations.

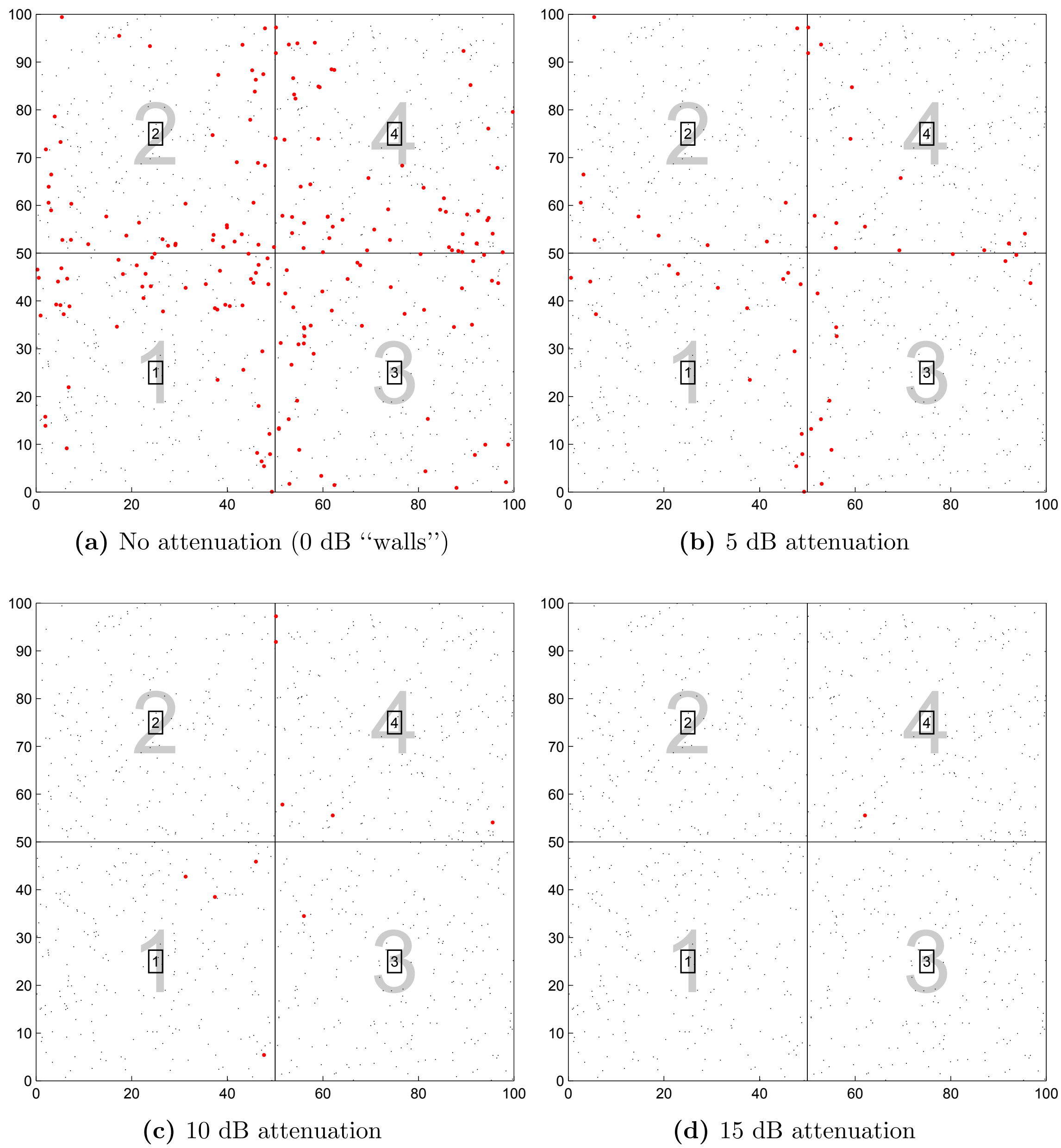
The first of these examples, the results of which are shown in Table 4.3 and graphed in Figure 4.7, are for a simulation with one AP placed in the center of each quadrant. This example is not very encouraging: as the results are not dissimilar from those for the 5000 simulations trial, showing a zero attenuation correct location determination percentage of 80.6% as compared to the average of 81.4% seen over 5000 random AP placement trials.

However, the second of these examples, the results of which are shown in Table 4.4 and graphed in Figure 4.9, are very encouraging. In this simulation four APs were placed in each quadrant, equidistant from the two closest boundaries and the center. The results for the zero attenuation trial show a correct location determination percentage of 90.8%, and the correct location determination percentage reaches 100% while the attenuation factor is still within the range expected for interior walls.

The second set of these results suggest that if some planning is made in the placement of APs in the areas—or, at least, the APs to be used in location determination are carefully chosen—the probability of making correct location determinations can be greatly improved.

Attenuation Factor	0.0 dB	2.5 dB	5.0 dB	7.5 dB	10.0 dB	12.5 dB	15.0 dB	17.5 dB	20.0 dB
Percent Correct	90.8%	96.8%	98.8%	99.6%	99.9%	100%	100%	100%	100%

Table 4.4 – The percent of correct location determinations when four APs were placed equally spaced around the center of each quadrant.



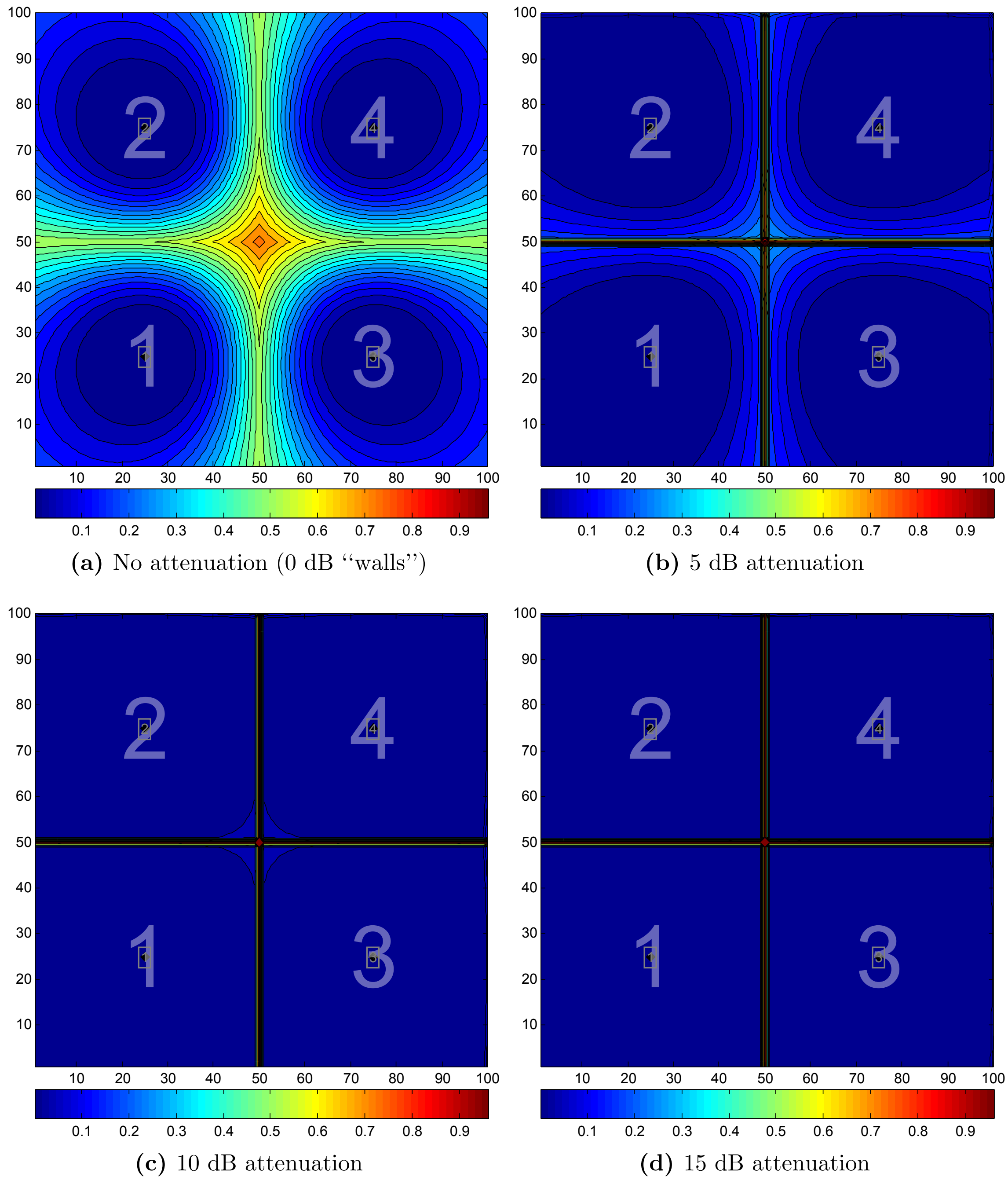
(a) No attenuation (0 dB ‘‘walls’’)

(b) 5 dB attenuation

(c) 10 dB attenuation

(d) 15 dB attenuation

Figure 4.7 – A simulation of the attenuating effect of walls on the simple Wi-Fi location method. This example places one AP in the center of each area.



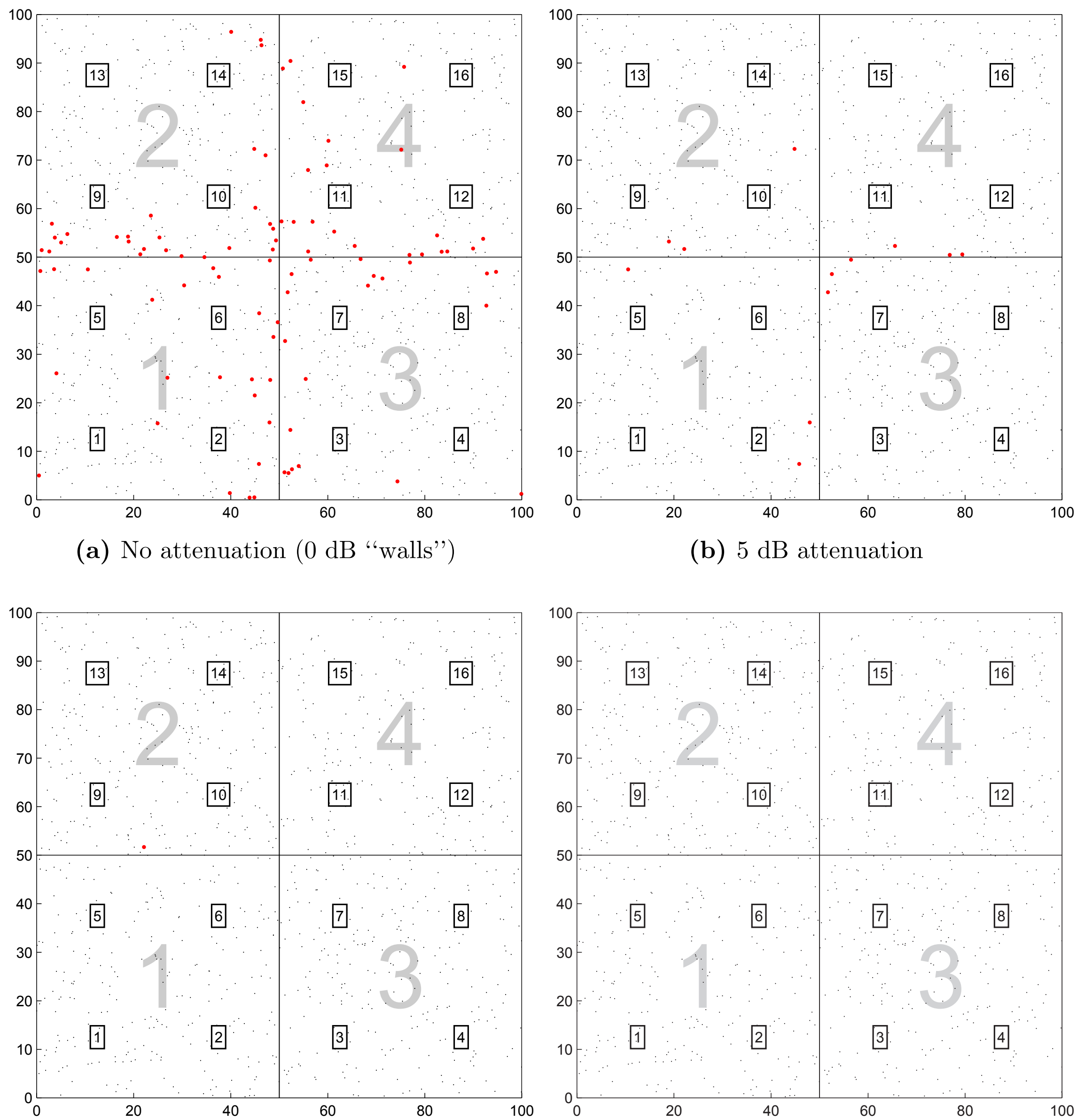
(a) No attenuation (0 dB "walls")

(b) 5 dB attenuation

(c) 10 dB attenuation

(d) 15 dB attenuation

Figure 4.8 – Using centered AP locations shown in Figure 4.7, and calculated using Equation 4.1, these diagrams highlight the probability of an incorrect location determination throughout the simulated space.



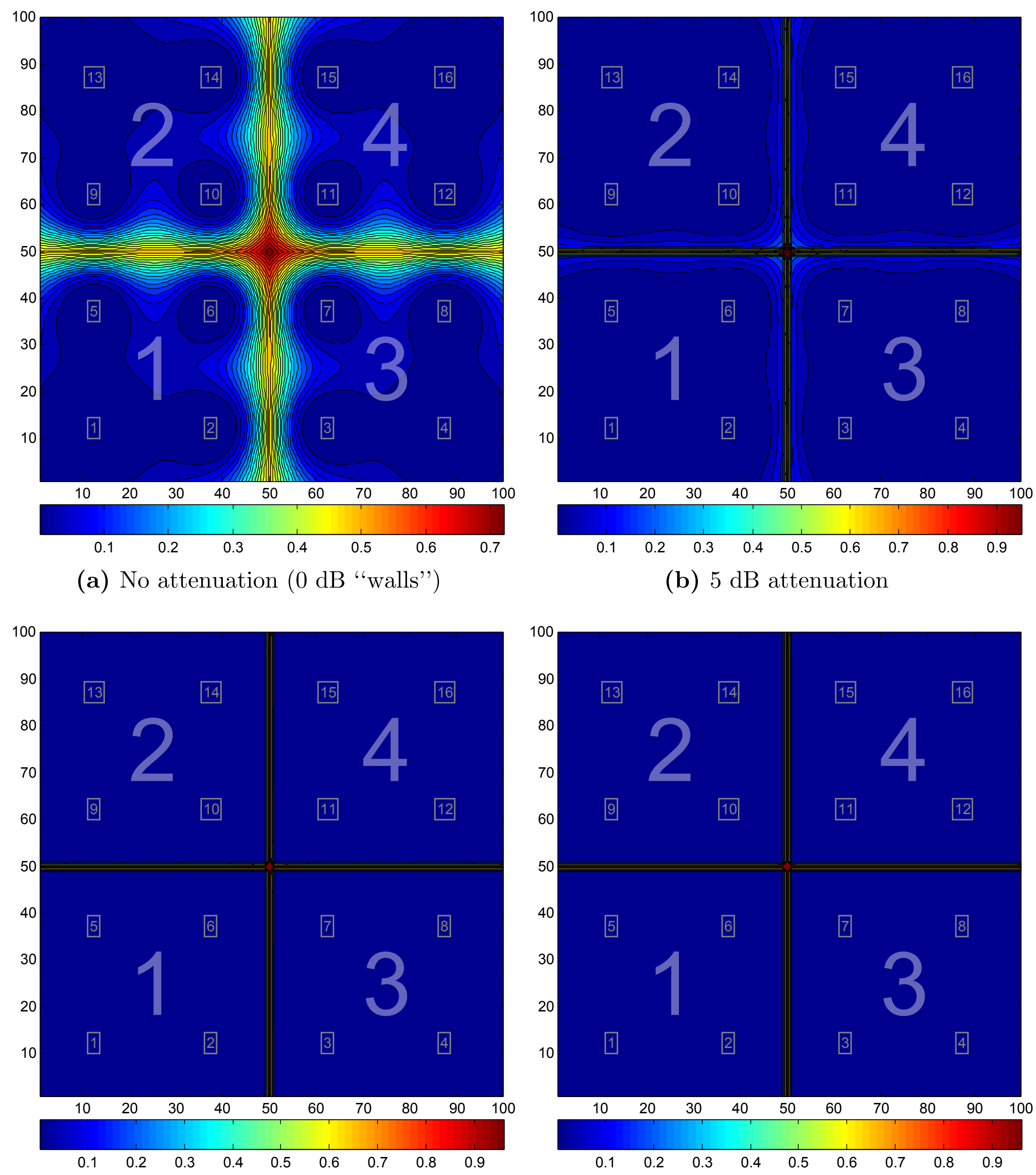
(a) No attenuation (0 dB "walls")

(b) 5 dB attenuation

(c) 10 dB attenuation

(d) 15 dB attenuation

Figure 4.9 – A simulation of the attenuating effect of walls on the simple Wi-Fi location method. This example places four APs equally space in each quadrant.



(a) No attenuation (0 dB “walls”)

(b) 5 dB attenuation

(c) 10 dB attenuation

(d) 15 dB attenuation

Figure 4.10 – Using the four APs equally spaced APs in each quadrant shown in Figure 4.9, and calculated using Equation 4.1, these diagrams highlight the probability of an incorrect location determination throughout the simulated space.

Chapter 5

Implementation and Validation

The discovery that simple indoor location methods can be surprisingly effective, as well as the investigation of their potential, has the obvious need of an actual implementation. Section 5.1 begins by describing the initial application that gave this result.

Further data was gathered by two applications written for the Android mobile operating system. The first application, described in Section 5.2, was designed to explore the Wi-Fi scanning functionality of different models of Android devices to help estimate what percentage of Android devices are capable of quickly scanning their Wi-Fi environments. The second application, described in Section 5.4, was created to both capture and manage the Wi-Fi access point data, as well as to perform simple device location functions for the purposes of validation. A desktop application, described in Section 5.5 was also written to process data capture logs from the Android devices and allow for the analysis of that data at a workstation.

5.1 Original Symbian Application

The first experimental application was created using the PyS60 Python interpreter for Symbian devices. The first step was to collect a list of BSSIDs and the building areas in which they were located, and this was done by walking up to the obvious Wi-Fi AP antennas in the ECS building and capturing their BSSIDs using a Windows laptop running the Wi-Fi scanning application Vistumbler[1]. A list of BSSIDs and

[1]Vistumbler: `http://www.vistumbler.net/`

their respective areas of the building was hard-coded into the Python application. The application would perform the simple comparison of the BSSID with the strongest RSS and display the matching area name.

This initial application was originally intended simply as a "Hello World" example for Wi-Fi location related work. However, the application proved to be surprisingly successful and it became the starting point for the rest of the work found in this document.

5.2 Scan Rates

To examine the capabilities of the myriad available Android OS devices to scan local Wi-Fi access points, an app was created to determine the average scan time on these devices. This was of interest early on in the development process as the Android device chosen for testing (Samsung GT-P1000M) appeared to have a very long Wi-Fi access point scan time. Interestingly, out of all the devices tested, this particular device was found to be the slowest[2].

The scan rate application was originally intended for testing by a small group of colleagues and friends. To simplify installation this app was uploaded to the Android Market, and this had the side benefit of making the app available to anyone. To our surprise, and despite the warning *"This app is part of a university research project and is not of much use unless you wish to contribute data to the project"*, the app

[2]It is worth noting that the other Samsung models represented in the data set scanned Wi-Fi access points at rates on average with those from other manufacturers. The Samsung GT-P1000M is an unusual exception.

	Time (ms)
Avg	1906
Stdev	1864
Min	364
Max	7019

Table 5.1 – The results of the WiFi access point scan speed test. These results represent a sample of 58 different Android mobile device models running 78 different versions of the Android operating system.

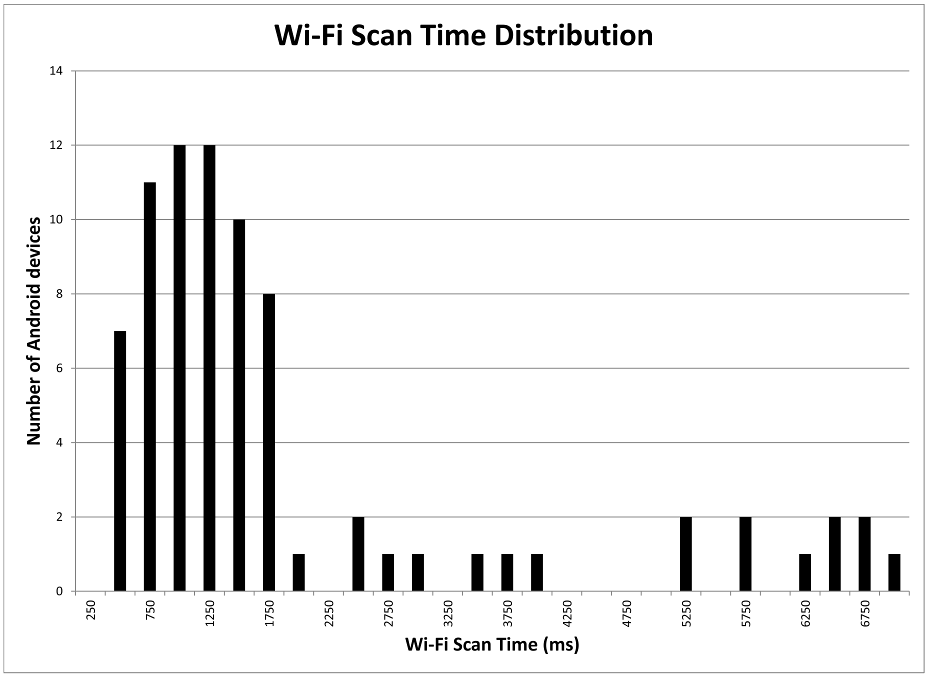


Figure 5.1 – The distribution of Wi-Fi scan times found in a sample of 78 different versions of the Android operating system running on 58 different device models.

(as of November 8, 2011) was downloaded 461 times and 125 data samples were sent in. This data sample currently 59 different Android device models and 78 different versions of the Android operating system.

As shown in Table 5.1, and graphed in Figure 5.1, the scan times varied widely. Some devices would return data in less than half a second while other devices might take up to seven seconds to complete a scan. Almost immediately it became apparent that some devices did not return unique results on each scan request. For example, the GT-P1000M used for development had an average scan time of 6727ms, but in reality it only returned new data on every second scan. Essentially this device had an effective scan time of over thirteen seconds. This result was only the case with the stock Samsung firmwares[3] and tests with the open-source CyanogenMod 7[4] firmware showed that new data was being returned on every scan. This suggested that a device's firmware plays an important role in the Wi-Fi scanning process, and this later was proven with the introduction of the Android 4.0 based CyanogenMod 9 firmware for the GT-P1000M: average Wi-Fi scan times decreased to around the

[3]The tested firmwares were JMJ v2.2.1, JMQ v2.3.3, and JPE 2.3.3
[4]CyanogenMod: `http://www.cyanogenmod.com/`

1000ms mark. This was quite surprising given the previous results and, after extensive testing with several other GT-P1000M units, it was shown to be a consistent result.

5.3 Power Consumption Results

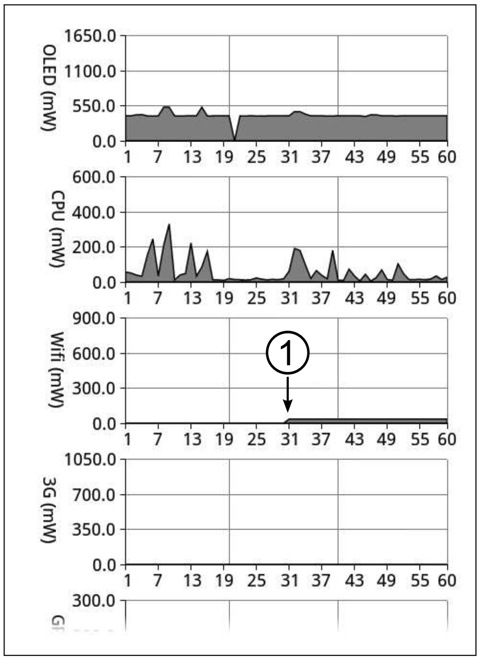
In tests of the power consumption of the scanning application on Android devices, it was found that the default Wi-Fi scanning uses the same amount of power as simply having the Wi-Fi turned on. The conclusion from this is that the Android operating system performs a passive receive-only scan of the local Wi-Fi access points that are broadcasting their presence and that it does not actively transmit to look for access points. This also fits the fact that Android does not return information regarding local ‘‘hidden’’ access points that are not broadcasting their SSIDs.

The screenshots shown in Figure 5.2 show some power test results acquired using an application called PowerTutor[5]. With the graph data travelling from left to right on the screen, Figure 5.2a shows the results of the device's Wi-Fi having been on and then deactivated at the point marked ①. Figure 5.2b shows the Wi-Fi system being activated at point ② and the resulting peak of energy use at point ③ as the device transmits and connects to a local access point.

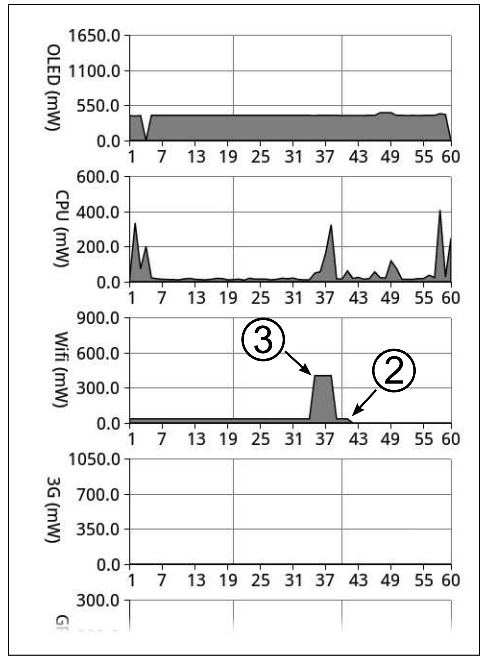
The last two screenshots compare the power use between Wi-Fi scanning and Wi-Fi web browsing using the device. Figure 5.2c is the case where the scanning application is running, and it shows a continuous low power usage that matches the connected but not transmitting power use seen in Figure 5.2a and Figure 5.2b. Figure 5.2d shows the power use seen while web browsing, with the peaks of power use that can be associated with the device transmitting data to the network.

These experiments suggest that the power use by the scanning system is very similar to that seen when the device's Wi-Fi is turned on. They also suggest that the CPU usage of the scanning system is quite low, although no work was done to compare the power usage that might be seen when using various intensities of computation. A futher discussion of this can be found in Chapter 6 on future work.

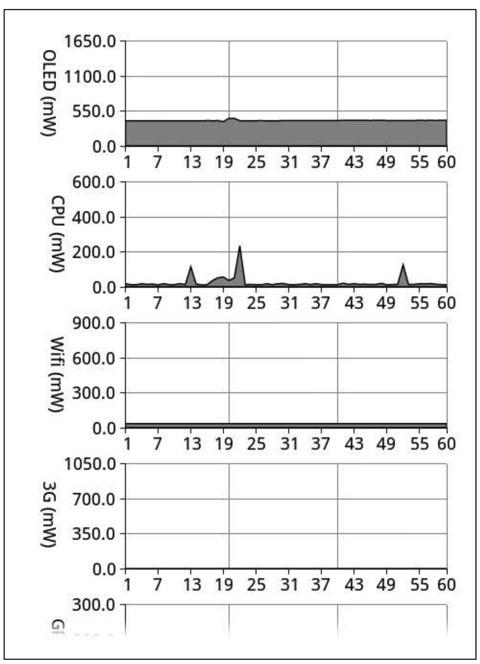
[5]PowerTutor: `https://market.android.com/details?id=edu.umich.PowerTutor`



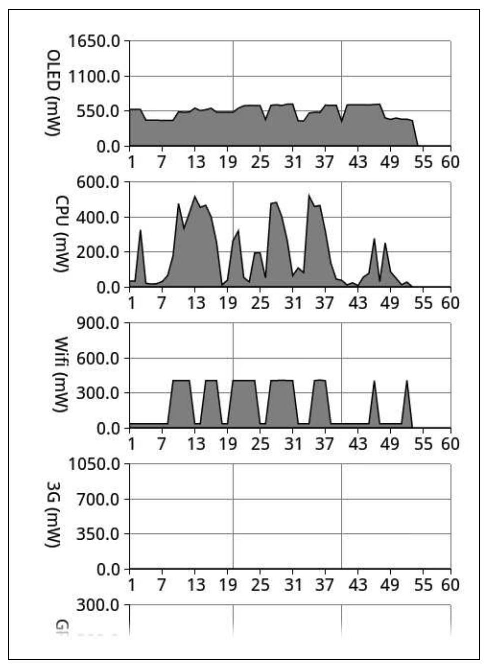
(a) Wi-Fi deactivated at point 1



(b) Wi-Fi activated at point 2, AP connection power use at point 3



(c) While Wi-Fi scanning



(d) While web browsing using Wi-Fi

Figure 5.2 – An example of power use data collected from an Android Nexus One device while scanning the local Wi-Fi APs and while browsing the web using the Wi-Fi connection.

This fact regarding passive Wi-Fi scanning appears to have not gone unnoticed by commercial companies. On July 18, 2012, Skyhook Wireless[6], a company that was an early leader in outdoor mapping using Wi-Fi BSSIDs, sent out a press release entitled "*Skyhook Introduces Always-On Location With Unmatched Power Management for Persistent Location*" that states: "Skyhook's new Always-On features allow apps to check user location (on an opt-in basis) as often as every 30 seconds throughout the day, with little or no noticeable impact on the device's battery life" [82]. Skyhook Wireless did not publish more information regarding how their method works, but their description does match the use of a passive scanning system.

5.4 Location Application

The Android application developed for capturing scanning data consists of several parts that are separated by tabbed screens: functionality for scanning access points and connecting the RSS/BSSID tuples with defined locations (see Section 5.4.1), the display of the device location based on the current data set (see Section 5.4.2), a system to test the accuracy of this method (see Section 5.4.3), and tools for maintaining the data set and for defining new locations (see Section 5.4.4). A raw scan data collector was later added to allow for analysis and experimentation at a workstation (see Section 5.5), and that was joined by functionality for automatically uploading the current location determination to a website (see Section 5.6).

5.4.1 Data Collection Scanner

As a proof of concept of this simple location method, the scanner functionality of the application (see Figure 5.3) begins by requiring the user to enter the current location. For this prototype, a location is defined by three pieces of information: a building name (ex: ECS), a floor (ex: Fourth), and an area (ex: West).

Once the user has set the current location, the known RSS maximums for that area are listed (marked "RSS Maxes" in the figure). The user can then press the Start

[6]Skyhook Wireless `http://www.skyhookwireless.com`

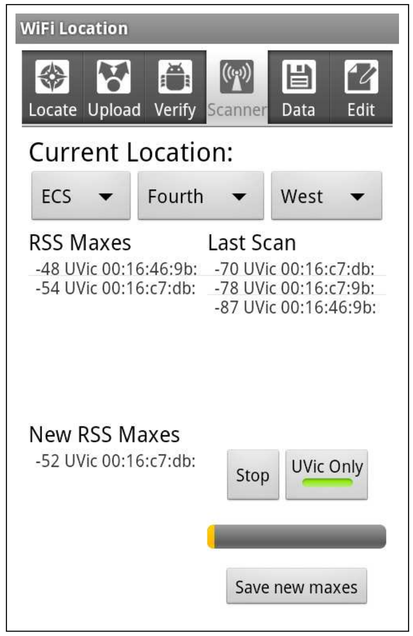


Figure 5.3 – A screenshot of the Wi-Fi data scanner / data collection tool from the proof of concept Android application.

button to begin a new scan. In typical use, the user would enter the specified area, press Start, walk the length of the area, and press stop. (Note that this application has a filter button, marked "UVic Only" in the figure, as an option to limit the data set to the University of Victoria's own wireless network access points.)

While the area scanning task is in progress, the results of the latest Wi-Fi scan are shown (marked "Last Scan" in the figure) to assure the user that a scan is in progress. Following Algorithm 1, the Phase 1 algorithm presented in Section 4.1.1, after each scan the RSS of every BSSID in the scan data is compared with the maximum known RSS in the current data set. Should a new maximum be found for a given BSSID, or should it not be in the current data set, that BSSID is added to a list of newly discovered RSS maximums for the current area (marked "New RSS Maxes" in the figure).

After the scan of an area is complete, the user has the option to add the contents of the newly discovered RSS maximums to the current data set by pressing the "Save new maxes" button. This option is provided to help prevent the accidental addition of data to the wrong area. If the user chooses a new location the newly discovered RSS maximums list is automatically cleared.

Figure 5.4 – The simple location display from the proof of concept Android application.

The time required to acquire an accurate data set for a given area can be as little as the time required to walk through that area. This is dependant on the device used, however, as devices with faster scan rates may capture the peaks in the RSS values that would be missed by a device with a slower scan rate.

5.4.2 Location Finding

The location functionality of the proof of concept application is very simple: the user presses a button marked "Locate Me", the application performs a Wi-Fi scan and compares the maximum RSS/BSSID tuples to the current data set, and if a matching location is found the area name will be displayed. (See Figure 5.4.) This follows Algorithm 2, the Phase 2 algorithm presented in Section 4.1.1.

The functionality of this screen was meant as a simple demonstration that the method works as described. It was soon expanded to perform automated accuracy testing as described in the next section, and it was the basis for the automatic location uploading experiment described later in Section 5.6.

5.4.3 Location Accuracy Testing

To investigate the accuracy of this method, the location finding functionality was expanded to perform automatic location comparisons. The user chooses the area the device is currently located in and the automated test assumes that the user will remain in the specified area. The software will then repeatedly scan the local Wi-Fi APs as quickly as possible and make a location determination as described in Section 5.4.2. The software records whether its location determination matches the area chosen by the user and, in the case of an incorrect match, the type of incorrect match was found. The software will categorize incorrect matches as being in the wrong area, a floor too high, a floor too low, off by multiple floors, being in the wrong building, and having detected an unknown location.

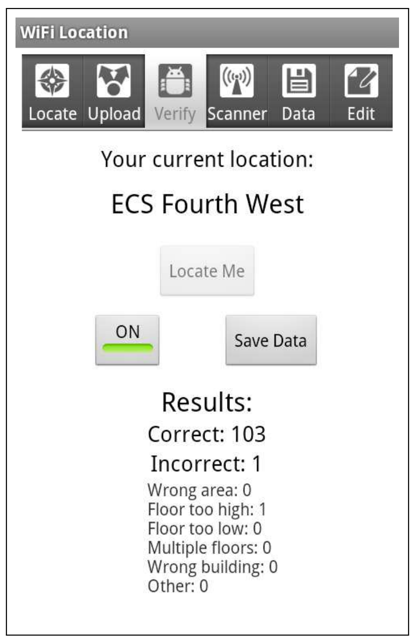


Figure 5.5 – The automatic location verification function.

With the interface shown in Figure 5.5, the user first clicks the "Locate Me" button. The app then reports back the location in which it believes the device to be located. Should this be correct, the user then clicks the scanning toggle button to activate the scanning. The display records the results of the location detection for each scan, and the app continues to scan until the scan toggle is turned off or until the "Save Data" button is pressed. A text entry dialog box is displayed before any data is saved so that the user can have an opportunity to record any notes to be saved with the data.

Two data files are generated from each run of the automated tester, and each is named according to the current date, time, and location the data was collected. The first data file is a summary of the results, listing the number of correct and incorrect location detection attempts, the breakdown of the incorrect locations found, and the comments entered by the user. The second data file is a complete list of locations detected during the scan, listing the building ID, floor ID, area ID, and the text name of the area.

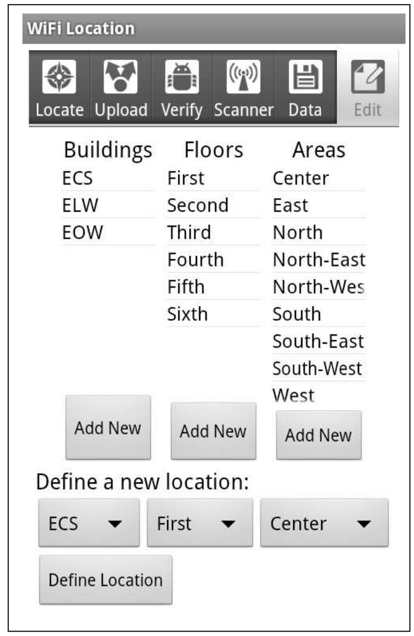
5.4.4 Maintaining The Data Set

Two application tabs are dedicated to maintaining the data set on the device. The first of these is simply called “Data” and, as shown in Figure 5.6a, is made up of three functions for importing, exporting, and resetting the database. Besides the obvious convenience of having such functions in the application, the export function was needed to simplify copying the database off the device. Android applications, by default, have private data storage areas that are not easily accessible by the user. The task of backing up or swapping database files was therefore quite tedious, and adding functionality to the application to copy the current database to the public storage was the simplest solution.

The “Export Database” button and the “Import Database” button are essentially opposites of each other: the export function copies the database file from protected storage into a location and filename of the user’s choice, while the import function allows the user to choose a database file that is then copied into protected storage. This functionality provides the user with the means to quickly swap out database files for testing.

To give the user the ability to reset the database to its original state, and to allow the user to collect a new data set, a “Reset Database” button was added. Only the BSSID/RSS pairs and the location where they were seen at a maximum strength is deleted, and the information regarding the buildings and locations is left in place.

(a) Database handling



(b) Defining areas (map features)

Figure 5.6 – The functionality for handling databases and for defining new map areas.

The second of the data maintenance functions is called "Edit" in the application's tab row, and it provides the functionality for defining new buildings, floors, and areas, as well as combining these building features into a location definition that can be used for Wi-Fi location purposes. Once a new location is defined on this interface, it is made available to the data collecting scanner and to the device location features.

There are, of course, data consistency issues related to allowing the end user to define building features and new locations. For an application to be in widespread use, a method would be required for merging the databases. If end users are defining features and new locations such merging would become difficult. This would require further research, but it should be possible to match locations defined by different users based on the BSSID/RSS combination that was seen at maximum in that new location.

5.5 Desktop Application

To further expedite the analysis of data, another function was added to the Android application: the raw data collector. This collector performs scans in the same way seen in other parts of the application, but with a key difference: all data collected from every scan is stored and can be saved to file for later use. As shown in Figure 5.7, this part of the Android app has a start/stop button for controlling the scanning, a button for saving the currently collected data to local storage, and a button for flagging a turn in a walk.

An important question was asked during the initial testing of this method: how many times does the user need to walk down a hallway to collected an optimum sampling of the maximum RSS values? To collect this data the ‘‘turn flag’’ button was added to the raw data collection function to allow the user to place a marker in the data when the user reached the end of the hallway and had turned around.

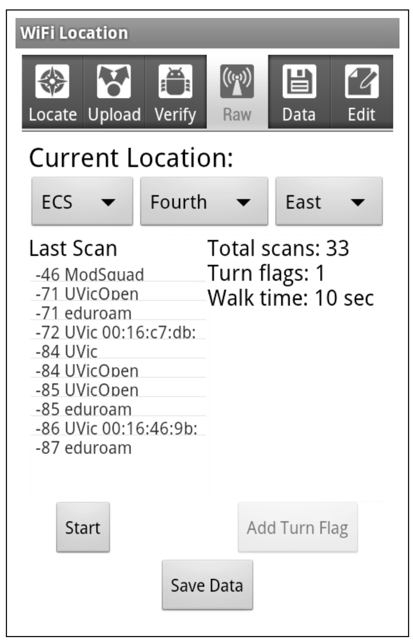


Figure 5.7 – The functionality for capturing all collected Wi-Fi data during sampling walks.

The desktop application was written in Java to make use of the same Java classes that were in use in the Android location app. The initial stage of the application loads the raw saved data files from the Android surveys and generates SQLite database files of the format that would be created by the Data Collection Scanner described previously in Section 5.4.1. As these data files have “turn flags” embedded in the data, the user can choose how many walks down a hallway will be used to create the database file, and which walks out of those available will be used. (Typically five walks down each hallway were collected.) Once generated, these database files can be loaded onto an Android device and used for location determinations.

With the database files created, the desktop application can then run experiments against those databases using other collected data. The results of these experiments will be described in Section 5.8.

5.6 A Real World Test

A real world test of this method was conducted in November 2011, while attending the 12th GENI Engineering Conference (GEC12)[7] in Kansas City, Missouri. This conference was held in two connected buildings at the Marriott Downtown Kansas City Hotel and Conference Center and was spread across two buildings, six floors, and twelve rooms. A seventh floor and a thirteenth room was added to represent a hotel room.

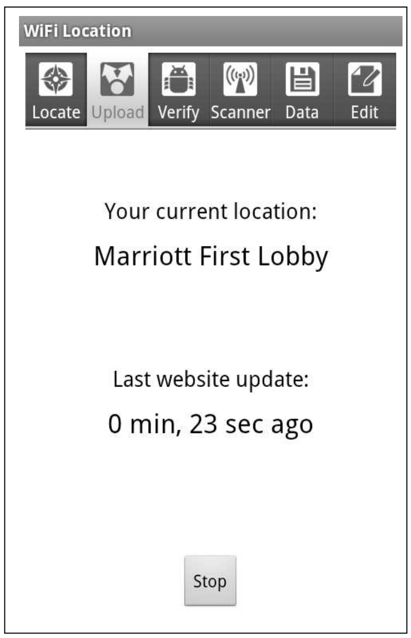
The Android application was used as described in the previous sections. To begin, the location definition functionality described in Section 5.4.4 was used to define the conference room locations. Eighteen locations were defined in total, with the large plenary session room being further divided into six separate areas defined as Front-Left, Front-Center, Front-Right and Back-Left, Back-Center, Back-Right. To accomplish this with the existing software, which is limited to the building/floor/area model, the plenary room was defined as a floor and the six interior regions defined as areas.

With the locations defined, the data collection scanner was then used as described in Section 5.4.1 to find the BSSID/RSS max pairs for each location. For most locations this was accomplished with a single slow walk through each room. For the large plenary session room, each region was scanned by standing at the furthest point from the other regions. For example, Back-Left was scanned by standing in the area close to the back and left walls.

[7] The 12th GENI Engineering Conference: `http://http://www.geni.net/?p=2052`

5.6.1 Automatic Location Upload

To make this test effective required the expansion of the application to include functionality for automatically uploading the user's current location to a website. Another tab was added to the Android application for presenting this functionality, as shown in Figure 5.8a. The user is presented with a simple display that initially shows no location, but that shows when the last website update was made. A "Start" button is then pressed to begin the automated process.



(a) The location upload tool

(b) The current location web page

Figure 5.8 – The current location automatic upload experiment that was tested at GEC12.

The automatic location uploader begins by following Algorithm 2, the Phase 2 algorithm presented in Section 4.1.1, in the same way as the functionality described in Section 5.4.2 for the "Location" tab: it scans the local Wi-Fi access points to determine its location based on the BSSID with the strongest RSS. However, the previous version of the scanner would simply display the results of the current location determination, and this could rapidly change from one location to another when an incorrect determination occurs. To prevent this the location information is then buffered in a twenty item list[8] and the software would only consider the device's location to have changed when the majority of the locations in the list differed from the current location. Once this location-changing threshold had been crossed the software sent an HTTP GET request to a website with the new location encoded into the URL.

For this experiment a simple Django[9] website was configured to receive location updates via HTTP GET requests and to display the last known location. Figure 5.8b shows the minimalistic web page that was created to provide the user's current location.

5.6.2 Successes

The system worked very well during this test and it showed an excellent level of accuracy. The device used for this experiment, a Google Nexus One, has a scan speed of approximately one second which meant that location changes would be (on average) sent to the web server within ten seconds of entering a new area.

The fast speed of these automated updates was inadvertently demonstrated when the device was pocketed and forgotten about while an attempt was made to locate a misplaced USB cable. The website was being watched at the time and the rapid changes between locations during the search for the cable were quickly noted.

5.6.3 Difficulties Experienced

A few difficulties, both expected and unexpected, were experienced during this test:

- The method used to both buffer and filter location switching did not work well when the device was located in the large plenary session room. This room had been logically divided into six locations in the application's database and, in

[8]The size of twenty for the buffer/filter list was chosen arbitrarily and different sized buffers were not tested.

[9]Django: `http://www.djangoproject.com`

some situations the maximum RSS values for two adjoining logical areas were essentially the same, the software would determine the device's location to be either one of those two locations approximately 50% of the time. The filtering method used would continuously be on the threshold of either of those locations being the majority location in the buffer and the application would rapidly upload new locations to the web server. This was clearly not the intended behavior, especially when the device was not in motion.

- There was only one access point in the room used for breakfast and lunch, and in many positions in that room the access points from a floor below had a stronger signal. As those rooms were used by the conference and had been scanned, the device would determine that it was located on the floor below.
- The building, floor, and area naming scheme was a limiting factor for deploying the software at this location. To divide up the plenary session room, the room had to be defined as a floor so that the areas could be used for defining the inner locations. It was also found that some of the names generated by this method were awkward, and that providing a separate free text naming field for each location would make for easier comprehension of a location.

5.7 Area Types

The results of the location determination testing, both from the initial location results collected by the automated location accuracy scanner (see Section 5.4.3) and from the desktop application, pointed to several classifications of area types that have an effect on the results. The primary testing was performed at the University of Victoria's Engineering and Computer Science (ECS) building, and this building can be a challenging environment for Wi-Fi radiolocation given its five story center atrium and many hallways that are partially open to that atrium.

5.7.1 Enclosed Hallways

For the type of hallway where there are rooms on either side, which will be referred to as *enclosed hallways*, the results are typically extremely good. This occurs mainly because the rooms attenuate the signals from the APs that are located in the hallway. An example of this type of hallway can be see in Figure 5.9.

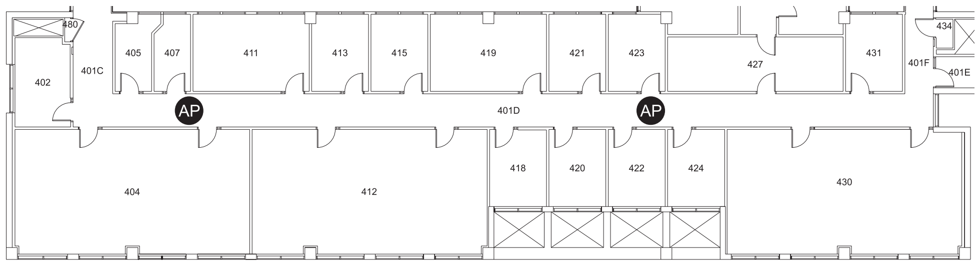


Figure 5.9 – An example of a typical enclosed hallway, with rooms on either side and two APs visible.

5.7.2 Half Open Hallways

Hallways where there are rooms on one side, but which are open to the building's atrium on the other, are referred to as a *half open hallways.* The results from this are type are generally very good. An example of this type of hallway can be see in Figure 5.10, while others will be discussed in the Location Results section, Section 5.8.

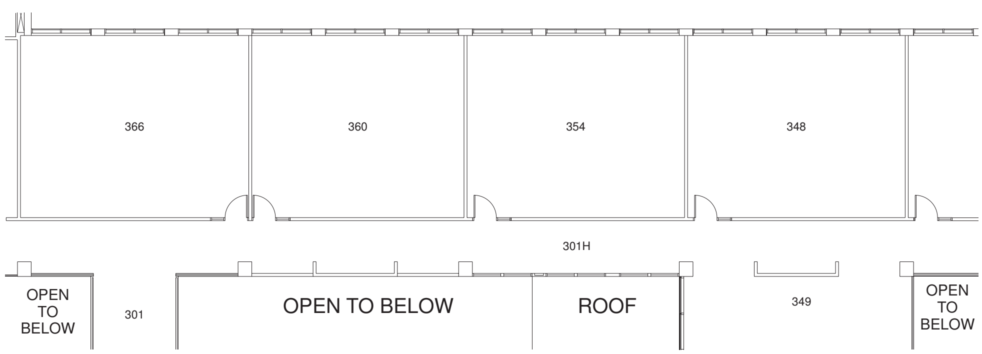


Figure 5.10 – An example of a half open hallway, with rooms on one side and open space on the other.

5.7.3 Partially Open Areas

Areas that are semi-enclosed, in that they have at least two walls and a ceiling, are referred to as *partially open areas.* This category is not well defined and covers many areas in the test samples but, for the most part, this method was shown to work in these areas. Different configurations of partially open areas will be discussed in the Location Results section, Section 5.8, and an example can be seen here in Figure 5.11.

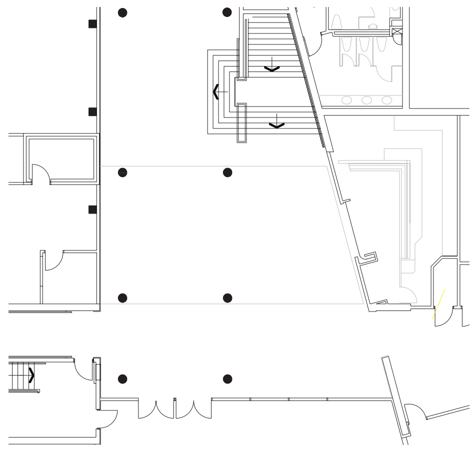


Figure 5.11 – An example of an partially open area from ELW, where the roof is higher in one area.

5.7.4 Completely Open Areas

Areas that are not enclosed and that are open to signals from all directions are referred to as *completely open areas*. Without any signal attenuating barriers defining this type of area, it is the one category of area type that this method cannot handle. The example shown here in Figure 5.12 is of the open bridges connecting the west and east wings of the ECS building. These bridges receive signals from many of the 120 APs in the building making them a challenge for any method other than those using detailed signal fingerprinting [14].

5.8 Experimental Results

The results of location determination testing were, to put it mildly, extremely promising. It should be noted that these results are from the simplest version of the algorithm, where only the BSSID of the AP with the maximum RSS value is used to determine a location (See Algorithm 2). Almost any form of filtering could be used to improve many of these results.

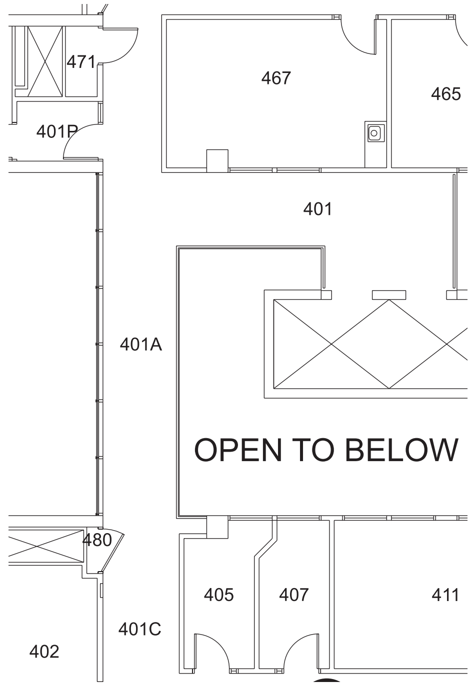


Figure 5.12 – An example of one of the atrium bridges between the wings of ECS, with windows on one side and open to the atrium on the other, forming a completely open area.

To begin, we will look at the question of the number of end-to-end walks down a hallway that are required to collect the database data for an area (Section 5.8.1), and we will follow this with a look at the actual location determination results and the types of incorrect determinations that can result from this method (Section 5.8.2).

5.8.1 The Number Of Walks

To estimate the amount of Phase 1 data collection this method requires, and given that this method involves walking back and forth through a hallway or area, the term *walk* is defined as the one-way walk from one end of the hallway to the other. A five-walk database would therefore contain the Phase 1 data from five end-to-end walks of a hallway.

The graphs on the following three pages represent the percentage of correct location determinations observed for one to five walks down each hallway. In each of these examples two Android devices were used for both the initial Phase 1 database data collection and the Phase 2 location determination trial data collection. As mentioned in the section on scan rates (Section 5.2), the Nexus One device by HTC has proven to be the fastest and most reliable for data collection, and its database files were used on both phones for the location determination trials. The second device was the Galaxy Nexus by Samsung and, as we will see in the following data, the Galaxy Nexus tended to out-perform the Nexus One in location determinations using a databases created by the Nexus One. The reason for this is unclear.

From these graphs it is obvious that one walk down a hallway is typically all that is needed to produce a database that provides excellent location determinations. There are some examples showing a 2% improvement in correct location determinations with more than one walk, such as that seen in Figure 5.13 for ECS Second East. There are even examples of similar sized degredations in correct location determinations with more than one walk, such as those seen in Figure 5.15b in the Clearihue First Center Galaxy Nexus data.

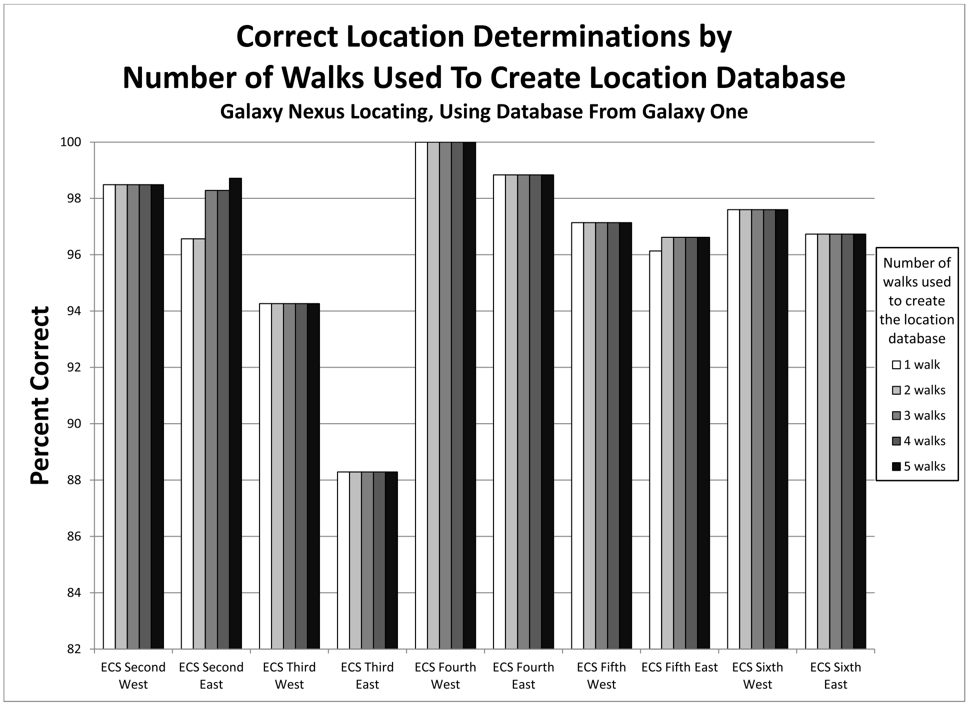
While percentage of correct location determinations for the Engineering Lab Wing (ELW) building data does not change depending on the number of walks, the results for ELW First Center and ELW Third Center are quite different from the rest. These low figures are the results of two different experiments which will be discussed in Section 5.8.2.

5.8.2 Location Determination Results

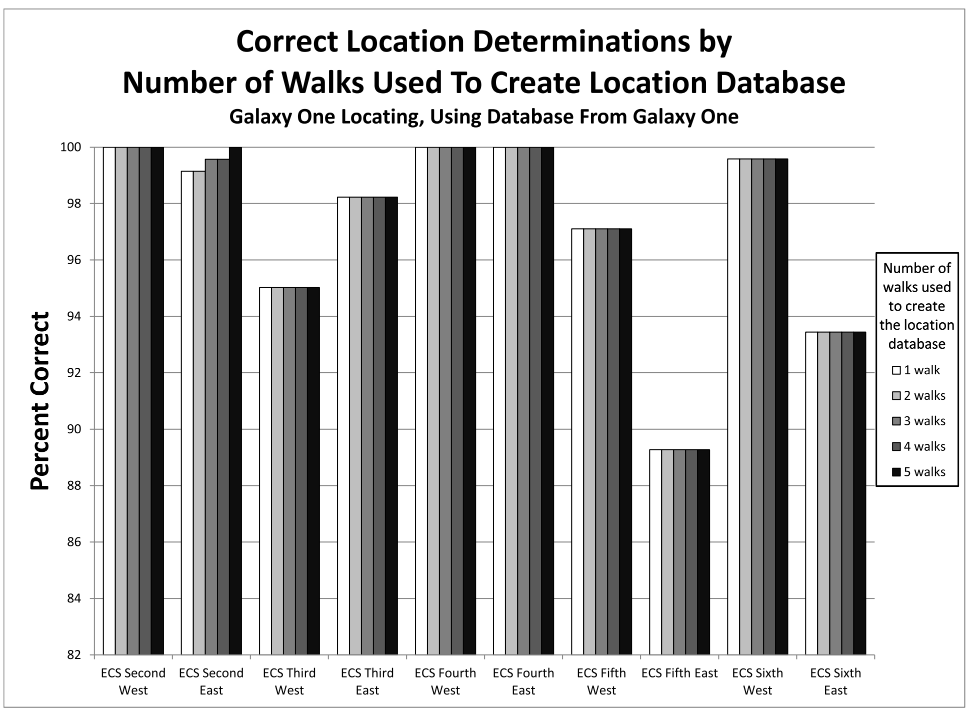
The results of the location determination trials were generally quite successful, as can be seen by results such as those in Table 5.2. While these results show high percentages of correct location determinations, they also point to interesting features of each area. Note that all results in this section are from a five walk database, and they are all calculated using the best AP method described in Section 4.1.1.

Engineering and Computer Science Building Results

The results from the location determination scans for the Engineering and Computer Science (ECS) Building are very good, with areas such as the second floor and the

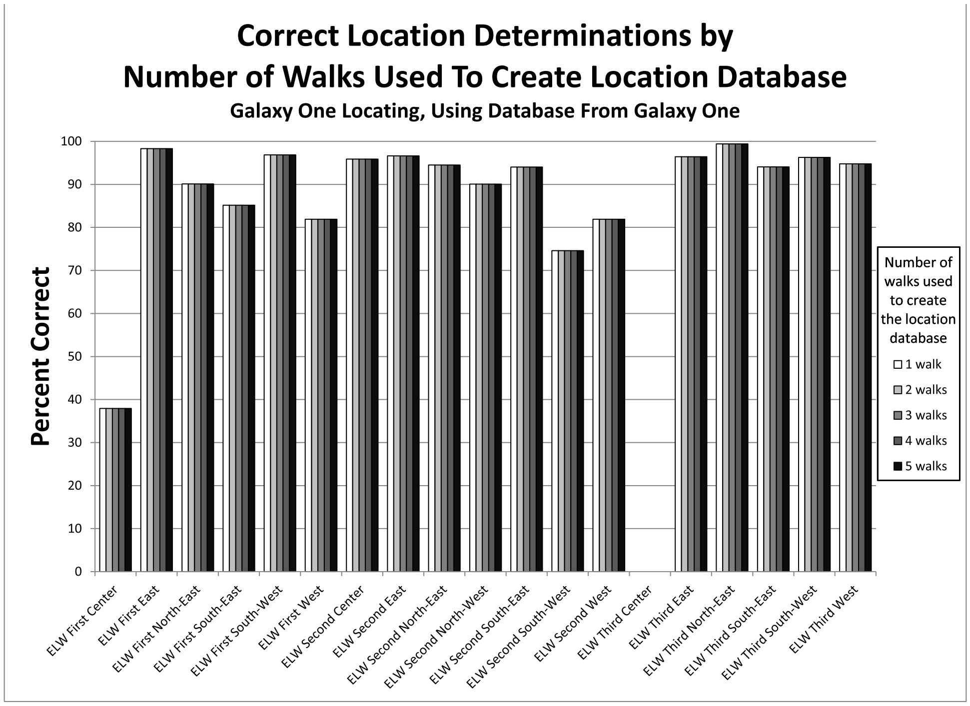


(a) The Galaxy Nexus using database from the Nexus One

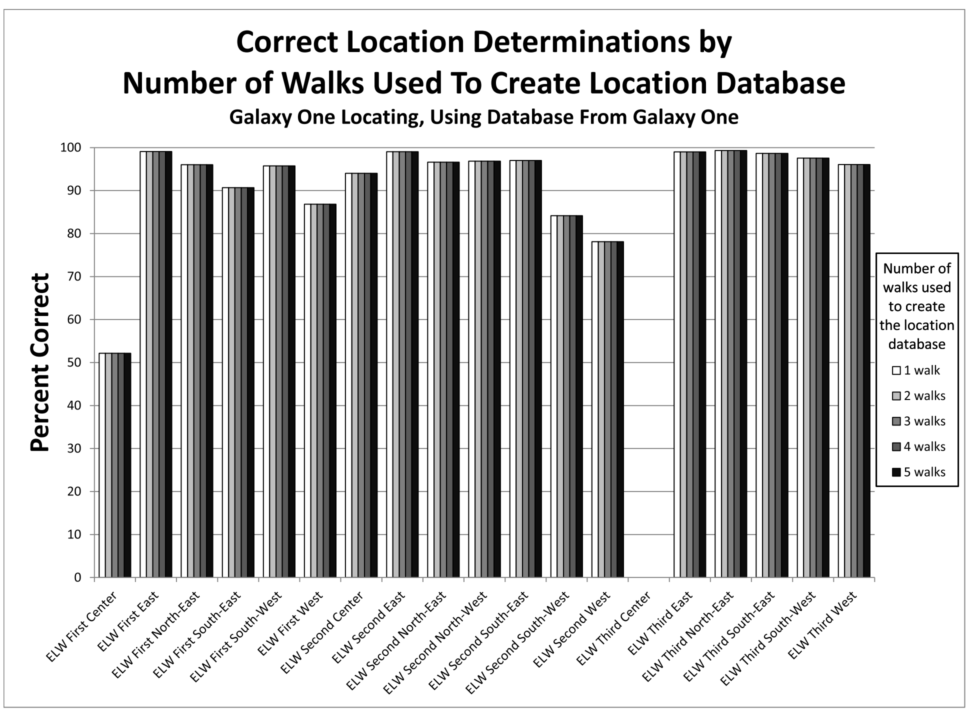


(b) Galaxy One

Figure 5.13 – A comparison of the number of walks used to create the location database and the percentage of correct location determinations.

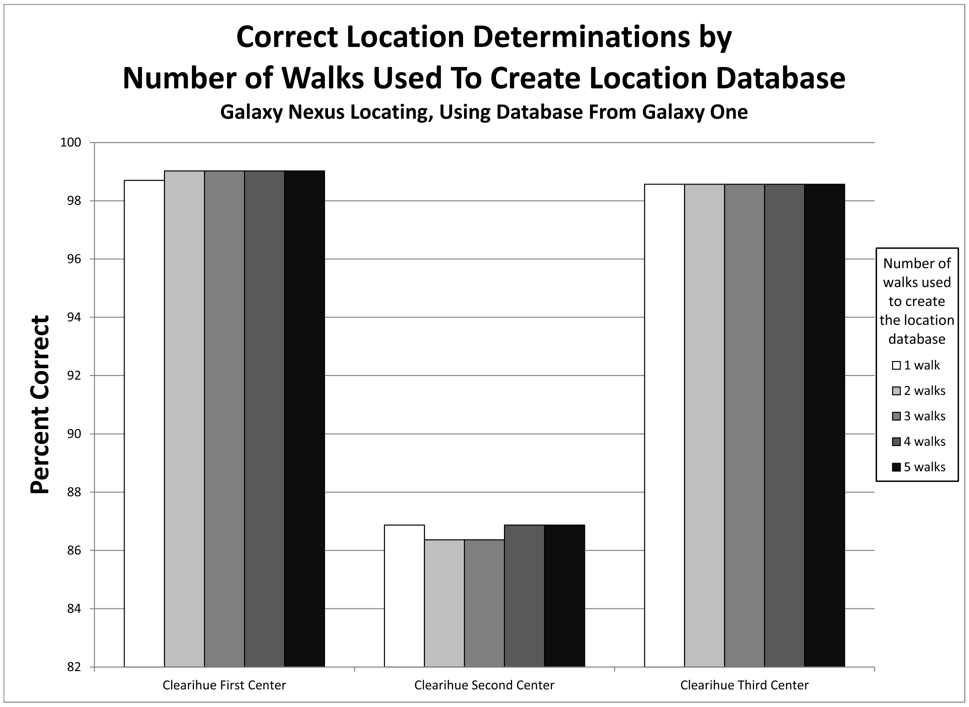


(a) The Galaxy Nexus using database from the Galaxy One

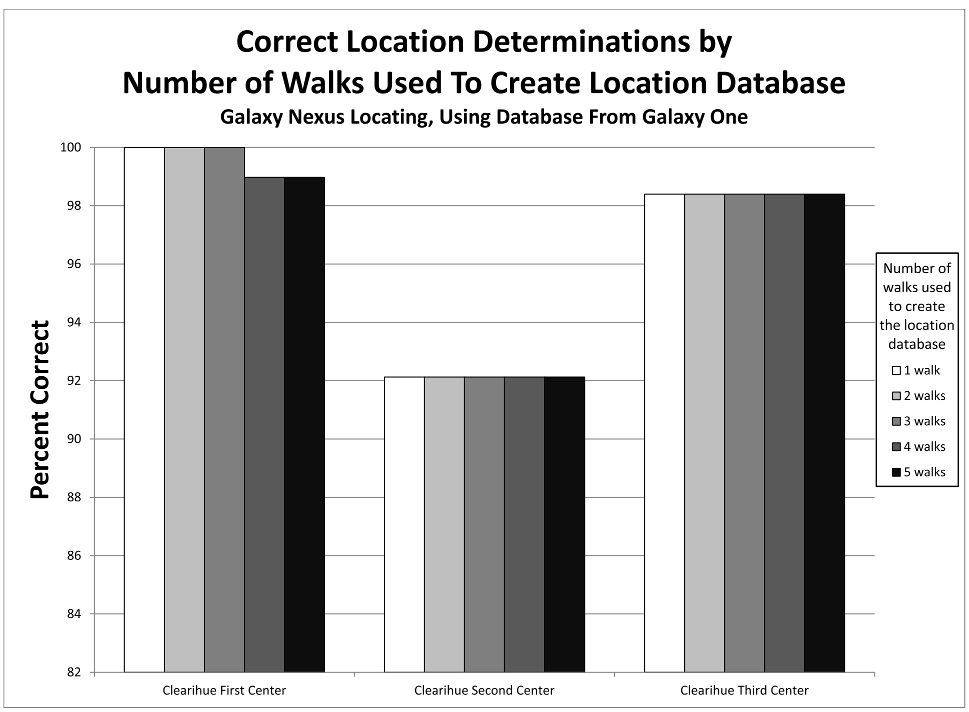


(b) Galaxy One

Figure 5.14 – A comparison of the number of walks used to create the location database and the percentage of correct location determinations.



(a) The Galaxy Nexus using database from the Galaxy One



(b) Galaxy One

Figure 5.15 – A comparison of the number of walks used to create the location database and the percentage of correct location determinations.

fourth floor showing 100% accuracy. The results from the location determination scans for the Engineering and Computer Science (ECS) Building are very good, with areas such as the second floor and the fourth floor showing 100% accuracy, but an astute map reader will quickly notice that no data collection walks were performed on the bridges that connect the west and east sides of the building. These bridges, shown in Figure 5.12 and marked as ① and ② on the ECS 2nd Floor map in Figure C.1, receive signals from many of the approximately 120 APs in the building making them a challenge for any methods other than those using detailed signal fingerprinting [14].

					Type of Incorrect Determinations						
Location	Scans	Correct	Incorrect	Percent Correct	Building	Floor	Area	Floor -1	Floor +1	Floor $\pm > 1$	Max Run of Incorrect
ECS 2nd West	197	197	0	100	0	0	0	0	0	0	0
ECS 2nd East	234	234	0	100	0	0	0	0	0	0	0
ECS 3rd West	241	229	12	95.02	0	12	0	0	12	0	6
ECS 3rd East	226	222	4	98.23	0	2	2	2	0	0	1
ECS 4th West	251	251	0	100	0	0	0	0	0	0	0
ECS 4th East	148	148	0	100	0	0	0	0	0	0	0
ECS 5th West	207	201	6	97.10	0	6	0	6	0	0	1
ECS 5th East	205	183	22	89.27	0	22	0	22	0	0	6
ECS 6th West	242	241	1	99.59	0	1	0	1	0	0	1
ECS 6th East	244	228	16	93.44	0	2	14	2	0	0	5

Table 5.2 – ECS Location Determination Results

Beginning with the results from the walks of ECS 2nd West and ECS 2nd East (see the ECS 2nd floor map in Figure C.1) we find that these two walks were extremely successful with 100% correct location determination results. This is not surprising for the ECS 2nd West walk as the enclosed hallway type is the "perfect candidate" for this method. However, the ECS 2nd East walk may be more surprising as it has the half open hallway characteristics in the area marked Ⓐ on the map, and it lacks an AP in the area marked Ⓑ on the map. The data suggests, however, that there is a hidden AP near Ⓑ that is providing the needed unique BSSID for this area.

Both walks on the third floor of ECS (see the ECS 3nd floor map in Figure C.2) have some typical characteristics of this method. The ECS 3rd East walk again shows good results for a half open hallway type, but incorrect area location determinations were seen around the point marked C on the map. Receiving strong signals from areas other than straight up and down is typical of this type of area which lacks signal attenuating walls. However, the number of "a floor too low" determinations for ECS 3rd West is unusual for an enclosed hallway. The clustering of these incorrect determinations, seen at a maximum of six in a row and at the end of the walk near the point marked D, suggests that the AP one floor directly above is the strongest signal at the end of the ECS 3rd West walk.

The results for the fourth floor of ECS (see the ECS 4th floor map in Figure C.3) were 100% correct, but from the map it would be expected that the part of the walk near E would generate errors due to the attenuating walls separating it from the closest visible AP. While there are no official UVic APs directly above or below this area, there is a hidden AP in the room near E. Between this extra data and the lack of other APs, the system provides a continuous stream of correct location determinations throughout this area.

On the fifth floor of the ECS building (see the ECS 5th floor map in Figure C.4) there is an example of the problem with unexpected network changes: there had previously been an AP near F on the map, outside of room 554. However, the results for the ECS 5th East walk remain strong with a correct location determination percentage of 89%. Similar to the area one floor down, it is assumed that there is a hidden AP somewhere near F on the map.

For the sixth floor of the ECS building (see the ECS 6th floor map in Figure C.5) we see an example of an enclosed hallway along the path taken by the ECS 6th West walk, and an excellent example of a half open hallway along the path taken by the ECS 6th East walk. The entire hallway, on both sides of the area marked G on the map, is open to the atrium. With the exception of a metallic wall/railing that reaches to waist height, there is no other attenuation of signals reaching this area, and as such we see higher counts for "wrong area".

Overall, and while keeping in mind that these results are from the simple max RSS location method, it should be noted that the maximum number of incorrect location determinations seen in a row in ECS was six and the average was two. These kinds of errors can be corrected for by using a slightly more complicated location determination method, or by simple filtering.

Engineering Lab Wing Results

The results from the location determination scans for the Engineering Lab Wing (ELW) were also excellent. Although the numbers provided in Table 5.3 may appear to show failures (ELW First Center and ELW Third Center), in actuality a few of the locations tested in this building were chosen as examples of where the defined areas must be tweaked in one way or another to achieve excellent results.

					Type of Incorrect Determinations						
Location	Scans	Correct	Incorrect	Percent Correct	Building	Floor	Area	Floor -1	Floor +1	Floor $\pm > 1$	Max Run of Incorrect
ELW 1st Center	138	72	66	52.17	0	64	2	0	64	0	28
ELW 1st West	76	66	10	86.84	0	0	10	0	0	0	3
ELW 1st SW	117	112	5	95.73	0	0	5	0	0	0	2
ELW 1st NE	150	144	6	96	0	0	6	0	0	0	4
ELW 1st East	107	106	1	99.07	0	0	1	0	0	0	1
ELW 1st SE	118	107	11	90.68	0	0	11	0	0	0	6
ELW 2nd Center	217	204	13	94.01	0	1	12	1	0	0	2
ELW 2nd NW	127	123	4	96.85	0	0	4	0	0	0	1
ELW 2nd West	105	82	23	78.10	0	2	21	0	2	0	6
ELW 2nd SW	164	138	26	84.15	0	6	20	1	5	0	10
ELW 2nd NE	147	142	5	96.60	0	0	5	0	0	0	2
ELW 2nd East	104	103	1	99.04	0	1	0	0	1	0	1
ELW 2nd SE	133	129	4	96.99	0	0	4	0	0	0	2
ELW 3rd Center	165	0	165	0	0	88	77	88	0	0	165
ELW 3rd West	101	97	4	96.04	0	0	4	0	0	0	1
ELW 3rd SW	164	160	4	97.56	0	0	4	0	0	0	2
ELW 3rd NE	147	146	1	99.32	0	0	1	0	0	0	1
ELW 3rd East	99	98	1	98.99	0	1	0	1	0	0	1
ELW 3rd SE	147	145	2	98.64	0	0	2	0	0	0	1

Table 5.3 – ELW Location Determination Results. The areas of each floor are grouped together to match their presentation in the discussion.

One of the most interesting examples is the ELW 1st Center walk on the first floor of the ELW building (see the ELW 1st floor map in Figure C.6). As shown on the map, an AP is located at the north end of this walk in an average hallway. However, as the walk moves south past H, the room opens up to a two story ceiling with a balcony from the 2nd floor overlooking the area and an AP on the ceiling at H. As the ELW 2nd Center walk was done on the second floor, the AP at H would be associated with that walk instead of the ELW 1st Center walk, and any location determinations in the area from H south should be expected to be reported as one floor too high. This is what is seen in the data, with a 52% accuracy that neatly divides the ELW 1st Center walk between the north area dominated by the first floor AP and the south area dominated by the second floor AP near H. There are also two "wrong area" determinations here that can be assumed to originate from the AP in the ELW 1st South-East walk area as there was a line-of-sight from the south end of the ELW 1st Center walk and that AP.

Looking next at the two walks in the west hallway, the ELW 1st West walk and the ELW 1st South-West walk, we see a phenomenon that was rare in the results from the ECS building: location determinations that were incorrect due to "wrong area" rather than "wrong floor". This is simply an artifact of dividing an area into two along a line with no signal attenuating features. Whenever the ELW 1st West walk or the ELW 1st South-West walk approached the other (the area marked J on the map), either of the APs in the hallway would potentially be the strongest signal source and could be used for the location determination. The solution to this type of problem, as will be discussed in Section 6.1 (Future Work), is as simple as implementing a location algorithm that uses more than just the single strongest RSS.

The final three walks for the first floor of the ELW building are on the east side: the ELW 1st North-East walk, the ELW 1st East walk, and the ELW 1st South-East walk. With all three walks we see that the incorrect determinations were all "wrong area", and the reasons for this seem to be relatively straight-forward for two reasons: there is no signal attenuating feature between the western part of the walk and the AP that is considered to be part of the ELW 1st North-East area. As the map suggests that this walk ends closer to that AP than to the AP in the center of the ELW 1st North-East area, wrong area determinations should be expected with the current algorithm, and should be fixed by the method discussed in Section 6.1 on Future Work. The higher number of "wrong area" determinations for the ELW 1st South-East walk are more difficult to explain, but may be related to the complex layout of that particular hallway and to the fact that there are locations in that walk where a signal attenuating feature (such as a wall) may be between the AP and the mobile device.

Moving up one floor to the ELW 2nd Center walk (see the ELW 2nd floor map in Figure C.7), we should expect excellent results given where the AP (the same AP that caused difficulties for the ELW 1st Center walk) is positioned. However, while good results were seen, we can see a side-effect of the walk that was chosen: a winding path that starts in the area marked K on the map and follows the balcony around the area that's open from below, and along a portion of a hallway marked as L on the map. There are two problems with defining the ELW 2nd Center area with this walk:

- The area marked K on the map is in very close proximity to the AP that is included in the ELW 2nd North-West area, and it is also in line-of-sight of the AP that is included in the ELW 2nd North-East area. Without any attenuating features to block signals, "wrong area" location determinations would be expected from here.
- The area at L is essentially a bridge over the open area below, but what is not obvious from the map is that a wall of glass bricks between L and the AP gives the impression of an enclosed hallway. However, as a 0.5" glass divider[10] has an attenuation factor of 12 dB [78], which is more than the 5 dB to 10 dB expected from an interior wall, and so this is considered as an enclosed hallway. Examination of the map shows that the AP in the ELW 2nd South-East area is in direct line-of-sight with L and, as such, this area should be excluded from the ELW 2nd Center area.

Looking at the west side of ELW 2nd, we see that region divided into three areas by three walks, rather than the two seen on the first floor. This was due to an extra AP placed on this floor in the area defined by the ELW 2nd North-West walk. While this area shows excellent results, the ELW 2nd West walk and the ELW 2nd South-West walk show more incorrect area location determinations than did the similar areas on the first floor and the third floor. The reasons for this are unclear.

The east side of ELW 2nd shows excellent results, with small numbers of incorrect area location determinations seen by both the ELW 2nd North-East walk and the ELW 2nd South-East walk when near the ELW 2nd East area.

[10] This assumes that the glass bricks have an equal or greater signal attenuation than the 0.5" glass divider.

To complete the examination of the Engineering Lab Wing results, we move to the third floor of the building (see the ELW 3rd floor map in Figure C.8). Here we see good results that are similar to those seen elsewhere in the building, with the exception of the ELW 3rd Center walk. The area marked M on the map is an open study area, but one with no visible AP. The ELW 3rd Center walk was a test to see if there was a hidden AP nearby that could be used to define an ELW 3rd Center area. Given the zero correct location determinations for this area, there is no AP in the area around M.

Clearihue Building A-Wing Results

As one of the trials outside of the engineering buildings, one of the oldest buildings at the University of Victoria—the A-Wing of the Clearihue Building—was used.

					Type of Incorrect Determinations						
Location	Scans	Correct	Incorrect	Percent Correct	Building	Floor	Area	Floor -1	Floor +1	Floor ± > 1	Max Run of Incorrect
CLEA 1st Center	194	192	2	98.97	0	2	0	0	2	0	2
CLEA 2nd Center	127	117	10	92.13	0	10	0	0	10	0	2
CLEA 3rd Center	125	123	2	98.4	0	2	0	2	0	0	1

Table 5.4 – CLE-A Location Determination Results

The first floor of Clearihue A-Wing (see the CLE-A 1st floor map in Figure C.9) consists of a large hallway with three APs and a student computer center with a fourth AP. The remaining two floors (see the CLE-A 2nd floor map in Figure C.10, and the CLE-A 3rd floor map in Figure C.11) have somewhat shorter hallways with an AP at both ends. Only one area was defined on each floor, each by a straight walk path down the hallway. As shown in the Clearihue A-Wing results table (See Table 5.4), the results are similar to those seen in some areas of the ECS building. There are no closely adjoining areas that would lead to incorrect area location determinations, and so the only incorrect location determinations seen here are of the "plus or minus one floor" variety. Using the methods described in Chapter 6, the maximum number of incorrect location determinations in this data could easily be filtered out to provide near perfect location determinations.

Chapter 6

Future Work and Conclusions

Such impressive results from such a simple system with a simple and fast configuration phase was the motivator for writing this thesis. Most location-related work tends to focus on how precisely a real-world ground-truth position can be made. A lot of this thinking may come from our expectations of the always progressing improvement in the technology we use. Every now and then it is good to take a step back and check whether that progression is really leading us where we need to go.

Indoor Wi-Fi location seems to be a good place for taking a step back. While there has been a large amount of research on the topic over many years, there are very few real-world deployments. Most of the background research investigated for this thesis requires so much configuration and maintenance work that those methods are simply impractical to use outside of experimental situations. Using less precise methods, but methods that are inexpensive and fast to deploy, seems to be the only way to get indoor location technology out of the lab and into the real world.

One high-profile exception to the lack of real-world indoor location efforts has come from Google and their introduction of Indoor Maps to their Google Maps offering. While this holds the promise of bringing ubiquitous indoor mapping to mobile devices, opportunities to test Google's indoor maps are rare given how few locations are part of the service. Unfortunately, in the two opportunities to test this service before this document was published, both tests showed very poor results. The screenshot shown here in Figure 6.1 is from the San Jose International Airport, with the device located between Hudson News and Gate 27. As is clear from the image, Google Maps located the device outside the opposite side of the building and on the road. Google Maps did seem to be accurate for altitude, though, and it would almost always show the appropriate floor map for the interior of the airport.

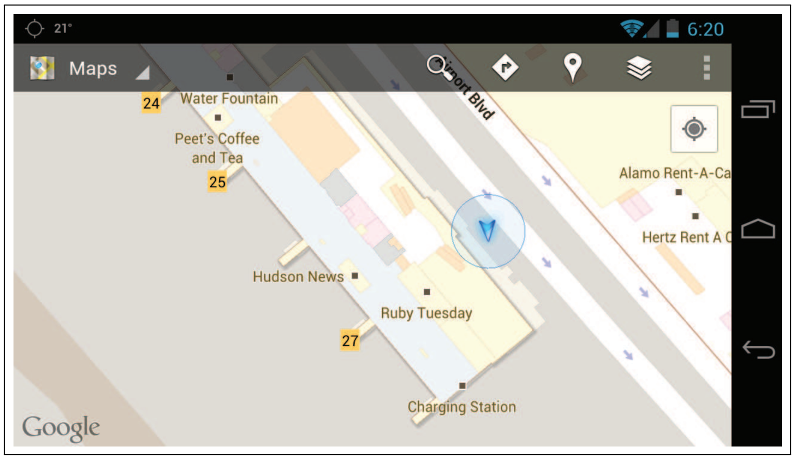


Figure 6.1 – A screenshot of the indoor mapping functionality of Google Maps. This example was captured at the San Jose International Airport when the Galaxy Nexus device was between Hudson News and Gate 27. However, Google Maps located the device outside and on the road.

6.1 Using A More Complicated Algorithm

What appears to be the most obvious target for future work would be to improve the algorithm by filtering and by using more than the simple strongest RSS to determine the device's current location. As was mentioned earlier in this document, using a more complicated algorithm was intentionally avoided to focus on how powerful the switch from absolute location to defined areas can be, and to show how signal attenuation inside buildings can be useful.

That point aside, it would be trivial to add filtering to the algorithm to remove the spurious location determinations that appear in sets of one, two, or three. Looking at the results shown in Section 5.8, it is obvious that the percentages of correct location determinations would be greatly improved by such a small amount of work. However, it might be considered bad form to demonstrate a simple method that provides near perfect results, and this work has remained focused on the nearly perfect results.

Without too much effort this method could be expanded to consider the RSS of more than one AP when making a location determination. This would be very effective in long hallways such as ECS 4th West, shown in Figure C.3, that have APs at either end. Determining whether the device is at one end of the hallway or the other, or somewhere in the middle, should simply be a matter of the ratio between the RSS of the two APs.

Further improvements could be found in using history functions, and determining if it is physically possible for the device to have moved from the previous location to the new location. This might be due to the amount of time it would take to move from point A to point B, or it might be due to whether there are barriers preventing direct movement between the two, but in either case it would require that the system have knowledge regarding the relative positions of the defined areas in the real world.

6.2 Using Device Sensors

The work presented here began out of an interest in using accelerometers to assist in determining location, and unfortunately that work did not make it into this thesis. However, there are many avenues of investigation open through the use of device sensors such as the accelerometer, but also including the gyroscopes and 3D magnetometers (compasses) that are now in most smartphones.

Accelerometers themselves can be used to track steps taken by the user of the device. Whether the device is in motion or not plays into whether location determinations need to be made, but they can also be used for a rough estimate of distance travelled and whether the determination of a changed location make sense in the physical world. Gyroscopes and compasses can assist here as well, as many steps taken while turning in a circle would suggest the device has not moved much of a distance.

As well, using accelerometers to gain a rough estimate of distance travelled could be useful in the Phase 1 configuration of a location system. Looking again at the example hallway of ECS 4th West, a rough estimate of distance travelled could provide the system with information regarding the spacing of the APs in the hallway, and perhaps prompt the user of an opportunity to divide a defined area in two.

What may prove to be the most important sensor for this simple system is the electronic barometer. Barometers provide an independent measurement of altitude by measuring ambient air pressure but, just like wall-mounted barometers in some old houses, their readings vary with the changing of weather patterns. Once calibrated with a known altitude, perhaps ground level as the device is brought into a building and loses its GPS signal, the electronic barometer has no difficulties in determining the device's altitude within a building and should be able to provide the necessary data to prevent the incorrect location determinations that fit into the $\pm$ 1 floor category.

6.3 User Testing and Crowdsourcing

True user testing will be an important step forward to ensure that the system is truly as easy to use as it appears. Widely deploying the colleague locator software at a conference could make for a test that is reasonably easily to control. Building out the application to include maps that show where the next event is and how to get there from the user's current location would not only be useful to a conference attendee, but could also be a driving factor to see the location software installed on a large set of devices.

Further developing the system to allow for users to submit data samples could be the beginnings of a crowdsourced system. While there are many potential issues to this, including security and data management, there is also a great potential to see the success seen in many other crowdsourced projects.

6.4 5 GHz Wi-Fi, IEEE 802.11ac, and The Future

While 5 GHz Wi-Fi has been around since IEEE 802.11a, it only began to appear in consumer equipment after the release of the IEEE 802.11n specifications. Wi-Fi equipment that uses 5 GHz is still generally more expensive than 2.5 GHz equipment, but dual-band Wi-Fi radios are starting to become a standard for mobile devices. With the use of a higher frequency / shorter wavelength radio signal comes the promise of even more signal attenuation and less signal penetration through obstacles. However there is not much work related to 5 GHz Wi-Fi and location determination, although the *3Com® Wireless Antennas Product Guide* [78] mentioned at the end of Section 3.7 also includes data on attenuation properties at 5 GHz. Shown here in Table 6.1 for comparison, we see that some materials do show a much higher signal attenuation at 5 GHz as compared to 2.4 GHz. However, not all of the numbers are higher, with such important examples as interior hollow walls showing *less* attenuation.

Building Material	**2.4 GHz**	**5.0 GHz**
Solid Wood Door 1.75"	6 dB	10 dB
Hollow Wood Door 1.75"	4 dB	7 dB
Interior Office Door w/Window 1.75"/0.5"	4 dB	6 dB
Steel Fire/Exit Door 1.75"	13 dB	25 dB
Steel Fire/Exit Door 2.5"	19 dB	32 dB
Steel Rollup Door 1.5"	11 dB	19 dB
Brick 3.5"	6 dB	10 dB
Concrete Wall 18"	18 dB	30 dB
Cubical Wall (Fabric) 2.25"	18 dB	30 dB
Exterior Concrete Wall 27"	53 dB	45 dB
Glass Divider 0.5"	12 dB	8 dB
Interior Hollow Wall 4"	5 dB	3 dB
Interior Hollow Wall 6"	9 dB	4 dB
Interior Solid Wall 5"	14 dB	16 dB
Marble 2"	6 dB	10 dB
Bullet-Proof Glass 1"	10 dB	20 dB
Exterior Double Pane Coated Glass 1"	13 dB	20 dB
Exterior Single Pane Window 0.5"	7 dB	6 dB
Interior Office Window 1"	3 dB	6 dB
Safety Glass-Wire 0.25"	3 dB	2 dB
Safety Glass-Wire 1.0"	13 dB	18 dB

Table 6.1 – Attenuation Properties of Common Building Materials, including data for 5 GHz Wi-Fi, from the *3Com® Wireless Antennas Product Guide* [78]

While the method presented in this document would still work with 5 GHz Wi-Fi, the next big challenge will be the IEEE 802.11ac standard which specifies the use of steerable antennas. The APs will have the ability to direct the radio signal towards a mobile device, and this has the potential of skewing the RSS values for the APs. This should not have an impact on any implementation similar to the Android app described in Section 5.4 as the scanning method used is passive; the device listens for the (presumably) omnidirectional beacons broadcast by each AP.

Bibliography

[1] K. Duong, "2012 Canada digital future in focus," March 2012. http://www2.comscore.com/l/1552/CanadaDigitalFutureinFocus-pdf/2zdy6q.

[2] Nielsen Mobile Insights, "Americas new mobile majority: a look at smartphone owners in the u.s.." http://blog.nielsen.com/nielsenwire/?p=31688.

[3] A. Shaw and D. Krug, "Heritage meets social media. designing a virtual museum space for young people.," in *Proceedings of World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education 2012*, 2012.

[4] C. Arthur, "Android overtakes symbian in smartphone sales," 2011. http://www.guardian.co.uk/technology/2011/jan/31/android-symbian-smartphone-sales.

[5] D. Melanson, "Google: 400 million android devices, one million activations a day," June 2012. http://www.engadget.com/2012/06/27/google-400-million-android-devices-one-million-activations-a-d/.

[6] Practical eCommerce Staff, "Chart of the week: Google's android mobile os will outpace the iphone, others," January 2010. http://www.practicalecommerce.com/articles/1575-Chart-of-the-Week-Googles-Android-Mobile-OS-Will-Outpace-the-iPhone-Others/print.

[7] R. Llamas, K. Restivo, and M. Shirer, "Android- and iOS-powered smartphones expand their share of the market in the first quarter, according to idc," May 2012. http://www.idc.com/getdoc.jsp?containerId=prUS23503312.

[8] B. Eriksson, P. Barford, J. Sommers, and R. Nowak, "A learning-based approach for IP geolocation," in *Passive and Active Measurement*, pp. 171--180, Springer, 2010.

[9] A. Popescu, ''Geolocation API specification,'' May 2012. `http://www.w3.org/TR/geolocation-API/`.

[10] J. Caffery and G. Stuber, ''Overview of radiolocation in CDMA cellular systems,'' *Communications Magazine, IEEE*, vol. 36, no. 4, pp. 38--45, 1998.

[11] G. Borriello, M. Chalmers, A. LaMarca, and P. Nixon, ''Delivering real-world ubiquitous location systems,'' *Communications of the ACM*, vol. 48, no. 3, pp. 36--41, 2005.

[12] A. Kushki, K. Plataniotis, and A. Venetsanopoulos, ''Kernel-based positioning in wireless local area networks,'' *Mobile Computing, IEEE Transactions on*, vol. 6, no. 6, pp. 689--705, 2007.

[13] M. McGuire, K. Plataniotis, and A. Venetsanopoulos, ''Estimating position of mobile terminals from path loss measurements with survey data,'' *Wireless communications and mobile computing*, vol. 3, no. 1, pp. 51--62, 2003.

[14] E. Hyun, M. McGuire, and M. Sima, ''Radloco: A rapid and low cost indoor location-sensing system,'' in *Communications and Networking in China, 2008. ChinaCom 2008. Third International Conference on*, pp. 630--634, IEEE, 2008.

[15] A. LaMarca, Y. Chawathe, S. Consolvo, J. Hightower, I. Smith, J. Scott, T. Sohn, J. Howard, J. Hughes, F. Potter, *et al.*, ''Place lab: Device positioning using radio beacons in the wild,'' *Pervasive Computing*, pp. 301--306, 2005.

[16] The European Telecommunications Standards Institute (ETSI), ''Mobile technologies gsm,'' February 2012. `http://www.etsi.org/WebSite/Technologies/gsm.aspx`.

[17] K. Thota, ''Broadband and Wi-Fi households global forecast 2012,'' March 2012. `http://www.strategyanalytics.com/default.aspx?mod=reportabstractviewer&a0=7215`.

[18] K. Pahlavan, P. Krishnamurthy, and A. Beneat, ''Wideband radio propagation modeling for indoor geolocation applications,'' *Communications Magazine, IEEE*, vol. 36, no. 4, pp. 60--65, 1998.

[19] M. Hazas and A. Hopper, ''Broadband ultrasonic location systems for improved indoor positioning,'' *Mobile Computing, IEEE Transactions on*, vol. 5, no. 5, pp. 536--547, 2006.

[20] C. Heywood, C. Connor, D. Browning, M. Smith, and J. Wang, ''GPS tracking of intermodal transportation: System integration with delivery order system,'' in *Systems and Information Engineering Design Symposium, 2009. SIEDS'09.*, pp. 191--196, IEEE, 2009.

[21] T. Espiner, ''UK Sentinel study reveals GPS jammer use,'' February 2012. `http://www.zdnet.co.uk/news/networking/2012/02/22/uk-sentinel-study-reveals-gps-jammer-use-40095106/`.

[22] H. El-Bakry and N. Mastorakis, ''Design of anti-GPS for reasons of security,'' in *Proceedings of the international conference on Computational and information science 2009*, pp. 480--500, World Scientific and Engineering Academy and Society (WSEAS), 2009.

[23] R. Want, A. Hopper, V. Falcao, and J. Gibbons, ''The active badge location system,'' *ACM Transactions on Information Systems (TOIS)*, vol. 10, no. 1, pp. 91--102, 1992.

[24] K. Cheung, S. Intille, and K. Larson, ''An inexpensive bluetooth-based indoor positioning hack,'' *Proc. UbiComp06 Extended Abstracts*, 2006.

[25] X. Li and K. Pahlavan, ''Super-resolution TOA estimation with diversity for indoor geolocation,'' *Wireless Communications, IEEE Transactions on*, vol. 3, no. 1, pp. 224--234, 2004.

[26] A. Kushki, K. Plataniotis, and A. Venetsanopoulos, ''Location tracking in wireless local area networks with adaptive radio maps,'' in *Acoustics, Speech and Signal Processing, 2006. ICASSP 2006 Proceedings. 2006 IEEE International Conference on*, vol. 5, pp. V--V, IEEE, 2006.

[27] K. Kaemarungsi and P. Krishnamurthy, ''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 on*, pp. 14--23, IEEE, 2004.

[28] N. Priyantha, A. Chakraborty, and H. Balakrishnan, ‘‘The cricket location-support system,’’ in *Proceedings of the 6th annual international conference on Mobile computing and networking*, pp. 32--43, ACM, 2000.

[29] T. Shiraishi, N. Komuro, H. Ueda, H. Kasai, and T. Tsuboi, ‘‘Indoor location estimation technique using UHF band RFID,’’ in *Information Networking, 2008. ICOIN 2008. International Conference on*, pp. 1--5, Ieee, 2008.

[30] C. Pearson, M. McGuire, and Y. Coady, ‘‘The application of Wi-Fi radiolocation research to mobile devices,’’ in *Communications, Computers and Signal Processing, 2009. PacRim 2009. IEEE Pacific Rim Conference on*, pp. 768--773, IEEE, 2009.

[31] A. Harter and A. Hopper, ‘‘A distributed location system for the active office,’’ *Network, IEEE*, vol. 8, no. 1, pp. 62--70, 1994.

[32] R. Tesoriero, J. Gallud, M. Lozano, and V. Penichet, ‘‘Using active and passive RFID technology to support indoor location-aware systems,’’ *Consumer Electronics, IEEE Transactions on*, vol. 54, no. 2, pp. 578--583, 2008.

[33] C. Ciavarella and F. Paternò, ‘‘The design of a handheld, location-aware guide for indoor environments,’’ *Personal and Ubiquitous Computing*, vol. 8, no. 2, pp. 82--91, 2004.

[34] Infrared Data Association, ‘‘IrDA background,’’ March 2012. `http://www.irda.org`.

[35] PDAdb.net, ‘‘Detailed technical datasheet of Compaq iPAQ h3630 / h3635 / h3650,’’ February 2012. `http://pdadb.net/index.php?m=specs&id=3&view=1&c=compaq_ipaq_h3630__h3635__h3650`.

[36] N. Priyantha, A. Miu, H. Balakrishnan, and S. Teller, ‘‘The cricket compass for context-aware mobile applications,’’ in *Proceedings of the 7th annual international conference on Mobile computing and networking*, pp. 1--14, ACM, 2001.

[37] D. Felix and M. McGuire, ‘‘Received signal strength calibration for handset localization in wlan,’’ in *IEEE International Conference on Communications*, 2012.

[38] C. Roberts, ‘‘Radio frequency identification (RFID),’’ *Computers & Security*, vol. 25, no. 1, pp. 18--26, 2006.

[39] H. Ishii, F. Harada, and H. Shimakawa, ‘‘Information sharing by evacuee collaboration for assured evacuation under lack of power supply,’’ in *Creating, Connecting and Collaborating through Computing, 2008. C5 2008. Sixth International Conference on*, pp. 54--61, IEEE, 2008.

[40] ‘‘Discover and learn - Wi-Fi alliance,’’ March 2012. `http://www.wi-fi.org/discover-and-learn`.

[41] W. Lemstra and V. Hayes, *The innovation journey of Wi-Fi: the road to global success*. Cambridge Univ Press, 2010.

[42] M. Youssef and A. Agrawala, ‘‘The horus location determination system,’’ *Wireless Networks*, vol. 14, no. 3, pp. 357--374, 2008.

[43] D. Madigan, E. Einahrawy, R. Martin, W. Ju, P. Krishnan, and A. Krishnakumar, ‘‘Bayesian indoor positioning systems,’’ in *INFOCOM 2005. 24th Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings IEEE*, vol. 2, pp. 1217--1227, IEEE, 2005.

[44] M. Laaraiedh, L. Yu, S. Avrillon, and B. Uguen, ‘‘Comparison of hybrid localization schemes using RSSI, TOA, and TDOA,’’ in *Wireless Conference 2011-Sustainable Wireless Technologies (European Wireless), 11th European*, pp. 1--5, VDE, 2011.

[45] D. Brown and D. Dunn, ‘‘Classification schemes of positioning technologies for indoor navigation,’’ in *Southeastcon, 2011 Proceedings of IEEE*, pp. 125--130, IEEE, 2011.

[46] T. Le, H. Le, N. Nguyen, D. Tran, and N. Nguyen, ‘‘Convert Wi-Fi signals for fingerprint localization algorithm,’’ in *Wireless Communications, Networking and Mobile Computing (WiCOM), 2011 7th International Conference on*, pp. 1--5, IEEE, 2011.

[47] I. C. S. L. M. S. Committee *et al.*, ‘‘Wireless LAN medium access control (MAC) and physical layer (PHY) specifications,’’ 1997.

[48] M. Youssef, A. Agrawala, and A. Udaya Shankar, ‘‘Wlan location determination via clustering and probability distributions,’’ in *Pervasive Computing and Communications, 2003.(PerCom 2003). Proceedings of the First IEEE International Conference on*, pp. 143--150, IEEE, 2003.

[49] P. Bahl and V. Padmanabhan, ‘‘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*, vol. 2, pp. 775--784, Ieee, 2000.

[50] J. Letchner, D. Fox, and A. LaMarca, ‘‘Large-scale localization from wireless signal strength,’’ in *Proceedings of the national conference on artificial intelligence*, vol. 20, p. 15, Menlo Park, CA; Cambridge, MA; London; AAAI Press; MIT Press; 1999, 2005.

[51] N. Priyantha, *The cricket indoor location system.* PhD thesis, Massachusetts Institute of Technology, 2005.

[52] M. Ocaña, L. Bergasa, and M. Sotelo, ‘‘Robust navigation indoor using wifi localization,’’ in *Proceedings of the 10th IEEE Internacional Conference on Methods and Models in Automation and Robotics*, pp. 851--856, 2004.

[53] M. Ocaña, L. M. Bergasa, M. A. Sotelo, J. Nuevo, and R. Flores, ‘‘Indoor robot localization system using Wi-Fi signal measure and minimizing calibration effort,’’ in *Industrial Electronics, 2005. ISIE 2005. Proceedings of the IEEE International Symposium on*, vol. 4, 2005.

[54] P. Kumar and S. Toscano, ‘‘Real-time indoor positioning system (R.I.P.S),’’ tech. rep., Unversity of Victoria, July 2009.

[55] A. Schwaighofer, M. Grigoras, V. Tresp, and C. Hoffmann, ‘‘GPPS: A gaussian process positioning system for cellular networks,’’ *Advances in Neural Information Processing Systems*, vol. 16, 2003.

[56] N. Chang, R. Rashidzadeh, and M. Ahmadi, ‘‘Robust indoor positioning using differential wi-fi access points,’’ *Consumer Electronics, IEEE Transactions on*, vol. 56, no. 3, pp. 1860--1867, 2010.

[57] B. Ferris, D. Hähnel, and D. Fox, ‘‘Gaussian processes for signal strength-based location estimation,’’ in *In Proc. of Robotics Science and Systems*, Citeseer, 2006.

[58] R. Wang, F. Zhao, H. Luo, B. Lu, and T. Lu, ‘‘Fusion of wi-fi and bluetooth for indoor localization,’’ in *Proceedings of the 1st international workshop on Mobile location-based service*, pp. 63--66, ACM, 2011.

[59] J. Astrain, J. Villadangos, J. Garitagoitia, J. González de Mendívil, and V. Cholvi, ‘‘Fuzzy location and tracking on wireless networks,’’ in *Proceedings of the 4th ACM international workshop on Mobility management and wireless access*, pp. 84--91, ACM, 2006.

[60] P. Castro, P. Chiu, T. Kremenek, and R. Muntz, ‘‘A probabilistic room location service for wireless networked environments,’’ in *UbiComp 2001: Ubiquitous Computing*, pp. 18--34, Springer, 2001.

[61] Bluetooth SIG, ‘‘Bluetooth FAQ,’’ February 2012. `http://www.bluetooth.com/Pages/FAQ.aspx`.

[62] Bluetooth SIG, ‘‘Specification of the bluetooth system,’’ *Core, version*, vol. 1, 2001.

[63] M. Rodriguez, J. Pece, and C. Escudero, ‘‘In-building location using bluetooth,’’ in *International Workshop on Wireless Ad-hoc Networks*, Citeseer, 2005.

[64] B. Sklar, ‘‘Rayleigh fading channels in mobile digital communication systems. i. characterization,’’ *Communications Magazine, IEEE*, vol. 35, no. 7, pp. 90--100, 1997.

[65] J. Andersen, T. Rappaport, and S. Yoshida, ‘‘Propagation measurements and models for wireless communications channels,’’ *Communications Magazine, IEEE*, vol. 33, no. 1, pp. 42--49, 1995.

[66] T. Chrysikos, G. Georgopoulos, and S. Kotsopoulos, ‘‘Wireless channel characterization for a home indoor propagation topology at 2.4 GHz,’’ in *Wireless Telecommunications Symposium (WTS), 2011*, pp. 1--10, IEEE, 2011.

[67] S. Bernard, ‘‘Rayleigh fading channels in mobile digital communication systems part ii: Mitigation,’’ *IEEE Communications Magazine*, vol. 35, no. 9, pp. 148--155, 1997.

[68] X. Dong and N. Beaulieu, “Average level crossing rate and average fade duration of selection diversity,” *Communications Letters, IEEE*, vol. 5, no. 10, pp. 396--398, 2001.

[69] N. Sagias, G. Karagiannidis, D. Zogas, P. Mathiopoulos, and G. Tombras, “Performance analysis of dual selection diversity in correlated weibull fading channels,” *Communications, IEEE Transactions on*, vol. 52, no. 7, pp. 1063--1067, 2004.

[70] A. Kamerman and N. Erkocevic, “Microwave oven interference on wireless LANs operating in the 2.4 GHz ISM band,” in *Personal, Indoor and Mobile Radio Communications, 1997.'Waves of the Year 2000'. PIMRC'97., The 8th IEEE International Symposium on*, vol. 3, pp. 1221--1227, IEEE, 1997.

[71] P. Watson, I. Watson, and R. Batt, “Total body water volumes for adult males and females estimated from simple anthropometric measurements,” *The American journal of clinical nutrition*, vol. 33, no. 1, pp. 27--39, 1980.

[72] Nokia Products Ltd., “Internal photographs, exhibit 9 (Nokia N96.” https://fjallfoss.fcc.gov/eas/GetApplicationAttachment.html?id=982660.

[73] Nokia Corporation, “Internal photographs, exhibit 9 (Nokia N95.” https://fjallfoss.fcc.gov/eas/GetApplicationAttachment.html?id=882658.

[74] Nokia Corporation, “Exhibit 09: Internal photos (Nokia E71).” https://fjallfoss.fcc.gov/eas/GetApplicationAttachment.html?id=932273.

[75] SGS Taiwan Ltd., “Internal photos(ver.01) (HTC Nexus One.” https://fjallfoss.fcc.gov/eas/GetApplicationAttachment.html?id=1208709.

[76] G. A. Fowler, “Culprit in Wi-Fi failures: Chicken wire - WSJ.com.” http://online.wsj.com/article/SB126221116097210861.html.

[77] P. Ockenden, “Whats killing your Wi-Fi? wrapping your house in tin foil — pc pro blog.” http://www.pcpro.co.uk/blogs/2011/04/14/whats-killing-your-wi-fi-wrapping-your-house-in-tin-foil/.

[78] 3Com Corporation, “3Com® wireless antennas product guide.” `http://www.scribd.com/doc/32613170/3Com%C2%AE-Wireless-Antennas`.

[79] M. Watts, J. Brunger, and K. Shires, ‘‘Do european data protection laws apply to the collection of wifi network data for use in geolocation look-up services?,’’ *International Data Privacy Law*, vol. 1, no. 3, pp. 149--160, 2011.

[80] H. Lim, L. Kung, J. Hou, and H. Luo, ‘‘Zero-configuration indoor localization over IEEE 802.11 wireless infrastructure,’’ *Wireless Networks*, vol. 16, no. 2, pp. 405--420, 2010.

[81] A. Ozgur, O. Leveque, and E. Preissmann, ‘‘Scaling laws for one- and two-dimensional random wireless networks in the low-attenuation regime,’’ *Information Theory, IEEE Transactions on*, vol. 53, pp. 3573 --3585, oct. 2007.

[82] B. Winkowski, ‘‘Skyhook introduces always-on location with unmatched power management for persistent location,’’ July 2012. `http://www.skyhookwireless.com/press/skyhooksdk4_6.php`.

[83] M. Ocaña, L. Bergasa, M. Sotelo, J. Nuevo, and R. Flores, ‘‘Indoor robot localization system using Wi-Fi signal measure and minimizing calibration effort,’’ in *IEEE ISIE*, pp. 20--23, 2005.

[84] B. W. Carroll and D. A. Ostlie, *An introduction to modern astrophysics*. Reading, Mass: Addison-Wesley Pub, 1996.

Appendix A

Calculation of the Wi-Fi Fading Effect Distances

As discussed in Section 3.2, the fading effect causes the power of a radio signal to change drastically when receiver displacements are on the order of half the radio signal wavelength [83]. The frequency of IEEE 802.11b/g radio is 2.4GHz, and the calculation of its wavelength is trivial:

$$\lambda = \frac{v}{f} \tag{A.1}$$

where λ is the wavelength, v is the velocity of the waves, and f is the frequency. Of course $f = c$, which is the speed of light. Using (A.1) we can calculate the 802.11b/g wavelength:

$$\begin{aligned}
\lambda &= \frac{v}{f} \\
&= \frac{c}{f} \\
&= \frac{299792458\,\mathrm{m/\,s}}{2.4\,\mathrm{GHz}} \\
&= \frac{299792458\,\mathrm{m\ s^{-1}}}{2.4 \times 10^{9}\,\mathrm{s^{-1}}} \\
&= 0.125\,\mathrm{m} \\
&= 12.5\,\mathrm{cm}
\end{aligned} \tag{A.2}$$

With a wavelength of 12.5 cm, we can then expect radio signal level changes due to fading at distances of 6.25 cm.

Appendix B

Radiant Flux of Betelgeuse

As a comparison of the received radio energy of a strong Wi-Fi source, we looked at the light energy received from the star Betelgeuse. Called *radiant flux*, this is the total amount of light energy of all wavelengths received from the source [84]. For the purposes of this comparison, we do not take into account any losses by the atmosphere.

We begin with the basic flux ratio equation from *An Introduction to Astrophysics* [84]:

$$\frac{F_2}{F_1} = 100^{(m_1-m_2)/5} \tag{B.1}$$

We will define star 1 to be the Sun, and star 2 to be Betelgeuse. For the Sun, we then define F_1 to be the total radiant flux as received at the Earth (the *solar constant*[1]), and m_1 to be the apparent magnitude. For Betelgeuse, we similarly define m_2 to be the apparent magnitude, and we solve for F_2 to calculate the total radiant flux as received at the Earth.

$$F_1 = 1.360 \times 10^3 \text{ W m}^{-2}, \quad m_1 = -26.81, \quad m_2 = 0.58$$

$$F_2 = \frac{100^{(m_1-m_2)/5}}{F_1} \tag{B.2}$$

[1]Note that this is a conversion of the solar constant $F_1 = 1.360 \times 10^6$ erg s^{-1} cm^{-2}

We can then solve for the total radiant flux of Betelgeuse received at the Earth:

$$
\begin{aligned}
F_2 &= F_1 \cdot 100^{(m_1-m_2)/5} \\
&= (1.360 \times 10^3) \cdot (100^{(0.58+26.81)/5}) \text{ W m}^{-2} \\
&= 1.505 \times 10^{-8} \text{ W m}^{-2} \\
&= 15.05\,\mu\text{W m}^{-2}
\end{aligned}
$$

Therefore, if we ignore any effects of the Earth's atmosphere, we see that the total amount of light energy per square metre reaching the Earth from Betelgeuse ($15.05\,\mu$W m^{-2}) is greater than the total radio frequency energy received by a Wi-Fi device when in close proximity to a home wireless router ($\approx 10\,\mu$W).

Appendix C

Maps

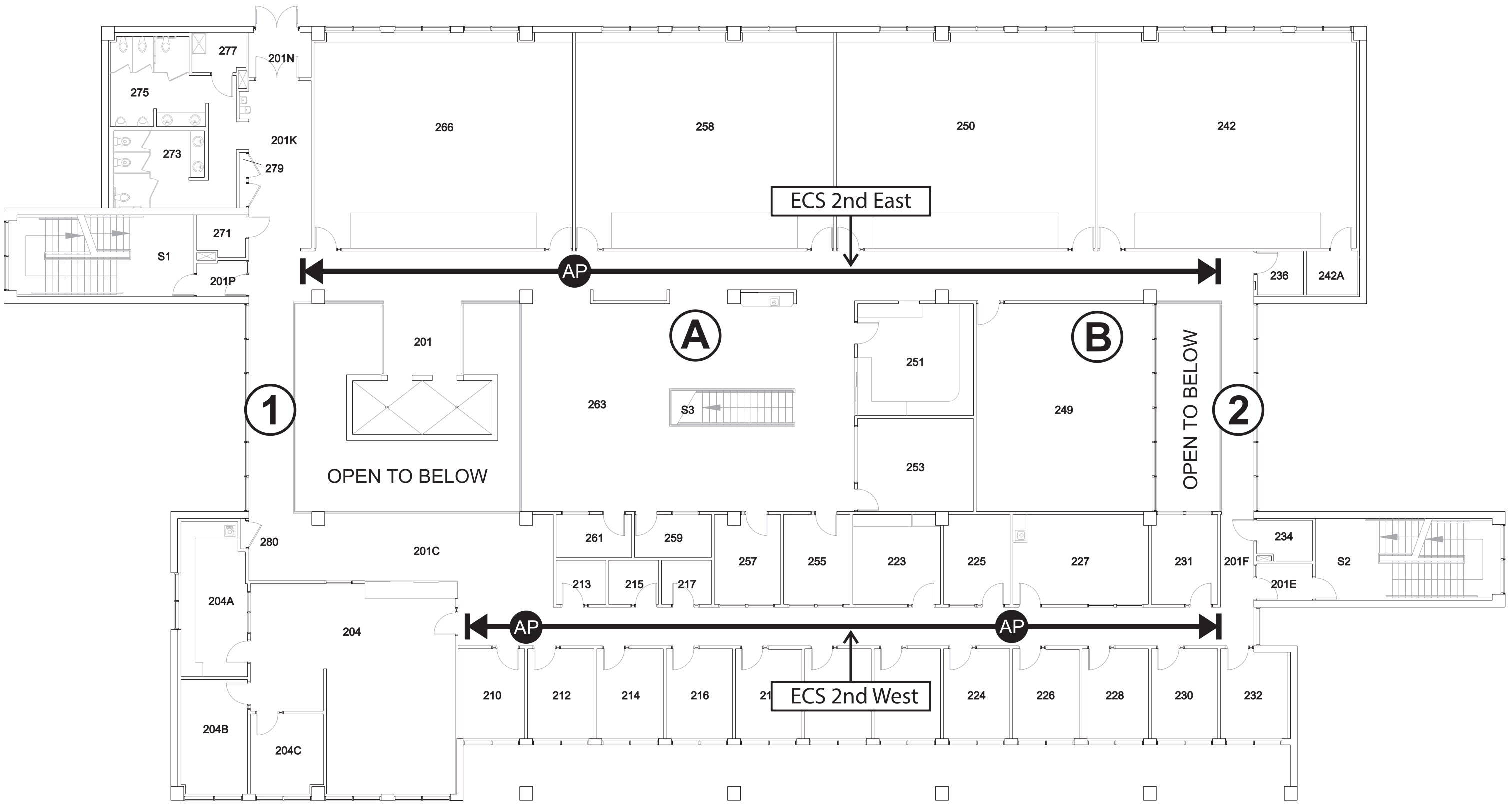


Figure C.1 – A map of the second floor of the Engineering and Computer Science Building (ECS), showing the data collection walks and points of interest. See Section 5.8.2.

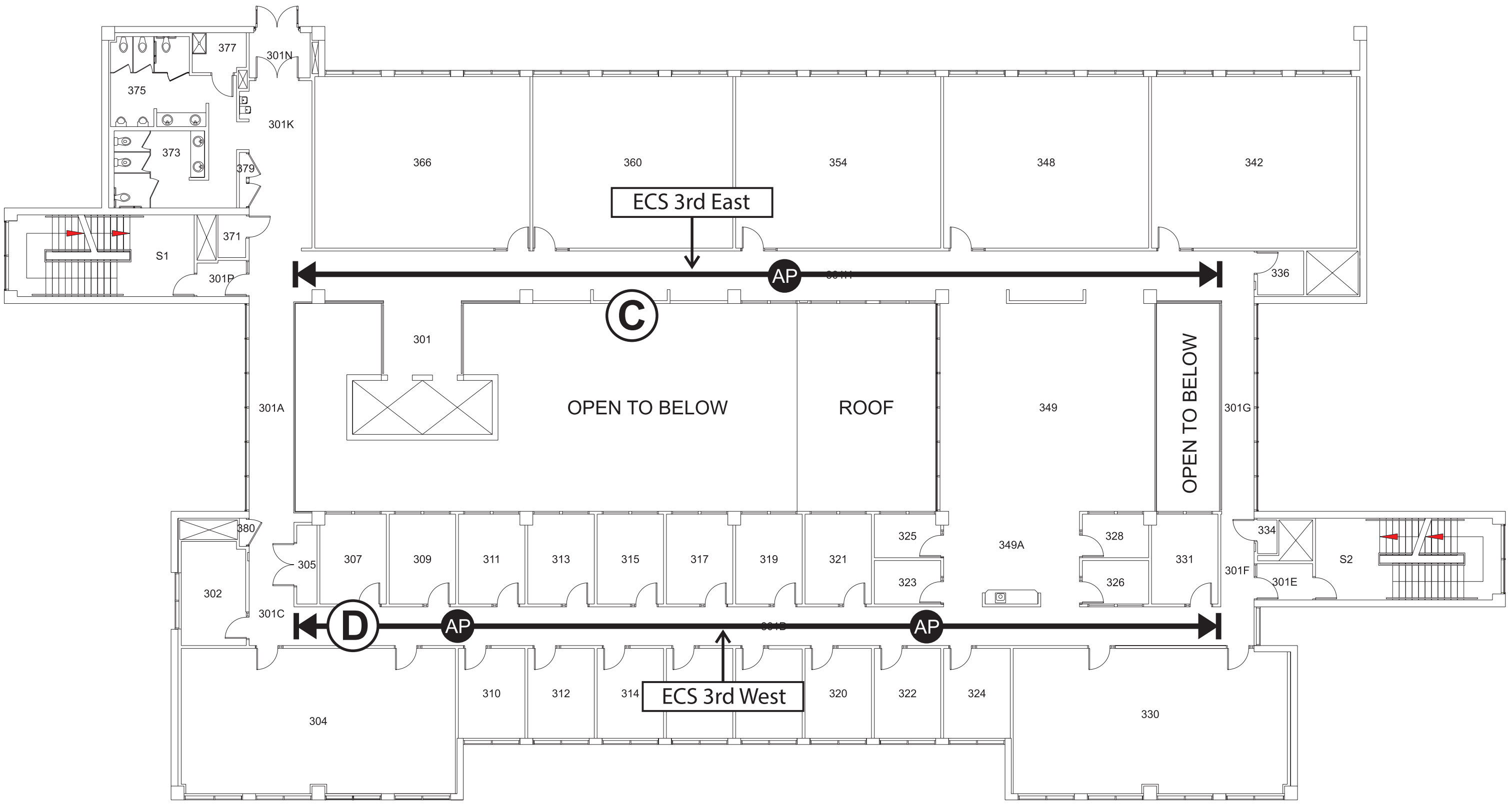


Figure C.2 – A map of the third floor of the Engineering and Computer Science Building (ECS), showing the data collection walks and points of interest. See Section 5.8.2.

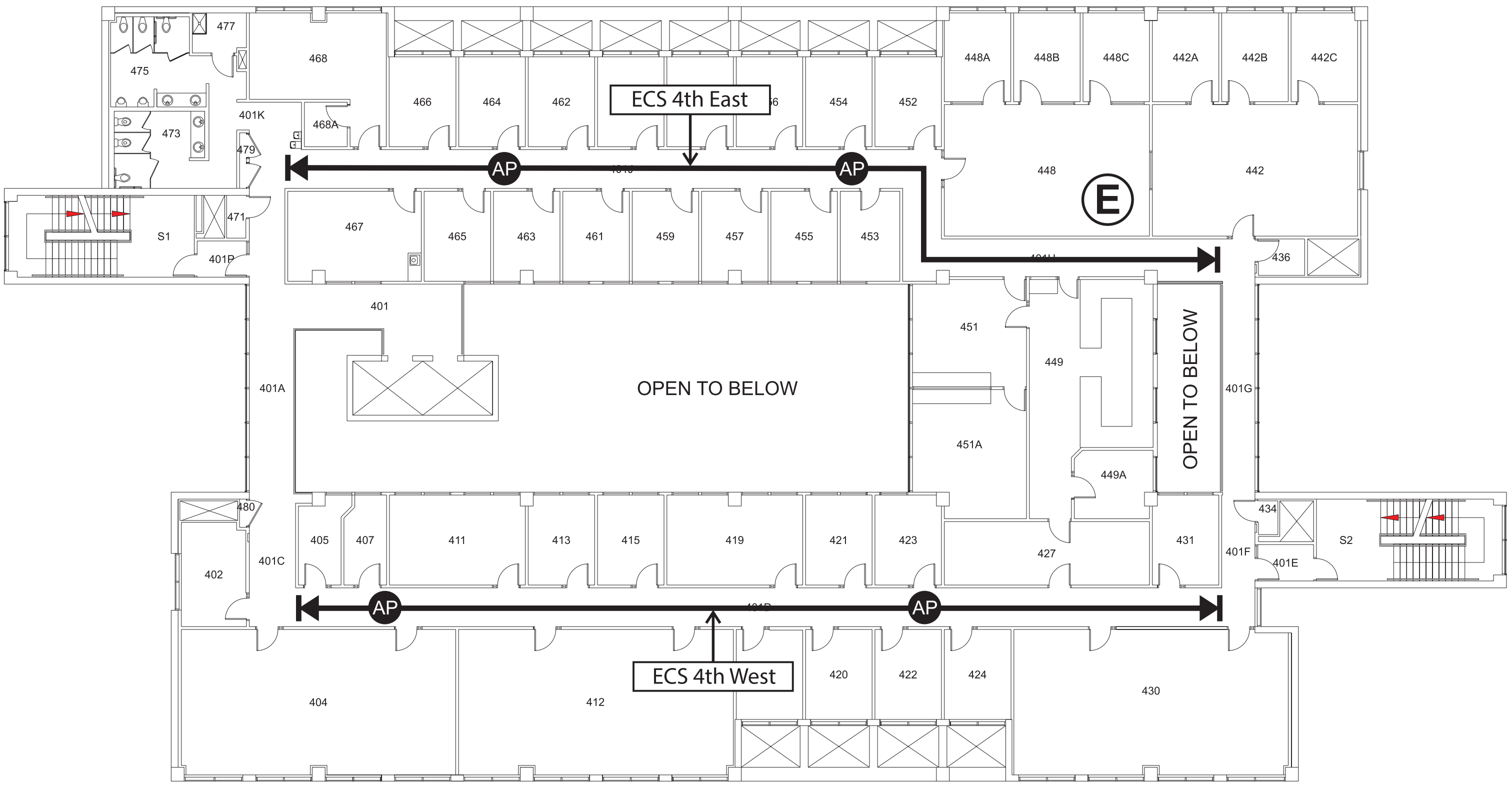


Figure C.3 – A map of the fourth floor of the Engineering and Computer Science Building (ECS), showing the data collection walks and points of interest. See Section 5.8.2.

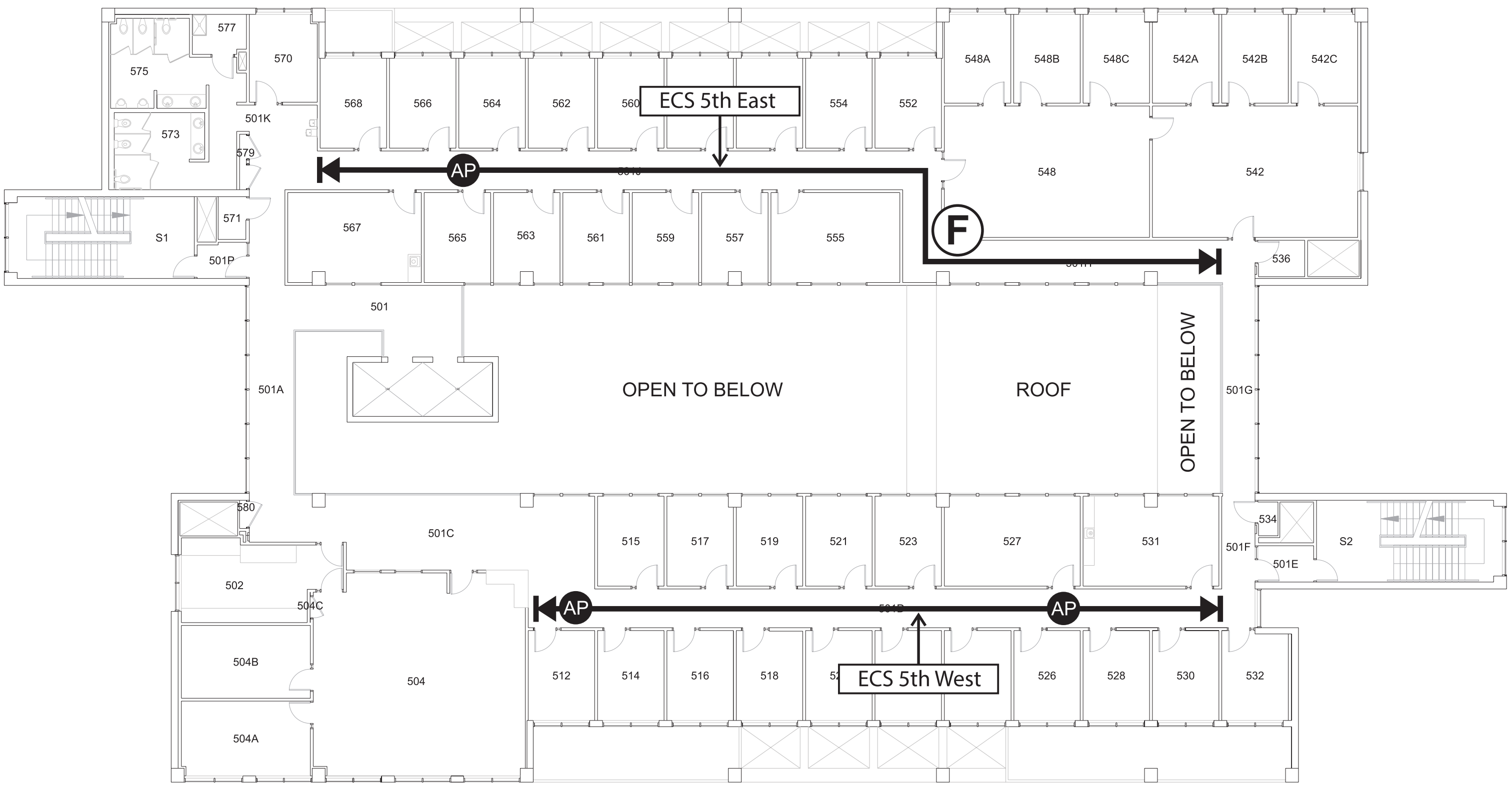


Figure C.4 – A map of the fifth floor of the Engineering and Computer Science Building (ECS), showing the data collection walks and points of interest. See Section 5.8.2.

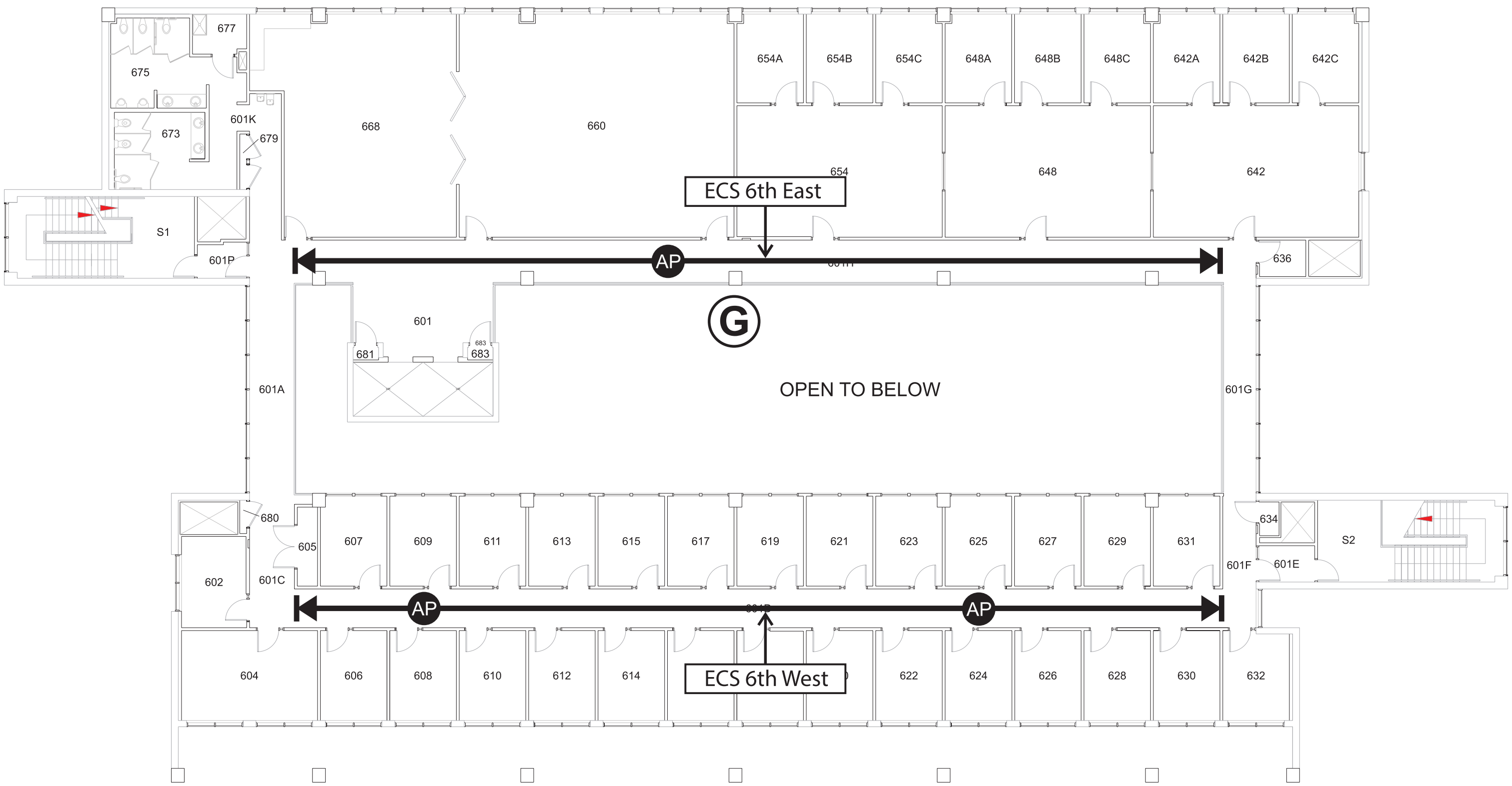


Figure C.5 – A map of the sixth floor of the Engineering and Computer Science Building (ECS), showing the data collection walks and points of interest. See Section 5.8.2.

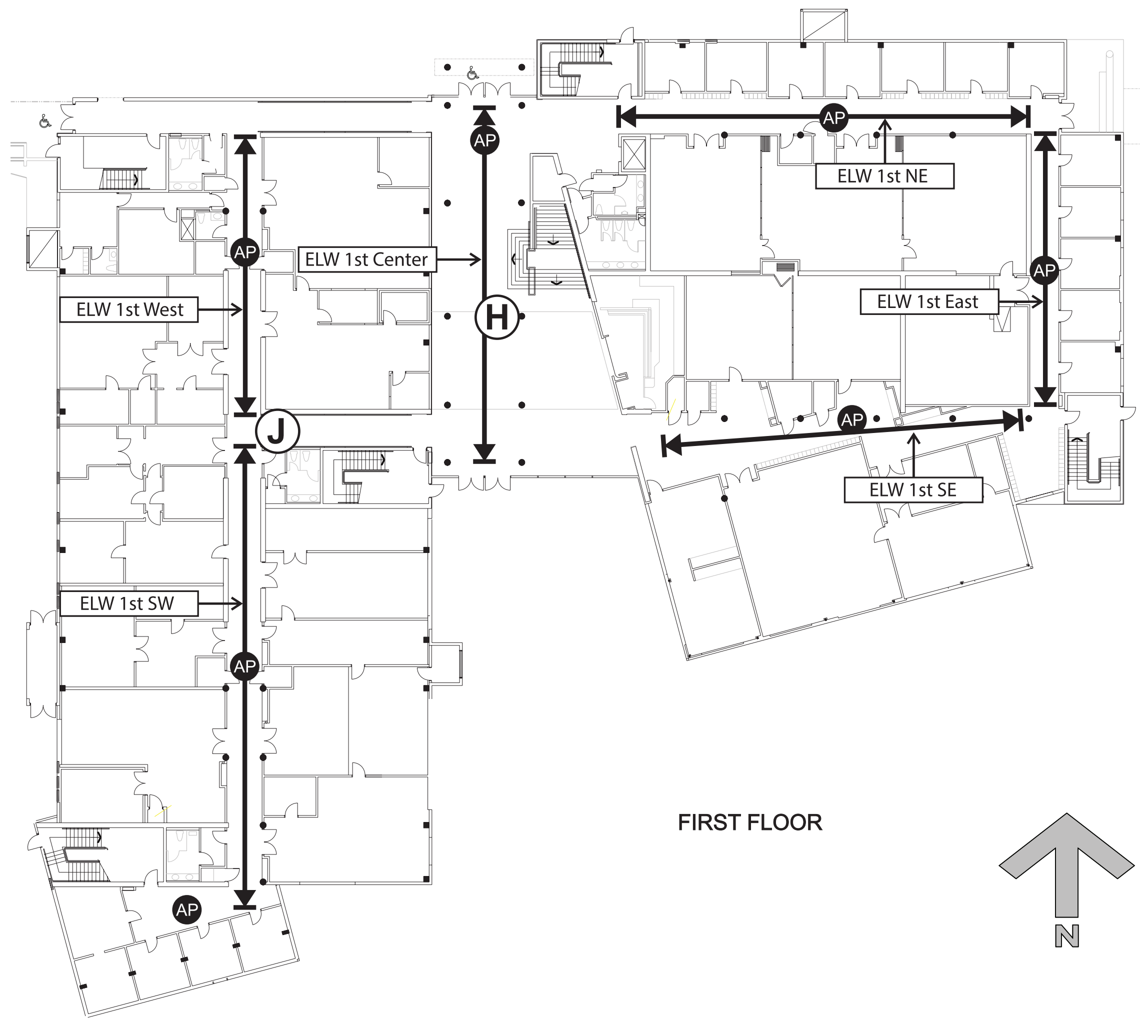


Figure C.6 – A map of the first floor of the Engineering Lab Wing (ELW), showing the data collection walks and points of interest. See Section 5.8.2.

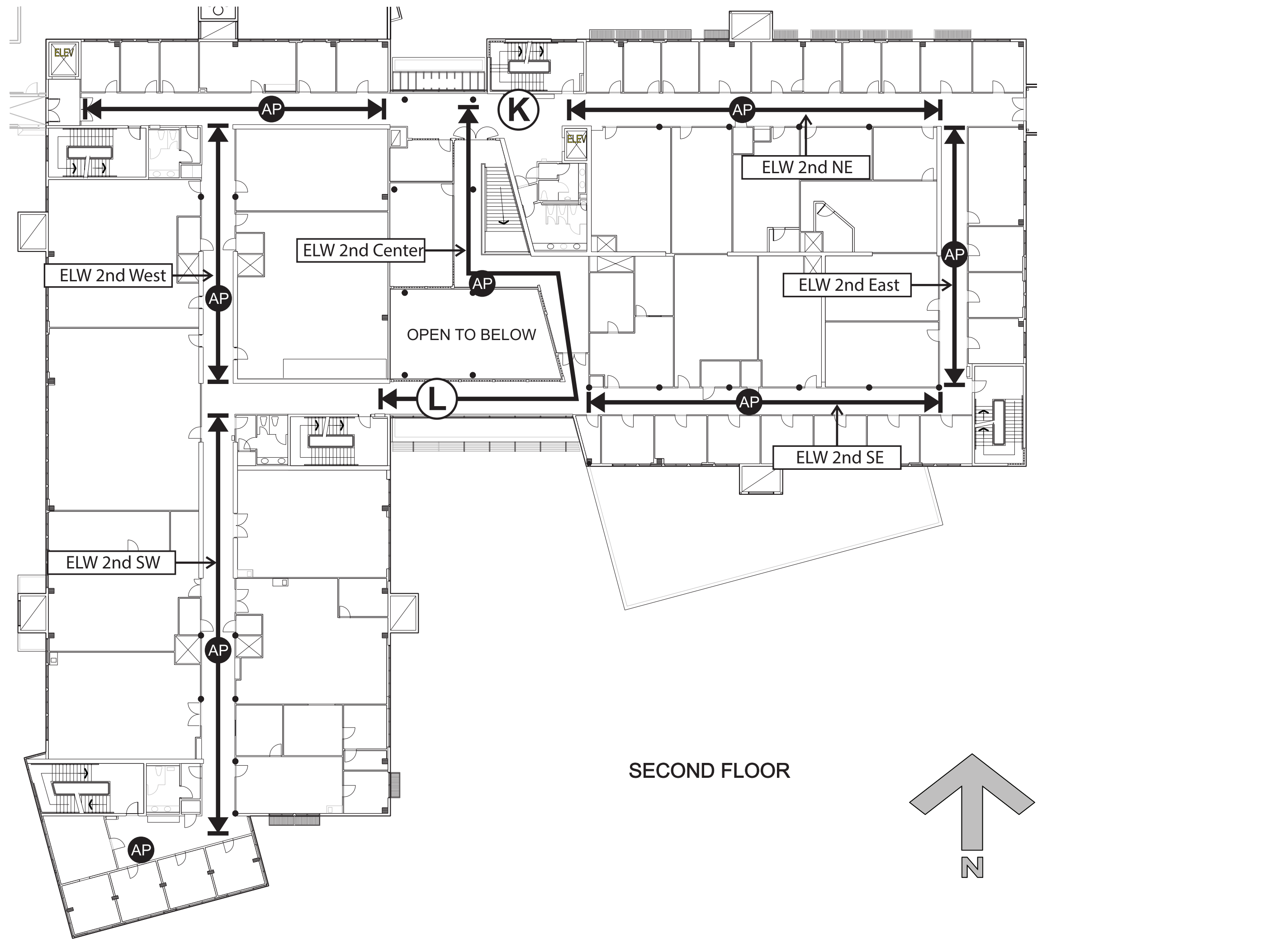


Figure C.7 – A map of the second floor of the Engineering Lab Wing (ELW), showing the data collection walks and points of interest. See Section 5.8.2.

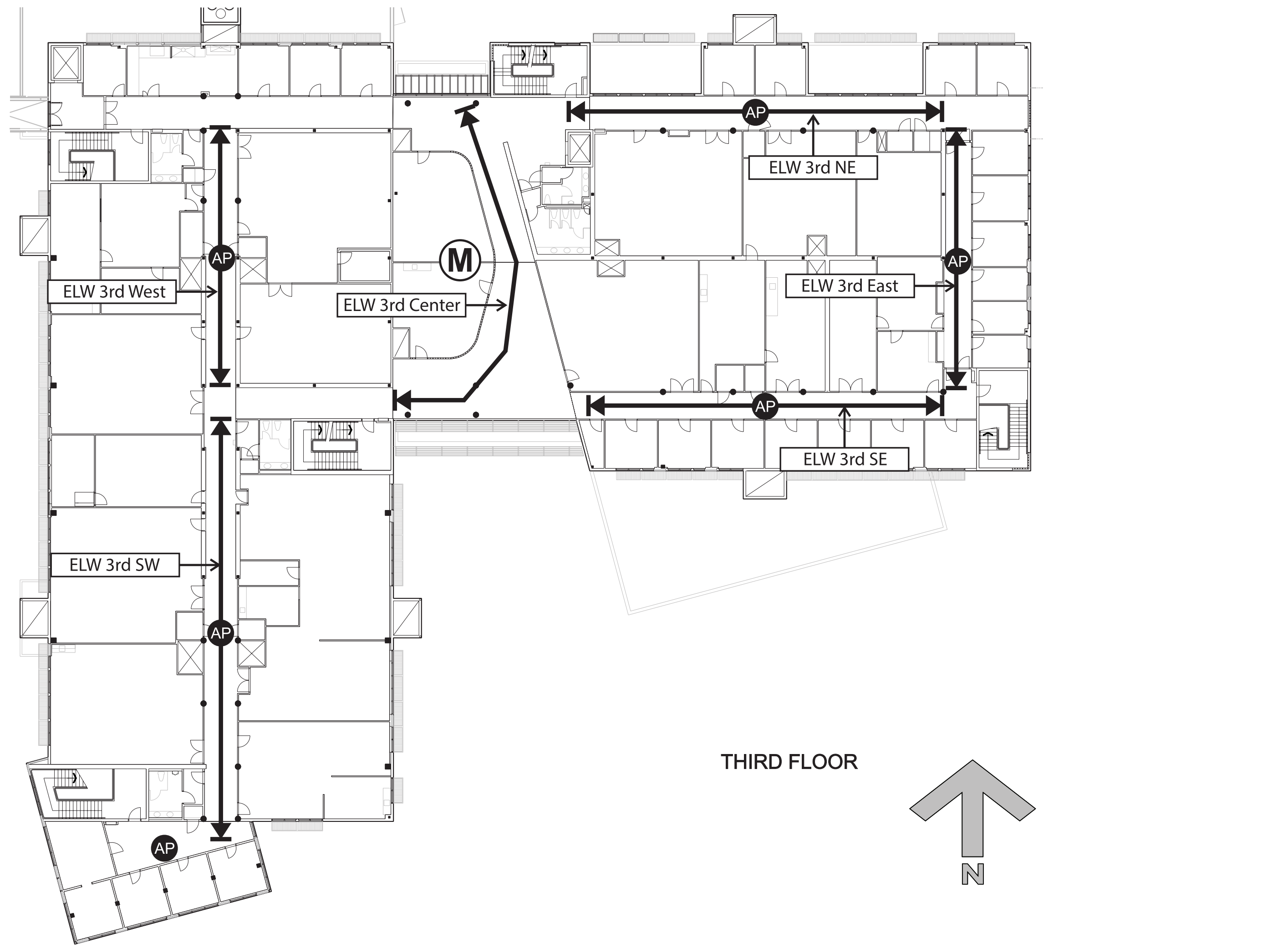


Figure C.8 – A map of the third floor of the Engineering Lab Wing (ELW), showing the data collection walks and points of interest. See Section 5.8.2.

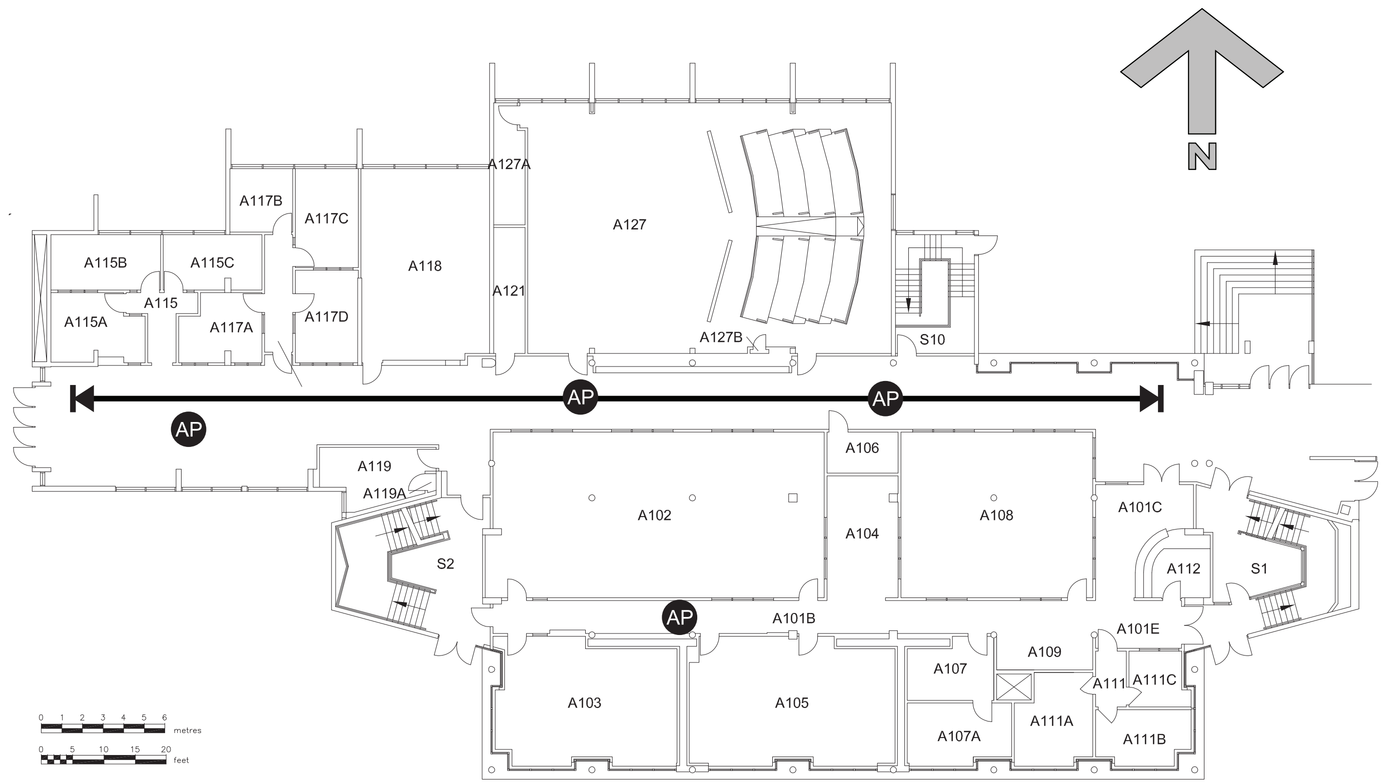


Figure C.9 – A map of the first floor of the Clearihue building, A-Wing (CLE-A), showing the data collection walks. See Section 5.8.2.

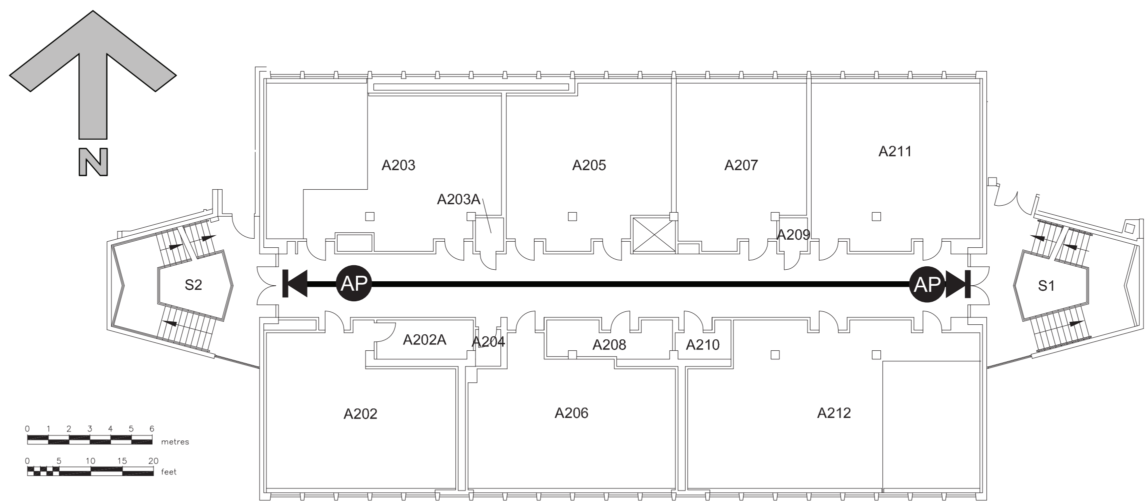


Figure C.10 – A map of the second floor of the Clearihue building, A-Wing (CLE-A), showing the data collection walks. See Section 5.8.2.

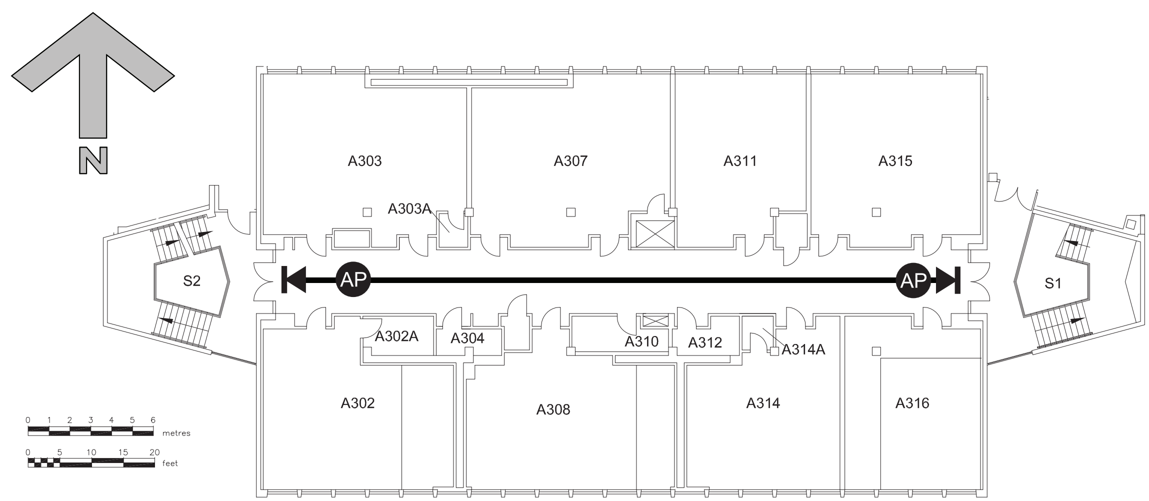


Figure C.11 – A map of the third floor of the Clearihue building, A-Wing (CLE-A), showing the data collection walks. See Section 5.8.2.