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Exploring Hybrid Indoor Positioning Systems

Nathan Paul Lemieux

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Nathan Paul Lemieux

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Abstract

Ubiquitous applications collect contextual information, process it, and then use this derived data to deliver valuable services. Location is one these contexts, and has been significant in providing navigation and guidance services for GPS devices. However, GPS is designed for outdoor use and is not precise enough, in terms of location accuracy for indoor applications.

There are many indoor location systems that rely on a single technology, but these systems are either inaccurate in uncontrolled environments or require the installation of a dedicated infrastructure. This has led to the investigation of hybrid systems. This thesis examines the creation of a hybrid indoor positioning system combining different technologies and techniques; Wi-Fi access points and their associated signal strength, image analysis using machine learning to create location specific scene classifiers, and an altimeter sensor to determine the user's current floor. This system is meant to provide indoor positioning data to location-aware applications.

Keywords: indoor location sensing, hybrid systems, Wi-Fi signal strength, altimeter

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Chapter 1
Introduction

With the continual developments in mobile computing and explosive growth of cell phone usage [1, 2], there has been an increased interest in determining the location of the user and/or device. A *positioning system* determines the location of an object. The Global Positioning System (GPS) is currently the most popular positioning system available. GPS receivers calculate a location (longitude and latitude) by detecting and reading signals from three or more satellites, using triangulation to determine the location [3, 4]. This technology works in most outdoor areas, but GPS signals barely penetrate buildings preventing GPS receivers from calculating locations due to the absence of line of sight to satellites.

Applications that use the position information are called *location-aware* applications. Examples of location-aware applications can be found in the numerous GPS services that use GPS and stored maps, points of interest and topographical information to help users navigate while driving, hiking, boating, and flying. An *indoor positioning system* determines the location of the user in an indoor environment and allows the user's device to make this information available to location-aware applications. Location-aware applications make use of the user's location as input in order to provide valuable services. Indoor location-aware applications are of interest because most of us spend more than 50 percent of our lives indoors [5], while sleeping, working, watching television and surfing the Internet. Indoor location-aware applications are emerging everywhere [6-10], especially in the retail sector. This is due to an increased demand to provide directions to a specific store, department, or service from a known location or pushing sales information and advertisements out to shoppers that come within range of the store. Other indoor location-aware applications are user specific and enforced by user specific policies, such as determining when a cellular phone should ring or vibrate, forward an incoming call to a location specific number or go directly to voice mail. There are numerous possibilities for indoor location-aware applications. Most indoor location-aware applications require a location accuracy of three to five meters for desirable results. Obtaining a higher accuracy is desirable but has proven to be very difficult in these real-world situations as installation of specialized hardware or tags is required [10-15], making them costly to deploy and maintain. Furthermore, seamless indoor and outdoor operation is essential along with ability to use the system with minimal disruption or distraction.

There have been many indoor positioning systems developed. Each system has its own benefits and shortfalls. Many indoor location systems require specialized infrastructure to support the transmission or reception of ultrasonic, infrared, and Bluetooth signals [10, 13, 16-18]. Systems with extensive infrastructure and tags, despite having relatively inexpensive hardware, primarily focus on optimizing location accuracy rather than large scale deployment. The recurrent concern associated with these systems is the deployment and maintenance cost, as this hardware is typically not found in indoor environments. This is why there is a good deal of research in indoor positioning systems using Wi-Fi signals [19-25]. Using an already available wireless infrastructure can significantly reduce system installation and deployment cost.

Wi-Fi indoor positioning systems normally compare the received signal strength indicator (RSSI) values from access points, referred to as a *fingerprint,* at a given (presumed to be unknown) location, to fingerprints for known locations of landmarks or preselected locations. The collection and analysis of fingerprints at landmarks and preselected locations, is called *radio mapping*, and usually is accomplished off-line. The off-line analysis of Wi-Fi signal strengths, and the collection of fingerprints for these systems is time consuming, but these systems have been able to provide acceptable location positioning accuracy. However, they can fail to adapt to normal signal fluctuations and access point changes which occasionally make it difficult to correctly distinguish locations. These limitations have led to more practical systems [26-28], which provide lower location positioning accuracy, but will reduce the time it takes to gather location fingerprint information. This is done by either combining the off-line and on-line phases, or providing the means for community effort to generate a list of known access points and their absolute location.

1.1 Thesis Focus

Relying on only Wi-Fi signal fingerprints is complicated because signal fluctuations make it difficult to distinguish locations within close proximity and on different floors. Using a single technology to generate location information has been shown to be possible with good results in optimal indoor test environments. However, given the wide range of strengths and weaknesses that different navigation technologies have in different circumstances, one promising approach is the development of a hybrid system. This system would combine a set of complementary technologies in ways that the advantage of one technology or technique compensates for the drawback of the other to provide superior performance. Weaknesses of a single technology usually limit its desirability for large scale indoor deployment. Infrared and ultrasound have line-of-sight requirements, Bluetooth and RFID require high distribution of tags throughout the environment, and all require installation of specialized hardware. Combining two or more location sensing technologies into one indoor positioning system will most likely be more accurate and reliable in real-world conditions. Evidence of this can be seen in some of the previous work.

For example, one of the first systems to suggest using multiple technologies to infer indoor location was the Easy Living project from Microsoft [29], which proposed using different technologies such as; GPS, infrared or ultrasonic badges, and stereo vision for object detection to give location estimations at different levels. One technology would be able to locate a user at a structure level (i.e. specific building), another could locate the user at a room level while the third technology would provide location estimations that were fine enough to interact with specific objects in the environment. Other hybrid systems include Place Lab [26], which relies on several signalling technologies and techniques. Geta Sandals [30] investigated the amalgamation of two step detection techniques to minimize drift error on the inertia sensors. Another [31] considers the use of two systems, an Inertia Navigation System (INS) and infrared tracking system. The use of a stereo vision tracking system and an INS has also been examined [32]. Shortfalls of existing hybrid systems range from reliance on only signalling techniques and technologies, lack of actual positioning accuracy results, installation/deployment costs, and scalability.

This thesis investigates the creation of a hybrid system. Due to the extensive implementation of Wi-Fi in indoor environments, the core of the system relies on this technology. One of the technologies that will be combined with the use of Wi-Fi is an altimeter sensor. An altimeter measures atmospheric pressure, to determine the floor the user is on. The other is a scene classifier, using image classification techniques, to determine what type of scene the user is in. The choice of these technologies will be explained later in the thesis. It is expected that these technologies, when combined, reduce the impact of signal fluctuations in the Wi-Fi system and allow the system to work effectively in multi-floor environments. All the technologies are inexpensive and predominantly off-the-shelf. This thesis demonstrates the system's ability in uncontrolled environments and shows that as other technologies are combined, there is an increase in both location accuracy and precision.

1.2 Overview

This thesis is organized as follows: Chapter 2 discusses background information and related work on this topic area. Chapter 3 discusses and describes the design of the proposed hybrid system. Chapter 4 presents observations and algorithms. Chapter 5 discusses the details of the implementation of the hybrid system into a proof of concept prototype. Chapter 6 details the experiments and results of the system. Finally, chapter 7 presents the conclusions, the contributions made, and the future work that could be done.

Chapter 2

Background and Related Work

This chapter focuses on introducing common indoor location technologies and techniques. The chapter introduces indoor positioning systems that rely on Wi-Fi signals using *fingerprints*. A fingerprint is associated with a known location and can consist of one or more identifying characteristics that can be used to infer this location. The received signal strength indicator (RSSI) from access points is most commonly used.

2.1 Positioning Properties

This section outlines the different positioning properties of indoor location systems.

Absolute vs. Relative Location: Absolute location systems use a shared reference grid for all located objects (i.e. GPS gives latitude, longitude and altitude for reporting location of a user). Relative location systems have their own frame of reference (e.g., in room 240 in Middlesex College).

Centralized vs. Localized Positioning: Centralized positioning systems calculate and/or maintain the position of the user in one central place. *"Maintaining location information for all users in one central place has the advantage that the users have to trust only one entity, but the disadvantage that everyone is vulnerable to this entity."* [33]

Localized location systems calculate positioning estimations on the user's device. *"This gives the user control over when their location is disclosed. Unfortunately, most current location devices are not as passive as we would like. For example, 802.11 broadcast its existence to the infrastructure regularly."* [34]

2.2 System Performance Measurements

This section describes some of the key indoor positioning system performance measurements used to evaluate systems.

Accuracy and Precision: A key metric for evaluating a location system is the accuracy. This is defined by how much the estimated position is deviated from the true position. The accuracy is usually denoted by an accuracy value and a precision value (e.g. 15cm accuracy over 95% of the time). The precision indicates the percentage of time the location system provides the given accuracy. The accuracy of a positioning system is often used to determine whether the chosen system is applicable for a specific application. Table 2-1 lists several location-aware applications and their required location accuracy. The most interesting location-based applications require approximately one meter location accuracy which is about the area within arms reach in any direction.

Potential Applications	***Location Accuracy Requirements (meters)***
Tool Positioning	0.01
Blind / Robot Guidance	0.01 – 0.5
Goods and Item tracking	0.5 – 1
Emergency Services	1
In-building Pedestrian Route Guidance	1 – 1.5
Location-based services	1 – 3
Warnings	1 – 5
Outdoor Route Guidance	5 –10
Advertising	1 – 100

Table 2-1: Location accuracy requirements for some location-aware applications

Scalability and Adaptability: Indoor location systems must be able adapt to changes (i.e. failed hardware or network topology) and expand to other buildings without affecting what is already currently implemented. Ideally, a location system should work seamlessly both indoors and outdoors.

Wear-ability: Personal navigation systems must be easy to wear and must not be a distraction to the user, such as always looking down at a screen or carrying a device.

Likewise, users should not have to wear special shoes, have restricting communication cables, or clip on numerous sensors to their body. Ideally users should be hands-free by displaying information on a Head-Up Display (HUD).

Environment: The performance of most location systems positioning estimates are dependent on the environment in which the location system is deployed. Factors such as building materials, wall density, location of tags, and the positioning device's location relative to the user's body can greatly affect the performance.

Responsiveness / Latency: Location systems should provide position estimates in real-time. Having a centralized server calculate position estimates of the user takes time for wireless communication. Likewise, having the device calculate position estimates can take just as long, because most mobile devices lack the processing power needed for some algorithms.

Cost / Affordability: There are many costs associated with location systems including both direct cost (i.e. hardware) and indirect cost (i.e. disruption during installation). These costs should be kept to a minimum when evaluating or designing location systems. The different costs include the following:

- *Infrastructure (hardware) costs* – servers, access points (antennas, base stations), tags, sensors
- *Installation costs* – cabling, labour, renovations
- *Maintenance* – mean time between failures, re-calibration, repair time, spare parts, batteries, updating databases, re-positioning of tags
- *Setup* – tagging the environment, creating information databases, fingerprinting

Power: All mobile devices, sensors and tags require power. Low power consumption and energy efficiency of location system should be a goal, as it is tedious to replace or recharge batteries often.

2.3 Indoor Positioning systems

Research has involved using a wide range of technologies and techniques. Described in the following sections are some of the numerous location techniques that have been attempted to provide accurate indoor positioning. Techniques can be classified as follows: Wi-Fi signal-based, image-based and dead reckoning electronic sensors.

There are many other indoor positioning systems that rely on technologies such as Ultrasound [13,16, 35], Infrared [10, 31, 26], Bluetooth [12, 17, 37, 38], and Radio Frequency Identification (RFID) [11, 15, 18, 39, 40] that are not considered here, either because of extensive infrastructure costs, privacy issues, specialized hardware and/or tags, or poor indoor performance.

2.4 Wi-Fi Systems

Wi-Fi technology and techniques are the most commonly used indoor positioning systems. It is possible to have different signal strength measurements in the same location, on different days. The use of already available wireless infrastructure can significantly reduce system installation and deployment cost. Wi-Fi operates in the 2.4 GHz band and has become a popular choice for wireless communication. A typical bit rate depends on the standard being used (11 Mbps for the *b* standard and 54 Mbps for the *g* standard), and has a signal range of 50-100 meters. Wi-Fi networks have been deployed in many commercial, educational, and public buildings. Lately, even entire cities have setup Wi-Fi hotspot networks for general public usage. Wi-Fi localization has been attempted using several signalling techniques. However, radio signals have proven to be unreliable, as external factors such as obstructions, light, and activity affect its performance in terms of location accuracy [41, 42].

One technique models the propagation of radio signals [20, 23, 43]. Wi-Fi fingerprint comparison is based on a calculation of the distance (e.g., Euclidean distance, trilateration) from the fingerprint measured by the user's device to a fingerprint of a preselected location that is stored in a database. Essentially, this technique makes use of mathematical models of signal propagation. Most of the models developed assume idealized conditions that are rarely seen in practice.

Another technique uses empirical data [14, 19, 21, 25] to approximate location. Some of the systems developed use an off-line phase [14, 19] of measuring signal strengths at sampled locations to create a radio map. The radio map stores the distribution of signal strengths received from each access point for each sampled location. These systems have reported good results. However, they are costly in the time it takes to develop the radio map, and are susceptible to changes in access points.

Recently, other location positioning systems [26-28, 34, 44] using empirical data were developed. These systems do not require limited initial calibration, and changes in access points do not have the same maintenance costs associated with many of the systems mentioned earlier in this section. PlaceLab [34] is capable of periodically downloading an updated list of access points (e.g. latitude, longitude), which is provided by user groups collecting this information. WLoactor [28] is capable of updating finger-print information at known location in real-time, avoiding the recreation of radio maps from scratch.

In all systems, the comparison of fingerprints is challenging due to normal signal fluctuations. These fluctuations are caused by a number of factors, including signal propagation by reflection, interference of multiple signals from multiple points, etc. If two locations are physically close to each other, then there are most likely multiple access points with similar signal strengths found in the fingerprints. One example of these types of locations is found in long corridors of buildings. An access point located in a corridor does not have its signal obstructed and therefore the signal strength is substantially stronger along the entire corridor. The impact is that fingerprints along the corridor between 5 to 15 metres apart are difficult to distinguish since there is relatively little variation in the received signal as the result of no obstruction. The rest of this section describes the techniques that have been used in more detail.

2.4.1 Wi-Fi Techniques

Some of the more common Wi-Fi techniques are described in the following section.

2.4.1.1 Cell of Origin Signalling Technique (CoO)

User location is determined by first monitoring signal strengths of access points that can be detected at the current location. The AP with the highest RSSI (Received Signal Strength Indicator) is used to determine the user's location. A database with previously collected AP information is queried, using this data to obtain a relative location of the user (e.g. Middlesex College – Second Floor).

Location accuracy may not be sufficient for some applications. It is approximately 25 to 50 meters depending on the density of AP deployment and multiple secondary factors (e.g. type of building, time of day, user orientation to AP, number of training points). An example can be seen in Figure 2-1.

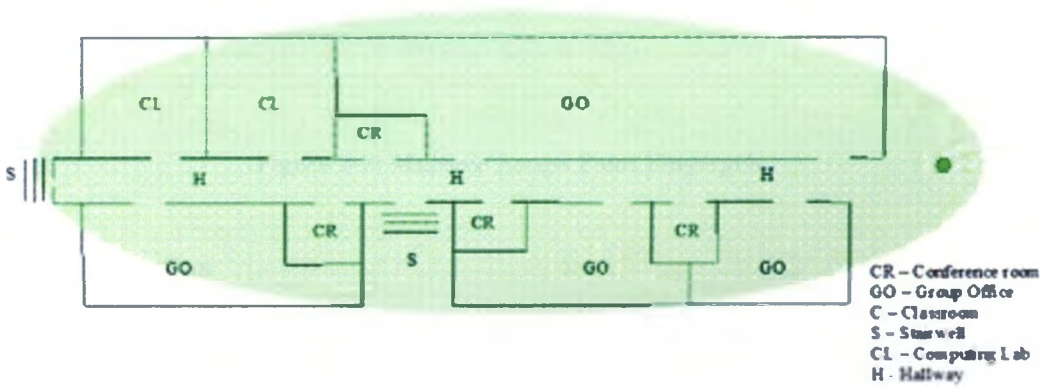


Figure 2-1: Cell of Origin

2.4.1.2 Multiple AP Fingerprinting Signalling Technique

This approach also determines user location by first monitoring signal strengths of APs that can be detected at the current location. However, instead of using only one AP, multiple APs are used. The fingerprint of the user's current location is compared with fingerprints of pre-determined locations (landmarks that are stored in a database). This comparison can be used to give a relative location of the user (e.g. Middlesex College – Conference Room 236 – Second Floor).

Location accuracy is usually finer grained than CoO. It is around five to ten meters depending on the density of AP deployment. Using more APs can result in better location accuracy. An example can be seen in Figure 2-2. The use of multiple APs involves more complex algorithms, and advanced database queries, to determine similarities between received and stored fingerprints than those needed for a single AP. A summary of some of these algorithms was described at the beginning of Section 2.4.

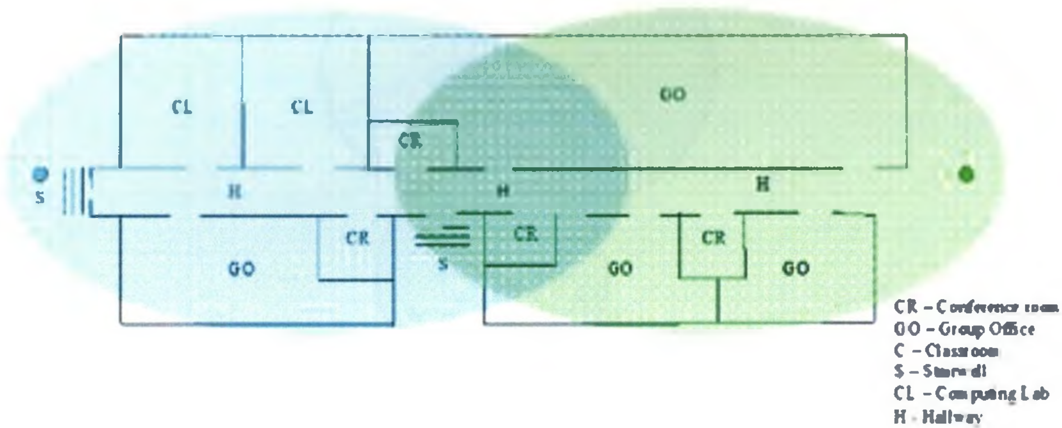


Figure 2-2: Multiple Access Point Fingerprint

2.4.1.3 Trilateration

This method determines the relative position of a user using the geometry of triangles in a similar fashion as triangulation. Unlike triangulation, which uses angle measurements (together with at least one known distance) to calculate the subject's location, trilateration [45, 46] uses the known locations of two or more reference points, and the measured distance between the user and each reference point. Distance can be calculated using signal level measurements, or Time-of-Flight (TOF) measurements, from each reference point. To accurately and uniquely determine the relative location of a point on a 2D plane using trilateration alone, generally at least three reference points are needed. An example of trilateration is found in Figure 2-3. Reference points P1, P2 and P3 are known. Using only two reference points, P1 and P2, measuring r1 and r2 narrows the location of the user to A or B. Using the third reference point P3, the third measurement r3 provides the user's location at B. This technique suffers from severe multi-path propagation (i.e., radio signals reaching the receiving antenna by two or more paths), reflection (i.e., radio signals bouncing off objects and walls before reaching the receiving antenna), and shadow fading (i.e., variation of radio signals characteristics resulting from motion of the receiving antenna).

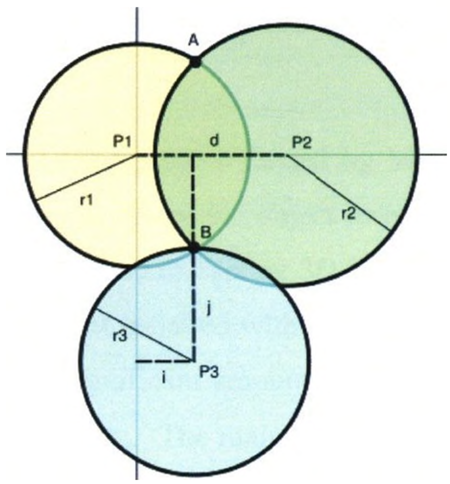


Figure 2-3: Trilateration Example

2.5 Image Analysis Systems

Vision location systems [32, 33, 47-50] constantly struggle with positioning accuracy because of increased scene complexity caused by occlusions and analogous features. An *occlusion* occurs when a closer object obstructs or masks an object further away from the viewpoint. Depending on the deployed environment, increased scene complexity usually leads to more false positive results. Another complication with vision location systems is the processing power required by scene analysis algorithms, and the requirement of installing cameras in public areas can limit the large scale deployment of vision location systems.

Indoor localization using camera phones [33]: This work demonstrated the feasibility of determining a user's location based on images captured from a Smartphone camera. A database of images was created. Common image comparison algorithms (i.e. colour histograms, wavelets, and shape matching) were used to explore the similarity between the images captured and images stored in the database. Three different methods for location determination were compared. Room-level accuracy was achieved 80% of the time. Uploading low-resolution images saved time, and reduced energy consumption by the phone. The drawback was the extra latency of sending images and receiving location updates on the phone, which takes a couple of seconds, on top of the location computation.

Easy Living [29]: The Easy Living project funded by Microsoft was one the first attempts at using computer vision to determine object location. Easy Living uses a high performance stereo vision camera used to capture 3D images. The tests were carried out in a home living room environment installed with three cameras. The positioning accuracy was variable and required significant amounts of processing power to analyze the frames captured by the stereo camera. The main shortfalls of this system are the cost of the infrastructure and processing power requirements.

The rest of this section briefly describes some of the vision techniques used.

2.5.1 Image Analysis Techniques (Scene Analysis)

Scene analysis involves examining a view from a particular vantage point to draw conclusions about the observer's location. The scene itself can be represented by visual images, such as frames captured by mounted surveillance video cameras or camera phones.

The majority of research in image comparison techniques for indoor positioning has been in the area of optical tracking. Optical tracking typically uses multiple two-dimensional imaging sensors (stereo cameras) to detect *active* infrared-emitting or *passive* retro-reflective markers affixed to some interaction device. Based on the information received from multiple cameras, the system is able to calculate the location of every marker through geometric triangulation within a pre-defined coordinate system. The purpose is to track moving objects automatically. The key problem of this approach is to make a distinction between usable features and unusable features from the input sequence of images in a reasonable amount of time. For example, a monitor in an image can be a usable feature for positioning someone in a personal office or computing lab. A less usable feature is a doorway or a person, as these features can be found everywhere (in hallways, classrooms, personal offices, etc.).

The more distinctive an object is the more relevant it is as a landmark. The integration of landmarks as orientation points should not be overlooked. In route direction, landmarks are more essential than just mentioning street names, since landmarks are easier to remember, usually are seen from a distance, and usually require less information to use.

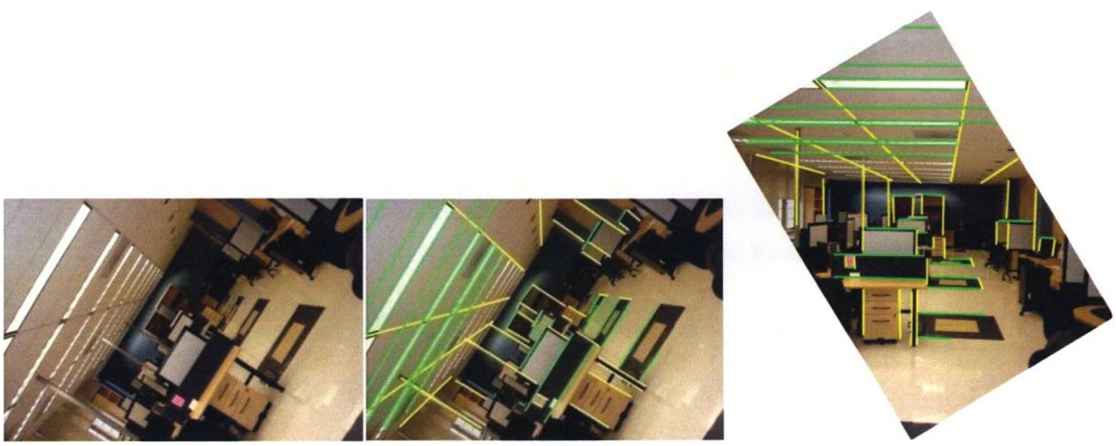
There are many techniques that can be used for feature extraction, the most common are based on colour or greyscale intensities, edges, corners, or optical flow of an image sequence. However for real-time usage, optical flow feature extraction [51] requires a good deal of computing power, which makes it unsuitable for many portable devices. Features are commonly represented as points, blobs, contours, or silhouettes. Once features are extracted, location can be determined using direct image comparison, or machine learning techniques such as, *nearest neighbour* [52] or *linear classifiers* [53, 54] for landmark recognition. Another popular method measures the movement of features from previous images to determine the distance travelled using prior knowledge of the camera's position. Scene analysis not only requires the detection and extraction of features, but also the ability to recognize useful features.

2.5.1.1 Colour or Greyscale Intensities Recognition (Histograms)

Features can be determined by using similar colour values or greyscale intensities of a point or region within the image. A histogram is created, which is a representation of an image derived by counting the *colour space* of each pixel. A colour space is a model describing the way colours can be represented as tuples of numbers. Examples of a colour space are RBG (Red, Blue, Green), CMYK (Cyan, Magenta, Yellow, Black), or HSB (Hue, Saturation, Brightness). This technique is mainly used in situations where speed of processing is a factor in the choice of an algorithm. As an example, some buildings paint different floor levels or departments with different colours for easy and fast recognition. An issue with using colours over greyscale for feature recognition is that a colour can change dramatically when examined in changing lighting conditions. This can lead to feature misclassification.

2.5.1.2 Vertical and Horizontal Edge Recognition (Wavelets)

Vertical and/or horizontal edges can be easily identified in images. These edges can be used to recognize usable features within the image, or the edges can be directly compared to a stored image. This technique is also useful when the image is taken with a mobile camera. Once edges are recognized, the image can be corrected so that the horizontal edges are parallel with each other. This can also be done for vertical edges. This correction transforms the image such that it represents the appearance that it has been taken square on, rather than on an angle.



(a) (b) (c)

Figure 2-4: Vertical and Horizontal Edge Detection Example

Figure 2-4 represents a vertical and horizontal edge recognition example. (a) Image captured, (b) Vertical and horizontal edge detection and (c) Corrected image to appear if it has been taken square on.

2.5.1.3 Object Recognition or Shape Matching

Knowledge of the pixel intensities and edges within an image can lead to simple object recognition for indoor objects. Some indoor objects that can be recognized include windows, doors, desks, chairs, lockers, signs, bookcases, garbage and recycling bins, computer monitors, and/or corners. Indoor localization using camera phones system [33] uses similar techniques to estimate the user's location with room level accuracy. An example of feature extraction can be found in Figure 2-5. The green dots outline some possible objects that can be recognized. This technique is primarily affective for extracting only a single object and requires machine learning.

Figure 2-5: Simple Feature Extraction Example

Earlier attempts at scene analysis had the environment scattered with encoded visual tags [55-59]. These tags are easily manufactured by normal printers. The visual tags can encode an extensive amount of data but must be in direct line-of-sight of the camera. The visual tags within the environment can be used to detect the user's current location or for object identification. Each tag is a bitmap pattern (circular or square) that must be decoded. Similar techniques described above, such as edge detection, and greyscale intensities, are used to decode a tag's information. Guide bars and center points are regions used to orientate the recognition algorithm for the visual tags. Figure 2-6 represents an example of visual tags used in early scene analysis systems. These tags can be scattered throughout the environment. Devices with a tag reader can retrieve information from them, or attach information to them. The image pattern can represent a unique identification or binary code that represents a string.

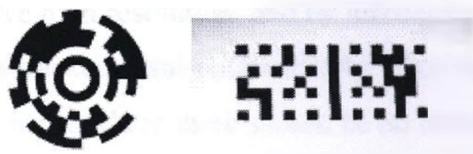


Figure 2-6: Example of Image Tags to Encode Location Information

Problems associated with a scene analysis location system are that images may be taken at different time of the day (i.e., lighting conditions), at different angles (i.e., moving camera) and may have clutter or obstructions that distort the image. These problems can make it difficult to determine usable features and can lead to feature misclassification. Usable features should be un-occluded (i.e., not obstructed) most of the time, somewhat stationary in the environment, and robustly trackable for a large range of camera rotations and translations.

2.5.2 Image Capture Technologies

Scene analysis techniques require images to be captured before examination. This section explores the possible technologies that are capable of capturing this information and their potential performance drawbacks.

Camera Phone: The latest in digital image capturing has been the wide spread adoption of low resolution cameras (1-2 mega pixels) in cellular phones. The latest generation of camera phones provide the ability to even capture video clips. Camera phones allow users to capture images on the move.

Webcam: A web camera is a real-time camera with low resolution (1-2 mega pixels), whose images can be accessed using many different applications. Generally, a digital camera delivers images to a web server, either continuously or at regular intervals. A webcam can be used to capture images in the first (i.e., attached to user while walking) and third person (i.e. stationary in environment) perspectives.

Closed-Circuit Television (CCTV): CCTV is often used for surveillance in areas where there is an increased need for security in both public and private areas. These digital video cameras usually have high resolution, and by linking the control of the cameras to a computer, objects can be tracked semi-automatically. For example, the application can track movement across a scene where there should be no movement, or it can lock onto a single object in a busy environment and follow it. The tracking process can even flow seamlessly between cameras.

Stereo Camera: Stereo cameras are a special type of camera with two or more lenses. This allows the camera to simulate human binocular vision, and therefore gives it the ability to capture 3-D images. Inexpensive stereo cameras consist of two separate still cameras spaced apart with a known distance. These cameras can be used to measure distance between objects and the proximity of objects.

One of the major shortcomings of scene analysis is that when cameras are attached to the walking subject rather than a robot, the shaking and rotations caused by walking can considerably degrade the performance of feature tracking and extraction algorithms.

2.6 Sensor Systems

Inertia Navigation Systems (INS) are currently being used in outdoor environments to aid GPS navigation. An INS uses a computer and motion sensors to continuously track the position, orientation, direction and speed of movement of a moving object. These systems currently focus on improving GPS navigation in outdoor areas where GPS performs poorly. Some INS developers, such as Honeywell [60] have proposed to use their systems indoors, but current results are biased since the tested indoor environments are most favourable for positive results (e.g., single floor buildings or stadiums). This section describes systems that contain accelerometers for the activity recognition of the user, and other sensors not traditionally found in INS systems. Most INS systems are part of hybrid systems and are listed in the next section. Several systems include the following:

PAWS [61]**:** The PAWS system uses an *acceleromete*r for determining possible activities. An accelerometer is a sensor used to measure the direction and magnitude (i.e. amount) of velocity change. The PAWS system proposes using INS for location sensing, but currently relies on measured RF signal strength at known locations, similar to Ekahau [19] RF location sensing technology.

SpotON [36]: SpotON tags are robust location sensing platforms containing other sensors, such as accelerometers and infrared detectors. However, currently only the radio signal strength is used to determine location. SpotON produces an ad-hoc network of SpotON tags that communicate received signal strength information, which is used to calibrate the system. The SpotON system uses an aggregation algorithm for three dimensional location estimations based on radio strength analysis. The accelerometer is used for activity recognition and not for positioning.

LuxTrace - Indoor positioning using building illumination [62]**:** LuxTrace investigates the use of solar cells to collect energy and track light level. It relies on the fingerprinting technique of radiant energy from indoor illumination, which is monitored by the solar cells to derive location estimations. The major shortfall of this approach is the assumption that building light sources are static. However, different types of fluorescent bulbs have different intensities and colours, and aging reduces these intensities over time. Therefore, changing light bulbs will require the system to be recalibrated

Smart Floor [63]: Created by Georgia Tech, the Smart Floor proximity location system uses pressure sensors embedded in the floor to detect footsteps. The system uses this information for position tracking and pedestrian recognition. Since it uses direct physical contact, the user does not have to carry a device or wear a tag. The shortfalls are scalability and cost. To deploy this system each building must be physically altered to install the pressure sensor grid.

2.6.1 Sensor System Techniques

INS determines the user's position by constantly monitoring and analyzing sensor data. Starting at a known location, the INS calculates the user's distance travelled and the user's heading (i.e., the direction the user is facing). The placement of the INS is important. Accelerometers in INS are sensitive to uneven ground and body sway. As a pedestrian walks the accelerometer pitches, rolls and yaws about the axis. The first attempts [64] to calculate the distance walked by a user placed accelerometers in footwear and had long cables from the foot to the measurement module carried elsewhere on the body. This has obvious problems, such as the user wearing special shoes that may not fit properly and cables possibly getting caught in the user's legs while moving. These problems lead to an alternative approach [65] which makes use of walking dynamics and allows INS to be located around the user's waist, inside a backpack or pocket.

2.6.1.1 INS Distanced Travelled Techniques

Determining the distanced travelled using an INS consists of two parts: detection of a step, and estimation of step length. Detecting a step can be determined by measuring the accelerometer's vertical acceleration. Every time a step is detected the length of the step is estimated. There have been different approaches attempted from using fixed step length [64, 66] to determining the user's activity [36, 61] (i.e. walking, running), which can help in developing adaptive step length estimates [65, 67].

There have been other attempts at determining the distance travelled. GETA Sandals [30] used pressure sensors in sandals to detect steps and ultrasonic transmitters and receivers to determine step length. The Visual Odometer [32] uses a pair of stereo cameras and an ego-motion estimation algorithm to calculate distance. Ego-motion is the determination of movement of the camera using the images it captures. Common features in images extracted from the left and right camera are detected and matched. Knowing the relative location and distance between cameras, the position of features relative to the cameras can be calculated. From this information, distance and direction of the user can be estimated from the difference in position of the tracked features in successive frames. Using other information from external sources, such as GPS, step length can be calibrated for different users.

2.6.1.2 INS Heading Estimation

User heading estimations are obtained by a compass or gyroscope sensor usually integrated in the INS.

2.6.1.3 INS Limitation

Inertial systems measure movement from a known initial position. However, without frequent and accurate position updates, INS suffers from a constant growing positioning error called *drift*. *Drift error* occurs due to slight errors introduced in the manufacturing process of the sensors themselves. These errors are usually small, but since the inertia navigation technique relies on previous calculations, the error is accumulative and grows in a linear fashion. So, using an INS over short time periods can produce quite accurate positioning estimates, but for long time usage, a solution is to reset the *drift error* periodically using one or more other technologies (i.e. GPS or RFID). Figure 2-7 [30] graphically depicts an example of *drift error*.

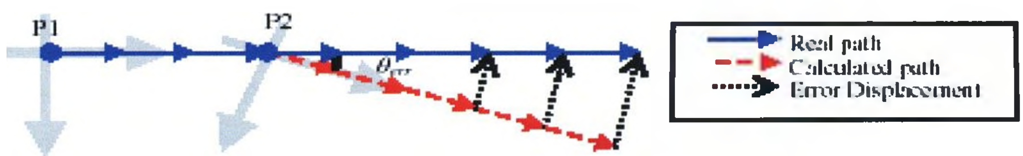


Figure 2-7: Demonstration of Drift Error

2.6.2 Sensor System Technologies

A sensor is a physical device that detects, or *senses*, a signal or physical condition. This section describes some of the sensors that appear in Inertia Navigation Systems. The INS technique is widely used with systems that may contain long communication delays (e.g., Bluetooth), or frequently dropped connections (i.e., GPS in urban canyons or indoors) to fill in the gaps from last known positions. Most of these sensors are used for flight management systems for projectiles and Unmanned Aerial Vehicles (UAV). Dead reckoning sensors can be integrated together using micro-fabrication technology to create INS.

Accelerometers: An accelerometer is a sensor that can measure acceleration forces [68]. These forces may be static, like the constant force of gravity, or could be dynamic, such as moving or vibrating the accelerometer. By measuring the amount of static acceleration due to gravity, the angle the device is tilted at with respect to the earth can be computed. By sensing the amount of dynamic acceleration, the movement of the device can be analyzed. There are many different types of accelerometers with different parameters. To perform three dimensional positioning, a 3-axis accelerometer, or two 2-axis accelerometers mounted at right angles to each other is needed. These have also been used to sense basic human activities such as walking, running, and standing still.

Digital Compasses: A digital compass is a sensor that can provide the direction (heading) of the user. These sensors determine the Earth's magnetic north which can deviate significantly from true north. Correction information can be obtained from the National Geophysical Data Center (NDGC). Furthermore, these sensors are affected by magnetic disturbances from notebook computers, and mobile phones, and should be kept as far away as possible.

Gyroscopes: A gyroscope is a device for measuring or maintaining orientation, based on the principle of conservation of angular momentum (i.e. inertia). The essence of the device is a spinning wheel on an axle. The device, once spinning, tends to resist changes to its orientation due to the angular momentum of the wheel. A gyroscope can be used to sense or measure the pitch, roll and yaw attitude of the object it is mounted to. Gyroscopes can be used to construct gyrocompasses which complement or replace digital (magnetic) compasses.

Barometric Pressure or Altimeter: A barometric pressure sensor can determine the altitude (i.e., height) of a user based on changes in air pressure. This sensor can be used to correctly determine the floor which the user is standing on. Since it measures air pressure, air circulation from opening doors and windows, changes in weather, slopes, and high populated areas are sources of error. Location Determination in Indoor Environments [69] was able to use an altimeter to correctly locate a user to a specific floor based solely on altimeter data.

Pressure: A pressure sensor can be used to detect physical contact with an object. The Smart Floor [63] and GETA Sandals [30] systems experimented with the use of pressure sensors to aid in determining location.

Light: A light sensor can measure the amount of light that it detects. It can accurately measure the frequency of fluorescent light flicker. The LuxTrace system [62] demonstrated that light sensors could be used for location determination using indoor building illumination. The LuxTrace system is not ideal for wide scale deployment, as the emitted frequency from fluorescent lights changes with age, type, and power.

2.7 Hybrid

Given the wide range of strengths and weaknesses that different navigation technologies have in different circumstances, one approach to developing a hybrid system is to combine a set of complementary technologies in ways that the advantage of one technology or technique compensates the drawback of the other, in order to provide acceptable performance.

The majority of hybrid location sensing systems are for outdoor use. These systems usually contain an INS and some other signalling technology, specifically GPS, which is used to provide a starting location. The major reason for the use of GPS is that it has already proven to be the user's choice for outdoor navigation, and the introduction of an INS helps make it more reliable. A GPS system alone only provides a location estimation that states 'you are in the vicinity of X'. A system is needed that determines the direction a user is facing. This allows location services to provide more precise directions or give information about what the user is looking at.

One of the first systems to suggest using multiple technologies to infer indoor location was the Easy Living project from Microsoft [29], which proposed using different technologies to give location estimation at different levels. One technology would be able to locate a user at a structure level (i.e. specific building) another could locate the user at a room level while the third technology would provide location estimations that were fine enough to interact with specific objects in the environment.

2.7.1 Why Hybrid

Using a single technology to generate location information has proven to be possible, with good results, in optimal indoor test environments. These optimal environments are usually on a single floor and the developers have complete control of the location of access points or have specialized hardware and/or tags installed. Combining two or more location sensing technologies into one indoor positioning system will most likely be more accurate and reliable in real-world conditions.

Quality of Service (QoS): Since there is more than one technology calculating location for the user, different levels of service for location accuracy for different users can be provided.

Security / Privacy concerns: With more than one technology calculating location (i.e., one centralized and one localized), both the user and provider can meet half way with respect to security and privacy concerns. By having different technologies, the provider knows which building a user is located for emergency reasons while the user knows where in the building they are located for personal use. However, the use has the option not to give up this information to the provider. Therefore the provider knows where users are, but at a lower location accuracy.

Reliability: Depending on the techniques and technologies combined, having more than one technology calculating the user's location, a single system can fail or become un-available without dramatically affecting the systems performance.

2.7.2 Hybrid Systems

This section briefly describes the latest attempts at creating a hybrid location system that does not include GPS.

Dead Reckoning and Stereo Vision Tracking [32]: This system investigates the use of co-operative location and tracking systems. The combination of stereo vision tracking system and Inertia Navigation System is proposed. The stereo vision tracking system requires the installation of cameras that are three meters above the ground, throughout the environment. Both systems are used to provide precise location accuracy. Currently this hybrid system is a work in progress with no results.

Place Lab [34]: The Place Lab positioning system listens for transmissions from multiple signalling technologies (802.11 access points, GSM cell towers, and Bluetooth devices). A beacon database is required and provides location information based on the identifiers of beacons detected by the user. Place Lab works both indoor and outdoors, and requires Wardriving or Warwalking to accumulate identifiers of signalling devices for the database and their relative location. Wardriving or Warwalking is the act of searching for Wi-Fi APs' MAC addresses by using a moving vehicle or walking. Published results showed that Place Lab is capable of obtaining 20 meter accuracy. The system's location accuracy relies on the 802.11 radio frequency technology utilizing the proximity technique.

Bridging the Gaps: [31]: This hybrid system combines multiple technologies to provide different techniques of tracking the user's position. These techniques differ significantly in location accuracy. The first technique deployed is an INS that relies heavily on derived knowledge from spatial maps and accessibility graphs to apply corrections to the user's positions as the INS drift error increases. The second technique is an infrared tracking system, which infers position from a set of infrared signals it receives.

GETA Sandals [30]: This system embeds sandals with multiple sensors, transmitters and receivers. This system uses the dead-reckoning technique and the position of the user is determined by detecting footprints, and then calculating the displacement vectors between them. The pressure sensors detect footsteps and the ultrasonic transmitters/receivers are used to calculate distance. Since there is a line-of-sight requirement for the ultrasonic transmitters/receivers, this system introduced an accelerometer that can be use when the foot-print based method is unreliable (i.e. walking upstairs). Likewise, the dead-reckoning technique suffers from *drift error*, which the system tried to reduce by placing passive RFID tags throughout the environment. Whenever a user walks over a tag, their location is updated to that location, essentially resetting the accumulated *drift error*.

2.8 Summary

The objective of this thesis is to investigate the effectiveness of combining multiple sources of information for indoor positioning. Previous research considered the combination of multiple sources of information for indoor positioning and suggested this can be more accurate than using a single source of information. Relying on a single source of information to determine the location of a user in an indoor environment has been shown to be difficult without installing specialized hardware to specifically determine the user's location. The problem with previously built hybrid systems is the additional sources of information were often intrusive, and they required additional hardware that was not always cost effective to install and maintain. The hybrid system that is described in this thesis is cost effective. It augments Wi-Fi fingerprint analysis with scene analysis and the current floor of the user, to better distinguish between similar fingerprints. This combination of technologies has not been investigated. Additionally the system allows for additional information to be incrementally added which is not found in other hybrid systems.

Chapter 3

Design

This chapter presents the design of an indoor positioning system developed for this thesis. Section 3.1 describes the observation made about Wi-Fi fingerprints that led to the selection of scene analysis and altimeter sensors as complementary technologies for the hybrid system. Section 3.2 provides an overview of the complete system, discussing all of the components used to infer location. Section 3.3 describes all of the system configurations that are examined during system testing. Section 3.4 presents an example scenario of the complete hybrid indoor location system.

3.1 Wi-Fi Fingerprints

This section shows how the normal fluctuations in Received Signal Strength Indicator (RSSI) values can make it difficult to use Wi-Fi fingerprints to determine location. Wi-Fi signals can fluctuate considerably (5 decibels to 35 db) at the same location at anytime. This can be seen in Figures 3-1 and 3-2, and Tables 3-1 and 3-2. These scans were captured every ten seconds for approximately one hour, and show all the access points that can be detected at a specific location. The examination of other AP scan rates, five and fifteen seconds, was also investigated. However, the scan rates did not impact the amount of fluctuation of RSSI values. These fluctuations explain why the location estimation algorithms have a range in RSSI values when querying the database for a list of possible locations. Most algorithms use a range in RRSI values for comparison and return locations that are 'similar' instead of looking for exact matches.

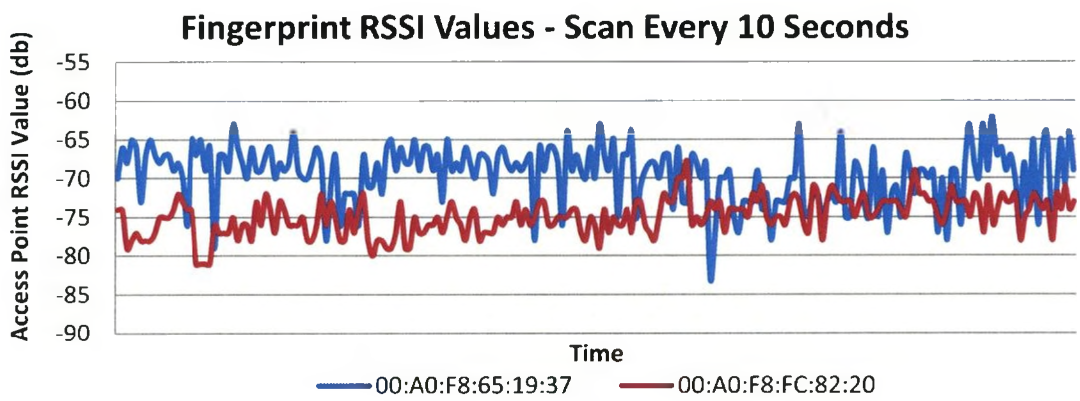


Figure 3-1: Middlesex College, Desk in Room 240, Not Connected AP Scan

Access Point – MAC Address	Min (RSSI)	Max (RSSI)	Range
00:A0:F8:65:19:37	-83	-62	21
00:A0:F8:FC:82:20	-81	-68	13

Table 3-1: Middlesex College, Desk in Room 240, Not Connected AP Scan

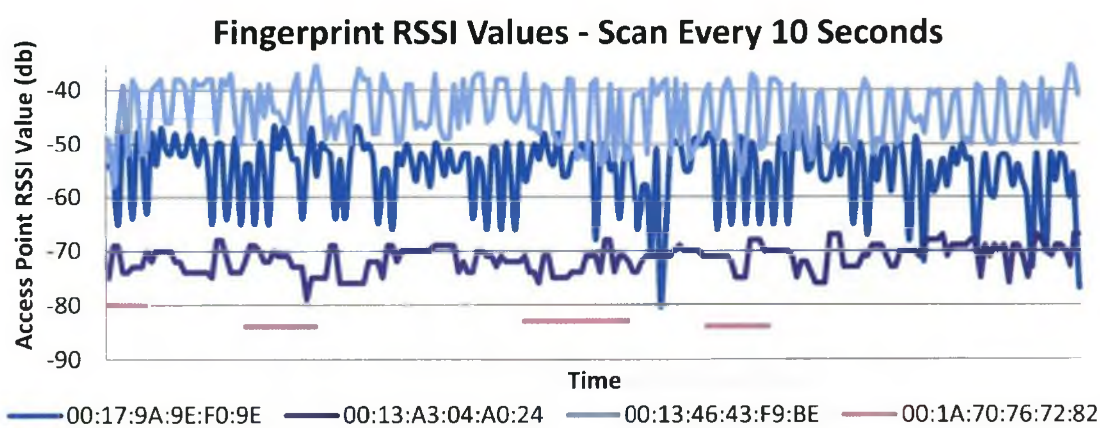


Figure 3-2: Townhouse, Living Room, Not Connected AP Scan

Access Point – MAC Address	Min (RSSI)	Max (RSSI)	Range
00:17:9A:9E:F0:9E	-80	-47	33
00:13:A3:04:A0:24	-79	-67	12
00:13:46:43:F9:BE	-58	-35	23
00:1A:70:76:72:82	-84	-80	4

Table 3-2: Townhouse, Living Room, Not Connected AP Scan

Table 3-3 compares two locations on two different floors, within Middlesex College. Table 3-4 compares two locations in different rooms, on the same floor in Middlesex College. Table 3-5 compares two locations, 15-20 meters apart, in the second floor hallway in Middlesex College. All three examples demonstrate how comparable different location fingerprints can be at different locations. Each of the tables show examples where the difference in the RSSI values of at least two fingerprints is small. As previously shown, Wi-Fi signals at the same location can vary. The amount of this variation for an access point can be greater for the same access point at different locations. This makes it difficult to distinguish locations. Due to these similarities, an altimeter sensor and scene analysis were chosen as complementary technologies to Wi-Fi to further distinguish between similar location fingerprints. An altimeter sensor was chosen to distinguish similar fingerprints on different floors. Scene analysis was selected to distinguish similar fingerprints, on the same floor but different rooms.

Point in Middlesex College Room 222		Point in Middlesex College Room 320		
MAC	RSSI	MAC	RSSI	Diff
00:A0:F8:5C:82:20	-65	00:A0:F8:5C:82:20	-70	5
00:A0:F8:E9:53:AC	-65	00:A0:F8:E9:53:AC	-70	5
00:A0:F8:E5:E8:A4	-73	00:A0:F8:5C:8E:76	-74	
00:A0:F8:65:19:37	-74	00:A0:F8:E5:E8:A4	-76	1
00:A0:F8:5C:83:88	-77	00:A0:F8:65:19:37	-75	1
00:A0:F8:64:D9:C9	-81	00:A0:F8:65:01:E0	-84	
00:A0:F8:6E:14:21	-84			

Table 3-3: Similar Fingerprint on Different Floors

Point in Middlesex College Room 240		Point in Middlesex College Room 222		
MAC	RSSI	MAC	RSSI	Diff
00:A0:F8:65:19:37	-71	00:A0:F8:5C:82:20	-65	7
00:A0:F8:5C:82:20	-72	00:A0:F8:5C:83:88	-75	7
00:A0:F8:5C:83:88	-82	00:A0:F8:E9:53:AC	-75	
		00:A0:F8:65:19:37	-78	7

Table 3-4: Similar Fingerprint on the Same Floor, Different Rooms

Point in MC 2nd Floor Hallway		Point in MC 2nd Floor Hallway		
MAC	RSSI	MAC	RSSI	Diff
00:A0:F8:65:19:37	-45	00:A0:F8:65:19:37	-43	2
00:A0:F8:5C:82:20	-65	00:A0:F8:5C:82:20	-69	4
00:A0:F8:E9:53:AC	-78	00:A0:F8:E9:53:AC	-74	4
00:A0:F8:65:01:E0	-78	00:A0:F8:65:01:E0	-74	4
00:A0:F8:5C:83:88	-80	00:A0:F8:64:FE:0E	-81	
		00:A0:F8:5C:83:88	-84	4

Table 3-5: Similar Fingerprints in the Same Area

3.2 System Design Overview

The indoor positioning system consists of three different components, each one representing an established indoor positioning technique. This hybrid system uses a combination of signalling, scene analysis, and sensor positioning techniques. The technologies selected provide different accuracies compared to the use of a single technology in an indoor positioning system. As a group, the different components combine information to improve position reliability, precision, and accuracy. Figure 3-3 provides an overview of system components.

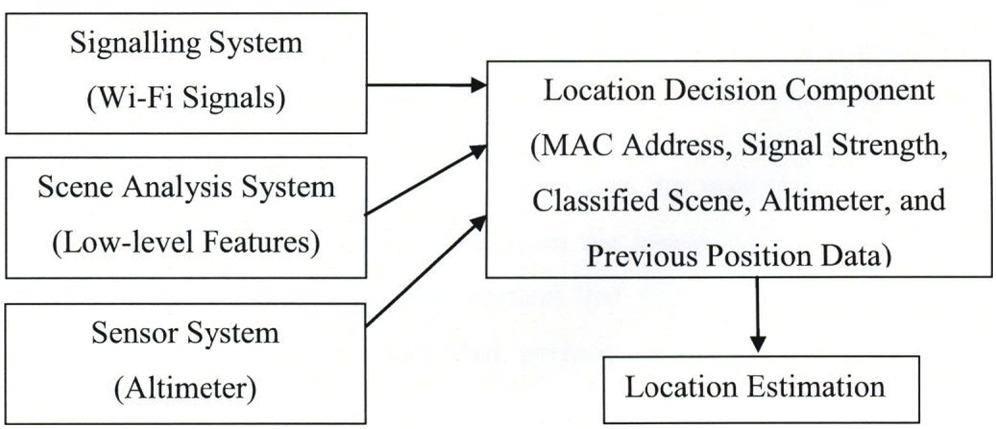


Figure 3-3: Proposed Hybrid Indoor Positioning System

3.2.1 Wi-Fi Signalling Positioning System

The developed system assumes an existing wireless infrastructure already in place that can be used to detect the position of the user within 10-25 meters accuracy. This large discrepancy in location accuracy depends on the number and position of the access points (AP) and the positioning algorithm used. The proposed system is related to Herecast [27], WLocator [28] and Place Lab [26] systems. These systems position the user in the proximity of an access point based on Media Access Control (MAC) addresses it can detect. Furthermore, the system uses RSSI values for detected access points from a given location (fingerprint), and compares the fingerprint to fingerprinted data that was stored. The fingerprint technique determines the user's location by comparing detected access point MAC addresses and RSSI measurements to previously stored values in a database. The similarity in the current information and the stored fingerprint data determines the likelihood of the user being at that location.

The proposed Wi-Fi system provides access point MAC addresses and associated RSSI information (fingerprint) to the Location Decision Component. The system developed allows for different Wi-Fi algorithms to be used. This is illustrated with the discussion and implementation of several Wi-Fi algorithms in Chapter 4.

3.2.2 Scene Analysis Positioning System

Cameras are used to periodically take pictures as the user moves. From the captured images, low-level features are extracted from the image (e.g., colour histograms (pixel intensities), wavelets (horizontal and vertical line detection) to classify the image as a particular scene. Similar systems that perform image comparisons using low-level features include [33, 50, 70].

The proposed scene analysis system provides the Location Decision Component with a probability that the captured image is a particular recognized scene. For example, in a building at a university, typical types of scenes include: classroom, hallway, computing laboratory, office, etc. The location accuracy for this system is assumed to be coarse (i.e. low). The user's location would be a scene/room in a particular building. Some of those scenes may be very distinct and others may be very similar. To know that the user is in an office is possible, but knowing which office is very difficult. More information is required for finer location results. The use of this information is intended to be used for distinguishing positions on the same floor that are difficult to distinguish based on fingerprints.

3.2.3 Sensor Positioning System

This system consists of an altimeter sensor to determine the current floor the user is on. This sensor was selected for ease of implementation and because most Dead-Reckoning Modules (DRM) have an altimeter sensor. Research [69] has examined the effectiveness of using an altimeter to determine the current floor of the user. Therefore, for this system, the location accuracy would be at the floor level. The use of an altimeter allows for the distinction of similar fingerprints on different floors.

3.2.4 Location Decision Component

Figure 3-4 outlines the decision component algorithm. This component combines the information derived from the three systems. It first collects signal strengths of detected APs (line 2), and applies a fingerprinting algorithm (lines 4, 5, 6) to determine the user's location by comparing the fingerprint just collected to a list of previously stored fingerprints collected earlier. The altimeter data is used next, by filtering out any locations that are on the incorrect floor (line 7). Depending on the relative floor value from the sensor positioning system, any location in the list of possible locations that is not on that floor is removed from the list of possible locations. Finally, it adjusts the likelihood (probability) of each location based on classified scene list (lines 8, 9, 10) from the scene classifier system. Each location in the list of possible locations, that has the same scene type as the scene type class determined from the scene analysis component (i.e. the scene type class with the highest probability value), has its location likelihood slightly increased. Likewise, a slight decrease in location likelihood is applied to locations with the scene type that is different from the current scene type class detected (these will be the scene types with the lowest probability values).

Input: A Collection of Wi-Fi Access Points (RSSI Values and MAC Addresses): apSet
An Relative Altitude value: floorValue
A list of Classified Scenes (Scene Type and Confidence): sceneSet
A Wi-Fi Signaling Algorithm Y
Output List of possible locations with corresponding likelihoods and scene type

```
apSet ← new apSet (Y)
floorValue ← retrieveAltitude()
sceneSet ← new sceneSet()
foreach ap X in apSet do
    LocationList ← Perform DB lookup(X)
    LocationList ← DetermineLocationLikelihood(LocationList, X)
end
LocationList ← RemoveIncorrectFloors(floorValue, LocationList)
foreach scene S in sceneSet do
    LocationList ← AdjustLikelihoodBasedOnScene(S, LocationList)
end
return LocationList
```

Figure 3-4: Decision Component Algorithm

3.3 Example Scenario

This example scenario illustrates the process of determining the user's location. It describes information needed and how each component is utilized to infer the user's location. In this situation, the user is located somewhere on the fourth floor in Middlesex College as shown in Figure 3-5, marked with an 'X'.

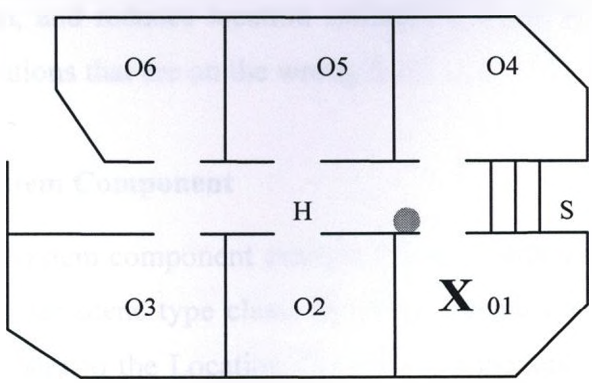


Figure 3-5: Middlesex College Fourth Floor

Wi-Fi System Component

The Wi-Fi system component obtains the fingerprint of the user's current location and a database is queried for possible locations of the user. The list of locations that the query retrieves is based on the similarity of current Wi-Fi fingerprint data to fingerprint data collected earlier. Locations are ranked based on similarities in the fingerprints. This list of locations is sent to the Location Decision Component. An example of data produced by this system can be seen in Table 3-6. More details on the likelihood computation are discussed in Section 4.2.

Possible Location	Likelihood (Rank)	Associated Scene
Stairwell	*85*	*Stairwell*
3rd Floor Office 1	*80*	*Office*
4th Floor Hallway	*80*	*Hallway*
Office 1	*75*	*Office*
3rd Floor Office 2	*75*	*Office*
Office 2	*70*	*Office*
3rd Floor Hallway	*70*	*Hallway*
Office 4	*65*	*Office*
Office 5	*65*	*Office*
Office 3	*60*	*Office*

Table 3-6: Example of the Wi-Fi System's Output

Sensor System Component

The sensor system component provides the Location Decision Component with altitude data from a barometric pressure sensor. This information is used to determine the current floor the user is on, and reduces location estimation errors by eliminating fingerprints associated with locations that are on the wrong floor.

Scene Analysis System Component

The scene analysis system component examines and classifies an image captured from a webcam as a particular scene type class, by using a generic multi-class classifier. This information is then sent to the Location Decision Component. An example of the data produced by this system can be seen in Table 3-7. The captured image is input into the scene analysis component which returns a list of scene type classes and their corresponding probabilities by determining and comparing image features.

Scene Type Class	Hallway	Classroom	Office	Stairwell	Group Office
Probability	*5*	*15*	*40*	*10*	*30*

Table 3-7: Example of the Scene Analysis System's Output

Decision Component

This particular component gathers information from the other components to infer the best possible location. Possible location probabilities returned from the Wi-Fi component are filtered and adjusted based on the data from the sensor and scene analysis components. An example of the final results produced by the decision component can be seen in Table 3-8. Possible locations on incorrect floors are filtered out and locations with similar scenes to the classified image scene type are given more weight as a possible location.

Possible Location	Likelihood (Rank)	Associated Scene
Office 1	*90*	*Office*
Office 2	*85*	*Office*
Stairwell	*85*	*Stairwell*
4^{th} Floor Hallway	*80*	*Hallway*
Office 4	*80*	*Office*
Office 5	*80*	*Office*
Office 3	*75*	*Office*

Table 3-8: Example Results for Scenario from Decision Component

3.4 Summary

This chapter provided an overview of the design for the hybrid system based on the use of Wi-Fi, scene analysis, and an altimeter sensor. The justification for using scene analysis and an altimeter is based on observations made about fluctuations in RSSI values. The additional sources of information are used to differentiate similar Wi-Fi fingerprints. An example of the use of the hybrid system was presented.

Chapter 4
Observations and Algorithms

The following chapter gives a detailed explanation of the algorithms used in the implementation of the hybrid indoor location system.

4.1 Investigating Wi-Fi Signals

This section discusses observations about Wi-Fi signals. These observations were applied to the algorithms used to determine the possible location of a user based on Wi-Fi signals.

4.1.1 Connecting to an Access Point

We investigated whether or not connecting to an Access Point would make any significant impact on fluctuating AP RSSI values. Figures 4-1 and 4-2, and Tables 4-1 and 4-2 show the fluctuations in signal strengths when connected to an AP. For comparison, Figures 3-1 and 3-2, and Tables 3-1 and 3-2 in the previous chapter, show the fluctuations in signal strengths when not connected to an AP. In most environments the user is more than likely connected to the wireless network. However, for security reasons, in some public environments the user may not be connected to a wireless network.

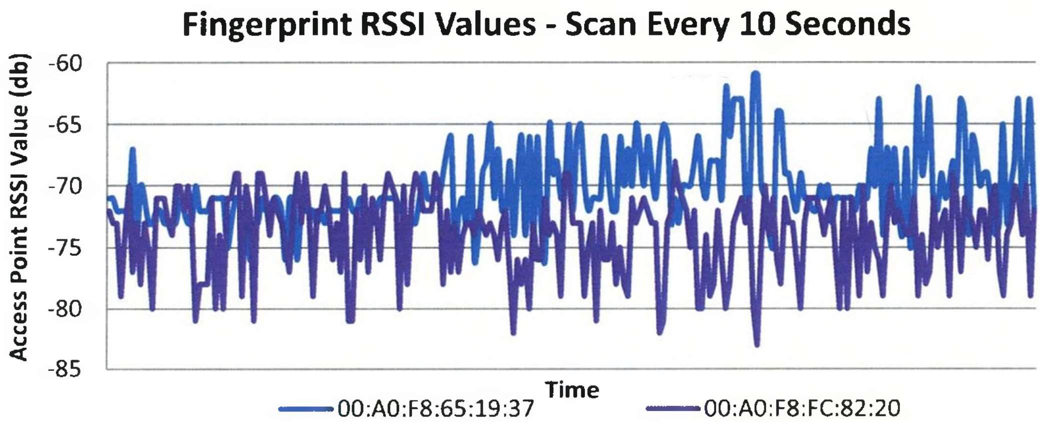


Figure 4-1: Middlesex College, Desk in Room 240, Connected AP Scan

Access Point – MAC Address	Min (RSSI)	Max (RSSI)	Range
00:A0:F8:65:19:37	-76	-61	15
00:A0:F8:FC:82:20	-83	-68	15

Table 4-1: Middlesex College, Desk in Room 240, Connected AP Scan

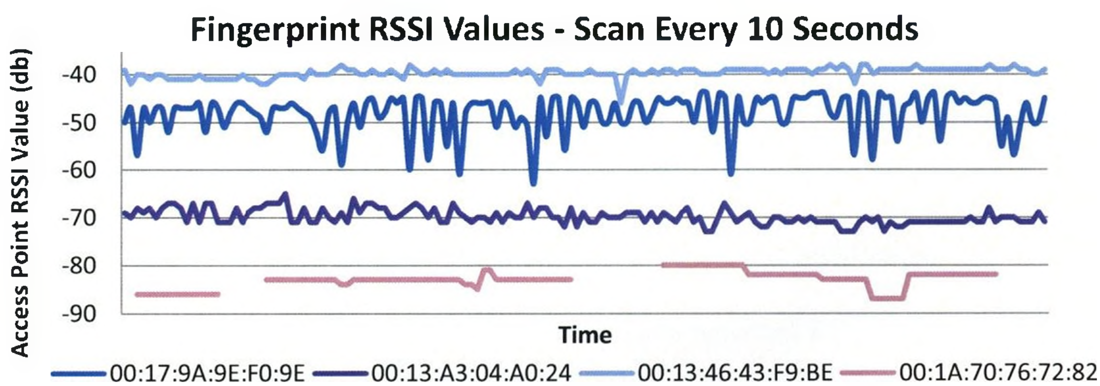


Figure 4-2: Townhouse, Living Room, Connected AP Scan

Access Point – MAC Address	Min (RSSI)	Max (RSSI)	Range
00:17:9A:9E:F0:9E	-63	-44	19
00:13:A3:04:A0:24	-73	-65	8
00:13:46:43:F9:BE	-46	-38	8
00:1A:70:76:72:82	-87	-80	7

Table 4-2: Townhouse, Living Room, Connected AP Scan

There is a noticeable reduction in the amount of RSSI fluctuation when the user is connected to an access point versus when the user is not connected. The main reason that the *Middlesex College, Desk in Room 240* location, has a marginal change in signal fluctuation when connected and not connected, is due to the fact that the location is positioned between two APs. When connected to this network, the connection can jump from one AP to the other. Neither has a strong enough signal strength to always be the primary AP connection.

4.1.2 Averaging Continual AP Scans

Next, we investigated averaging continual (consecutive) scans to build an average history of previous scans. This allowed us to see if there can be any improvements in reducing the fluctuating RSSI values. However, too much emphasis on previous history could be detrimental to the location estimation results, as users are likely to be moving. Although the time interval can be selected and changed by the user, the data shown in this section is based on a ten second interval between scans, as this was the same time interval used during system testing. Other time intervals where tested and similar results were obtained. The minimal time needed to gather AP data from the wireless adaptor is approximately five seconds.

History 2 scans – This is the average of the last two received RSSI values for each AP.

History 3 scans – This is the average of the last three received RSSI values for each AP.

History 4 scans – This is the average of the last four received RSSI values for each AP.

History 5 scans – This is the average of the last five received RSSI values for each AP.

The results, some of which are presented in Figures 4-3 and 4-4, and Tables 4-3 and 4-4, show that the more history information available, the less noise there is in Wi-Fi RSSI values. History information does reduce the impact of outliers on the data being collected to be used to determine the user's location.

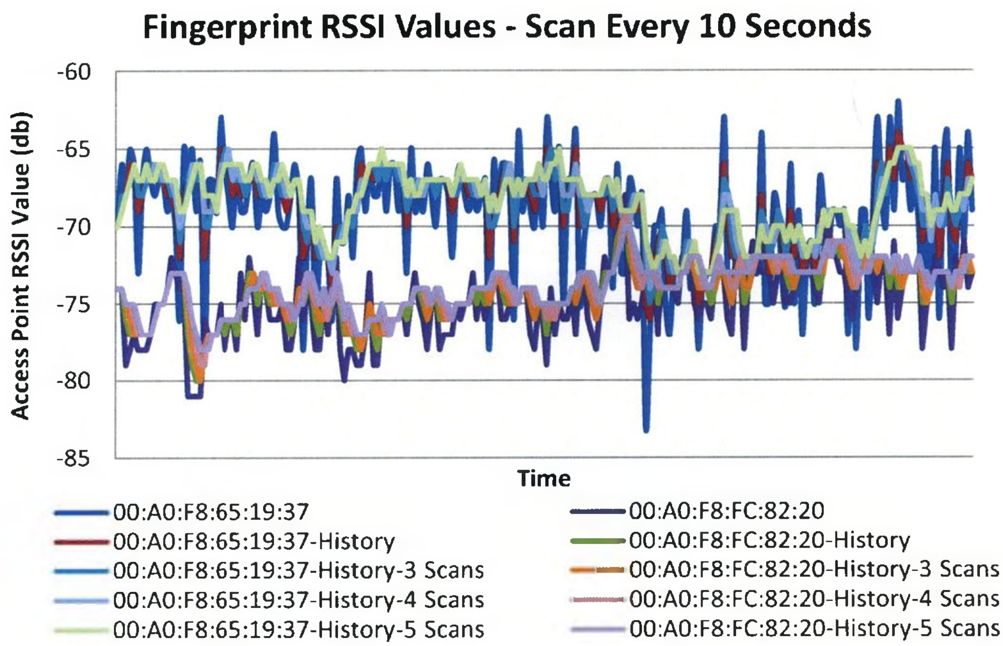


Figure 4-3: Middlesex College, Exploring History on AP Scans

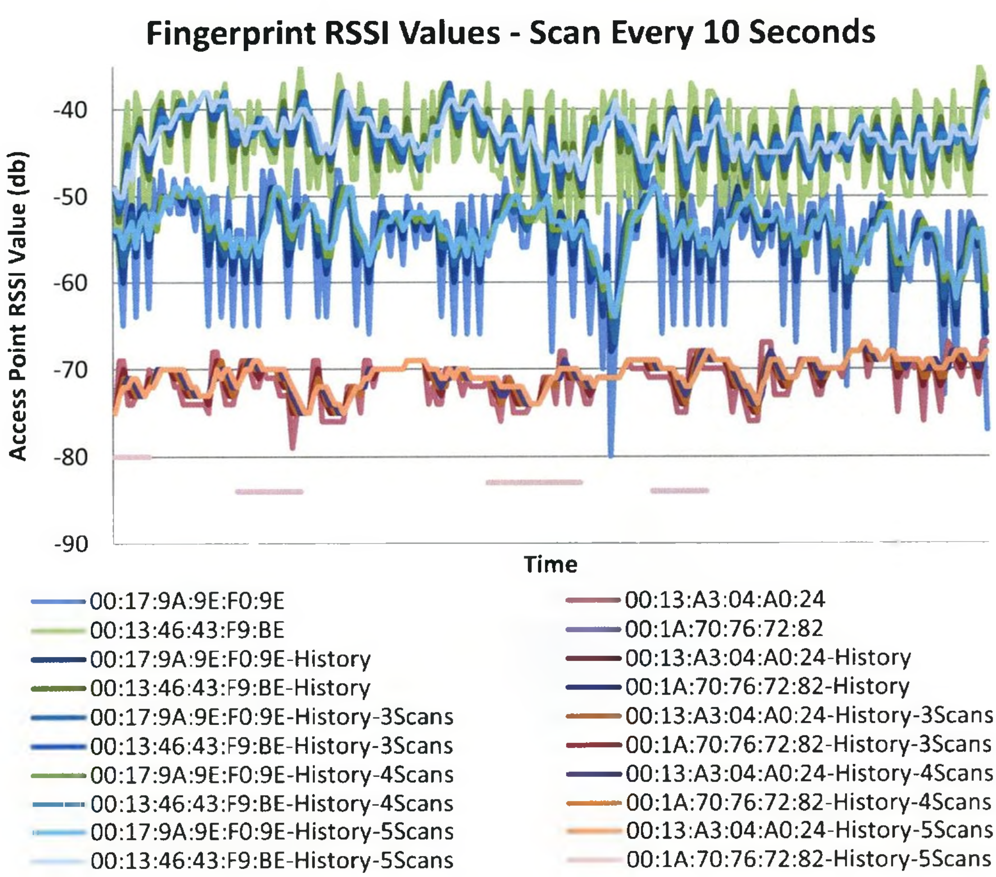


Figure 4-4: Townhouse, Exploring History on AP Scans

Access Point – MAC Address	Min (RSSI)	Max (RSSI)	Range
00:A0:F8:65:19:37	-83	-62	21
00:A0:F8:FC:82:20	-81	-68	13
00:A0:F8:65:19:37 – History	-76	-64	12
00:A0:F8:FC:82:20 – History	-80	-69	11
00:A0:F8:65:19:37 – History 3 Scans	-75	-65	10
00:A0:F8:FC:82:20 – History 3 Scans	-80	-69	11
00:A0:F8:65:19:37 – History 4 Scans	-74	-65	9
00:A0:F8:FC:82:20 – History 4 Scans	-79	-69	10
00:A0:F8:65:19:37 – History 5 Scans	-73	-65	8
00:A0:F8:FC:82:20 – History 5 Scans	-78	-70	8

Table 4-3: Middlesex College, Exploring History on AP Scans

Access Point – MAC Address	Min (RSSI)	Max (RSSI)	Range
00:17:9A:9E:F0:9E	-80	-47	33
00:13:A3:04:A0:24	-79	-67	12
00:13:46:43:F9:BE	-58	-35	23
00:1A:70:76:72:82	-84	-80	4
00:17:9A:9E:F0:9E – History	-68	-49	19
00:13:A3:04:A0:24 – History	-75	-67	8
00:13:46:43:F9:BE – History	-53	-37	16
00:1A:70:76:72:82 – History	-84	-80	4
00:17:9A:9E:F0:9E – History 3 Scans	-67	-49	18
00:13:A3:04:A0:24 – History 3 Scans	-75	-67	8
00:13:46:43:F9:BE – History 3 Scans	-52	-37	15
00:1A:70:76:72:82 – History 3 Scans	-84	-80	4
00:17:9A:9E:F0:9E – History 4 Scans	-64	-49	15
00:13:A3:04:A0:24 – History 4 Scans	-75	-67	8
00:13:46:43:F9:BE – History 4 Scans	-51	-38	13
00:1A:70:76:72:82 – History 4 Scans	-84	-80	4
00:17:9A:9E:F0:9E – History 5 Scans	-64	-49	15
00:13:A3:04:A0:24 – History 5 Scans	-75	-67	8
00:13:46:43:F9:BE – History 5 Scans	-50	-38	12
00:1A:70:76:72:82 – History 5 Scans	-84	-80	4

Table 4-4: Townhouse, Exploring History in AP Scans

4.1.3 Summary

Our observations suggest that the recorded RSSI value for an access point should be the average of its multiple scans, since the average is more stable and accurate than using one single RSSI value. The Wi-Fi Scanner refers to a device driver that scans access points and can be configured to use multiple scans of access points. The implication is that the recorded RSSI value of an access point in a fingerprint is the average of the RSSI values monitored over multiple scans. The use of multiple scans is referred to as history. We have also decided to use averages of multiple consecutive location likelihoods. Section 4.2 provides more information on the calculation of location likelihood. For real-time purposes, the AP scan history only contains the average of the last three scans. This reduces some of the noise generated by the RSSI values. The different combinations of the collected historic data are outlined below. These combinations were investigated to compare the impact that history has in determining the user's location. RT represents real time, and H represents history.

RT Scan/RT Location: The location likelihood value is calculated based on the most recent AP Scan. The location likelihood returned is the calculated location likelihood estimation.

RT Scan/H Location: The location likelihood value is calculated based on the most recent AP Scan. The location likelihood returned is the average of the last three location likelihood estimations.

H Scan/RT Location: The location likelihood value is calculated based on the average of the last three AP Scans. The location likelihood returned is the last calculated location likelihood estimation.

H Scan/H Location: In this combination, the location likelihood value is calculated based on the average of the last three access point scans. The location likelihood returned is the average of the last three likelihood estimations.

Another interesting observation about Wi-Fi access points is, APs with weak RSSI values do not always appear in consecutive AP scans at the same location. This observation is demonstrated in Figure 4-2. The access point with the MAC address 00:1A:70:76:72:82 (in red) periodically disappears from the list of detected APs.

4.2 Wi-Fi Algorithms

This section discusses the different Wi-Fi Signalling Algorithms used in the Wi-Fi system to determine the user's location. These algorithms are influenced by the observations of Wi-Fi signals described in Section 4.1. The algorithms vary in the number of access points used in a fingerprint. The reason that only a subset of access points is used, as opposed to all access points, is that using all access points increases the cost of calculating the location. It is also based on the observation that access points with weaker RSSI values are not good indicators of location. There are a number of algorithms used in the literature. Our goal in the design was to have an algorithm which is relatively robust to changes in access points.

4.2.1 1AP Fingerprint Algorithm

Figure 4-5 outlines the 1AP fingerprint algorithm. The algorithm is periodically invoked in fixed time intervals. When the time interval elapses, the wireless adaptor is queried for detected Wi-Fi APs and their associated MAC addresses, RSSI values and network names. A network name filter can be applied at this point to only capture desired network APs to be used in the creation of the location list (line 1). The results returned by *DetectAccessPoints* are used to determine a list of possible locations that within the user's close proximity (line 2). The AP with the strongest RSSI value is used to compare against stored fingerprint data. The reason for this is that the AP with the strongest RSSI value is usually the closest in proximity to the user's current location. If a location fingerprint has the detected AP within the given RSSI range then the location is added to the location list (line 2). The actual range depends on the environment. Our environment required the range of 11 db (-5 db to +5 db) to compare the measured fingerprint with the stored average fingerprint to calculate location likelihood. This range was selected due to the fluctuations observed in Wi-Fi signals in section 3.1.

For each of the locations in L*ocationSe*t, the location is either ignored (filtered out) or given a likelihood value (lines 3, 4, 5, 6, 7, 8). For a location that is retrieved from the database to be ignored, it must have an AP in its fingerprint with a higher RSSI value than the strongest AP detected at the user's current location. The reason for ignoring this AP is based on our observations that show when a Wi-Fi receiver is close to an access point, it will appear in the list of detected APs. This means if the possible location has an AP in its stored fingerprint scan with a higher RSSI value (15 db) than the first AP detected during the location scan, it will be removed from the list of possible locations. The reason for filtering the location is that this location is likely not to be the correct location; otherwise the AP should have shown up in *apSet*.

A likelihood value is given to each location based on how close the detected AP RSSI value is to the AP RSSI value in the fingerprint scan. The further away the RSSI value is from the stored value, the lower the likelihood. If the RSSI values are the same, the location is given a likelihood of 1. In our implementation, if the RSSI value is -1 db or +1 db from the stored value, then the location is given a likelihood of .95. If the RSSI value is -2 db or +2 db from the stored value, the location is given a likelihood of .70. If the RSSI value is -3 db or +3 db from the stored value, it is given a likelihood of .45. If the RSSI value is -4 db or +4 db from the stored value, the location is given a likelihood of .20. If the RSSI value is -5 db or +5 db from the stored value, the location is given a likelihood of .05. The list of possible locations and their associated likelihood is then returned to the decision component (line 9).

Input: A selected Time Interval: selTime
A predetermined RSSI range: range
A set of Network Names: netFilter (if null, do not filter)

Output: A List of possible locations with corresponding likelihoods and scene type

```
1.     apSet ← DetectAccessPoints(netFilter)
2.     LocationSet ← DbLookup(range, apSet, 1)
3.         foreach X ∈ LocationSet do
4              Eligible = DetermineEligibility(X)
5.             If Eligible
6.                 v = DetermineLikelihood(apSet[], X)
7.                 Add(X, v) to LikelihoodSet
8.             end
9.   return LikelihoodSet
```

Figure 4-5: 1AP Fingerprint Algorithm

4.2.2 2AP Fingerprint Algorithm

Figure 4-6 outlines the 2AP fingerprint algorithm. The algorithm is periodically invoked in fixed time intervals. When the time interval elapses, the wireless adaptor is queried for detected Wi-Fi APs and their associated MAC Addresses, RSSI values, and network names. A network name filter can be applied at this point to only capture desired network APs to be used in the creation of the location list (line 1). The results returned by *DetectAccessPoints* are used to determine a list of possible locations that the user's current location could be (Line 2). The two APs with the strongest RSSI values are used to compare against stored fingerprint data. The two APs with the strongest RSSI values are usually closer in proximity to the user's current location. If the location fingerprint has both of the detected APs within the given RSSI ranges then the location is added to the location list (line 2). The actual range depends on the environment. Our environment required a range of 19 db (-9 db to +9 db) to compare the measured fingerprint with the stored average fingerprint scan reading for the AP with the strongest RSSI value and a range of 11 db (-5 db to +5 db), to compare the measured fingerprint with the stored average fingerprint scan reading from the AP with the second strongest RSSI value detected to calculate location likelihood. This range was selected due to the fluctuations observed in Wi-Fi signals in section 3.1.

For each of the locations in *LocationSet*, the location is either ignored (filtered out) or given a likelihood value. For a location that is retrieved from the database to be ignored, it must have an AP in its fingerprint with a higher RSSI value than the strongest AP detected (lines 3, 4). The reason for ignoring this location is based on our observations that when a Wi-Fi receiver is close to an access point, that AP will be in the list of detected APs. This means that if the possible location has an AP in its stored fingerprint scan with a higher RSSI value (within a range of 15 db) than the first AP detected during the location scan it will be removed from the list of possible locations. The reason for filtering the location is that this location is likely not to be the correct location, otherwise the AP should have appeared in *apSe*t.

A likelihood value is given to each location based on how close the detected AP RSSI values are to the AP RSSI values in the fingerprint scan. The first AP detected has more weight for determining the likelihood of being at that location then the second AP. The weight for the first AP starts at 15, and is assigned if the RRSI values are the same. The weight decreases for the first AP to 6 if the RSSI value is in the range of -9 db or +9 db. The weight for the second AP starts at 10, and is assigned if the RRSI values are the same. This weight decrease to 5 if the RSSI value is in the range of -5 db or +5 db. This is intended to increase the likelihood of locations that have with the first detected AP as its strongest fingerprinted AP (lines 5, 6, 7). The calculated weights of both APs are added together and divided by the maximum possible total weight to return the likelihood value (line 8, 9). The list of possible locations and their associated likelihood is then returned to the decision component (line 10).

Input: A selected Time Interval: selTime
A predetermined RSSI range: range
A set of Network Names: netFilter (if null, do not filter)

Output: A List of possible locations with corresponding likelihoods and scene type

```
1.    apSet ← DetectAccessPoints(netFilter)
2.    LocationSet ← DbLookup(range, apSet, 2)
3.        foreach X ∈ LocationSet do
4             Eligible = DetermineEligibility(X)
5.            If Eligible
6.                apWeight[] = DetermineLocationWeight(apSet[], X)
7.            end
8.            v =CalculateLikelihood(X, apWeight[])
9.          Add(X, v) to LikelihoodSet
10. return LikelihoodSet
```

Figure 4-6: 2AP Fingerprint Algorithm

4.2.3 3AP Fingerprint Algorithm

Figure 4-7 outlines the 3AP fingerprint algorithm. The algorithm is periodically invoked in fixed time intervals. When the time interval elapses, the wireless adaptor is queried for detected Wi-Fi APs and their associated MAC Addresses, RSSI values, and Network names. A network name filter can be applied at this point to only capture desired network APs to be used in the creation of the location list (line 1). The results returned by *DetectAccessPoints* are used to determine a list of possible locations that the user's current location could be close to (line 3). The three APs with the strongest RSSI value are used to compare against stored fingerprint data. The three APs with the strongest RSSI values are usually closer in proximity to the user's current location. If the location fingerprint has all three of the detected APs within the given RSSI ranges, then the location is added to the location list (line 2). The actual range depends on the environment. Our environment required a range of 19 db (-9 db to +9 db) to compare the measured fingerprint with the stored average fingerprint scan reading for the AP with the strongest RSSI value detected. A range of 11 db (-5 db to +5 db) was used to compare the measured fingerprint with the stored average fingerprint scan reading from the AP with second and third strongest RSSI value detected to calculate location likelihood. This range was selected due to the fluctuations observed in Wi-Fi signals in section 3.1.

For each of the locations in *LocationSet*, the location is either ignored (filter out) or given a likelihood value. For a location that is retrieved from the database to be ignored, it must have an AP in its fingerprint with a higher RRSI value than the strongest AP detected (lines 3, 4). The reason for ignoring this location is based on our findings that demonstrate that when a Wi-Fi receiver is close to an access point, that particular AP will be in the list of detected APs. This means that if the possible location has an AP in its stored fingerprint scan that has a higher RSSI value (within a range of 15 db) than the first AP detected during the location scan it will be removed from the list of possible locations. The reason for filtering the location is that this location is likely not to be the correct location, otherwise the AP should have shown up in *apSet*.

A likelihood value is given to each location based on how close the detected AP RSSI values is to the AP RSSI values in the fingerprint scan. The first AP detected has more weight for determining the likelihood of being at that location then the second AP. The weight for the first AP starts at 15, and is assigned if the RRSI values are the same. The weight decreases for the first AP to 6 if the RSSI value is in the range of -9 db or +9 db. Likewise, the second AP detected has more weight for determining the likelihood of being at that location than the third AP. The weight for the second AP starts at 10, and is assigned if the RRSI values are the same. The weight decrease to 5 if the RSSI value is in the range of -5 db or +5 db. The weight for the third AP starts at 8, if the RRSI values are the same and deceases to 3 if the RSSI value is in the range of -5 db or +5 db. This is intended to increase the likelihood of locations that have with the first detected AP as its strongest fingerprinted AP (lines 5, 6, 7). The weights of all three APs are added together and divided by the maximum possible total weight to return the likelihood value (line 8, 9). The list of possible location and their associated likelihood is then returned to the decision component (line 10).

Input: A selected Time Interval: selTime
A predetermined RSSI range: range
A set of Network Names: netFilter (if null, do not filter)

Output: A List of possible locations with corresponding likelihoods and scene type

```
apSet ← DetectAccessPoints(netFilter)
LocationSet ← DbLookup(range, apSet, 3)
    foreach X ∈ LocationSet do
        Eligible = DetermineEligibility(X)
        If Eligible
            apWeight[] = DetermineLocationWeight(apSet[], X)
        end
        v =CalculateLikelihood(X, apWeight[])
      Add(X, v) to LikelihoodSet
return LikelihoodSet
```

Figure 4-7: 3AP Fingerprint Algorithm

4.2.4 Cell of Origin (CoO) Algorithm

For this algorithm, the AP with the highest RSSI value determines the user's location. This AP's MAC address is looked up in the database and its relative installed location (e.g. 3rd Floor – East Wing) becomes the user's location. Once this location is known, the signal strength is then used to determine how far the user is away from the access point. This algorithm was not tested during the experiments, as its location accuracy and precision are too coarse for any feasible location aware applications within a multi-floor environment.

4.3 Selecting a Scene Classifier Observations

A scene classifier calculates the probability that a scene is of a particular type. For example, in a typical university building, we can identify scenes that include classrooms, hallways, offices, group offices, etc. The scene classifier returns a set of scene types and the confidence (probability) that the current scene is of that scene type. This is intended to be used for distinguishing positions on the same floor that are difficult to distinguish based on fingerprints. The location likelihood of each location calculated using Wi-Fi fingerprints is adjusted.

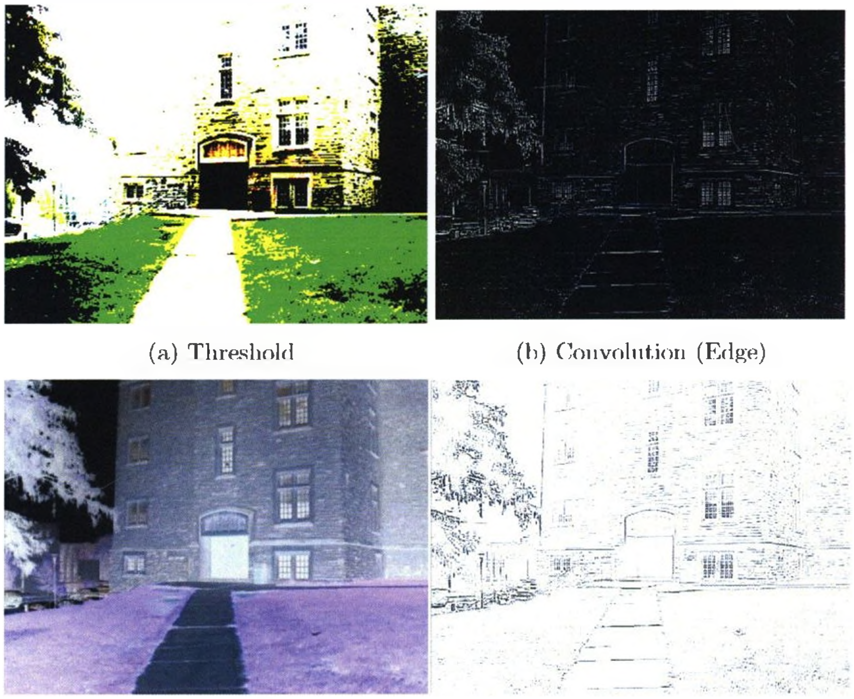
We used existing software for scene classification called PIXIT. In this section we do not describe a specific algorithm but rather we examine some of the different parameter combinations existing in the PIXIT software [71]. This software was selected for use because of its extensive API, its capability of robust multi-class classification, and its excellent performance for other image datasets [72-74]. The algorithms provided appear suitable for this work. Thus, the focus is not on the actual algorithms but rather on the different parameter combinations that can be used.

4.3.1 Overview of the PIXIT Software

The PIXIT software takes a set of labelled images consisting of a finite number of classes (scene types) called the learning/training dataset. After selecting a set of parameters, the software uses the learning set to build an image classifier model that can be used to predict the class and confidence of being that class for any new image. The software extracts sub-windows of specified size at random locations from the training images. These sub-windows are defined by their pixel values. The number of pixels used to describe the sub-window is based on the window size. It then takes a random set of these sub-windows and labels them with the class of its parent image, defined earlier when creating the learning/training dataset. A group of decision trees (Extra-Trees) are then generated to create the classifier model based on the sub-window value, location, and class. Once this model is created, a new image can be classified by randomly selecting sub-windows from the image, describing them and using this data as input into the classifier model to determine class probability.

The following is an overview of the PIXIT software:

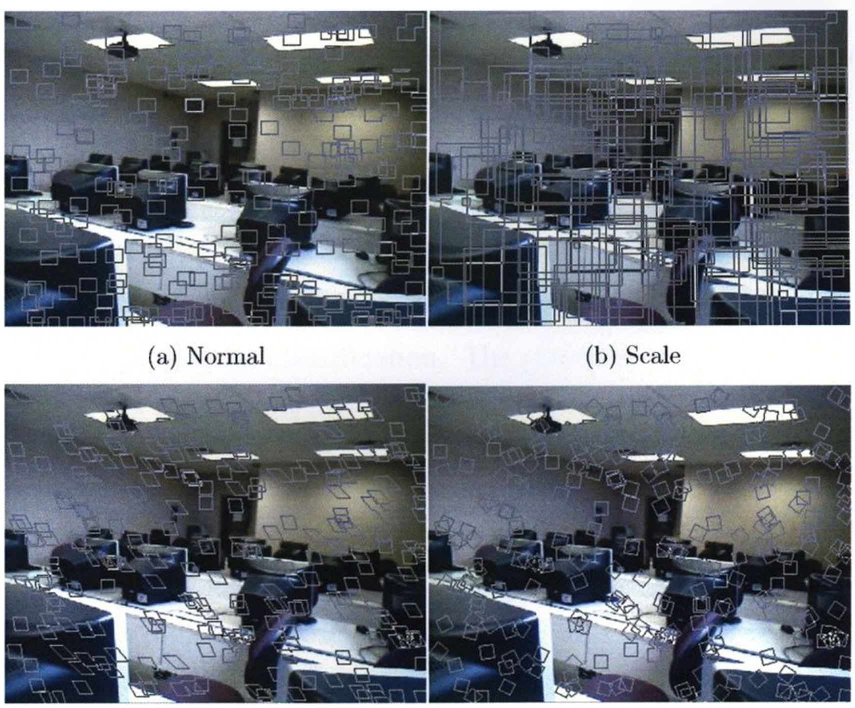
- PIXIT uses random sub-window extraction and a machine learning decision tree ensemble technique (Extra-trees) proposed by Raphaël Marée [54]. The use of random sub-window extraction helps reduce the impact that occlusions and varying image orientations can have on image analysis results.
- PIXIT is able to distinguish between multiple user defined classes, not limited to Boolean classification. Boolean classification returns true or false response to a single class, whereas multiple classes classification returns a confidence probability for each defined class.
- PIXIT algorithms for multi-class classification (scene classification) are robust to conditions of varying illuminations, scale, orientation, and occlusions.
- Parameters that can be adjusted include the following:
    - Colour Mode (HSV, RBG3, RBGI, Greyscale)
        - This refers to the number of bytes used to encode the colour of a pixel
    - Pre-processing filters. These are image algorithms that change the appearance of an image or part of the image by altering pixel data. Figure 4-8 provides several examples of different pre-processing filters applied to the same image.
    - The number and size of sub-windows
    - Sub-window modes (normal, scale, rotation, and shear). This refers to the appearance of the random windows selected from the image that are used to classify the image. Figure 4-9 presents several examples.
    - The number of decision trees (Extra-trees) and random tests used in the classifier model construction



(a) Threshold (b) Convolution (Edge)

(c) Inversion (d) Convolution and Inversion

Figure 4-8: Examples of PIXIT Pre-Processing Filters



(a) Normal (b) Scale

(c) Shear (d) Rotation

Figure 4-9: Examples of PIXIT Sub-Window Modes and Sizes

There are many combinations of settings that the PIXIT software can be configured to. These settings include colour mode, shape and size of sub-windows, number of sub-windows and image filters. To find the best settings for scene analysis, multiple tests were performed, looking for the best combinations of parameters.

4.3.2 Examining the Different Parameters

The tests to determine the best settings assumed a learning/training dataset of 150 images per scene. There were eight scenes in total (classroom, hallway, stairwell, computing lab, group office, office, conference room, and outside) for a total of 1200 images. The testing dataset consisted of anywhere between 25 to 100 different images per scene. These images were randomly selected from the gathered data, and represent at least one third of the distinct collected images per scene. Due to the variation in size and frequency of different scene types, an equal number of unique images per scene were not gathered.

The images were captured with a Microsoft Life Cam worn around the user's neck. The user walked around the environment snapping images every five seconds. The captured images have the resolution of 640x480 pixels.

All classifier learning models created used the settings of 10 trees and 35 random tests, unless otherwise specified. The 10 trees are the number of Extra-trees (decision trees) that were created from the learning/training dataset, and 35 was the number of random tests applied to them for classification. The classifier learning model was created using the images in the training dataset and was later used to create the classifier testing model. The classifier testing model used the same parameters (i.e. number of sub-windows, window size mode) of the classifier learning model, unless otherwise specified. The rest of the subsection below describes some of the different parameters and tests performed in trying to obtain the best possible scene classifier. All tests used 250 sub-windows, per learning image, to create the classifier learning model. More sub-windows per image and a higher number of learning images per class, in the learning model, would have been ideal for better classification results. However, due to memory constraints in

Windows XP, there is a maximum of 1.6GB per process, and these values had to be reduced, due to the amount of memory needed to create the learning model. The PIXIT developers claimed that increasing the number of randomized tree tests during model creation would improve classification performance.

Variation in Colour Model

The different colour models include greyscale, RBG (Red, Blue Green) (3 bytes), RBG (integer), HSV (Hue, Saturation Value) (float). The learning model assumed 250 sub-windows, a sub-window size of 20x20 pixels, normal sub-window appearance mode, and no pre-processing filters. We varied the colour model. The results are shown in Table 4-5.

Colour Model	Results (% Misclassified)
Greyscale	37.2%
RBG-Integer	36.8%
RBG-3 Bytes	28.6%
HSV	35.1%

Table 4-5: Results from Different Colour Models

From this test, RBG (3 bytes) or the HSV colour space models obtained the best results with no additional parameters selected.

Variation in Window Modes

The different Window mode options include normal and scale. There are additional window modes, rotation and shear; however these were not tested. The learning model assumed 250 sub-windows, a sub-window size of 20x20 pixels, a RBG (3 bytes) colour model, and no pre-processing filters. We varied the sub-window appearance mode. The results are seen in Table 4-6

Window Mode	Results (% Misclassified)
Normal	28.6
Scale	21.1

Table 4-6: Results from Different Window Modes

This test shows that Scale sub-window mode obtained superior results over normal sub-window mode.

Variation in Window Size and Variation in Window Mode

Different combinations of sub-window sizes, *16x16, 20x20 and 25x25* pixels were used with the window mode options normal and scale. The sub-window size of 20x20 pixels was the default parameter for this option. The learning model assumed 250 sub-windows, *scale* sub-window appearance mode, a RBG (3 bytes) colour model, and no pre-processing filters. We varied the sub-window size. The results are seen in Table 4-7.

Window size with scale mode	Results (% Misclassified)
16x16	22%
20x20	21.5%
25x25	22.2%

Table 4-7: Results from Different Sub-Window Sizes with Scale Mode

This test shows that the size of sub-window using scale appearance mode creates no considerable difference.

The learning model assumed 250 sub-windows, *normal* sub-window appearance mode, a RBG (3 bytes) colour model, and no pre-processing filters. We varied the sub-window size. The results are seen in Table 4-8.

Window size with normal mode	Results (% Misclassified)
16x16	29.5%
20x20	28.6%
25x25	28.5%

Table 4-8: Results from Different Sub-Window Sizes with Normal Mode

This test shown that the size of sub-window using normal mode creates really no considerable difference. However, again, there is a considerable difference in using scale mode versus normal sub-window appearance mode.

Variation in Different Edge Filters

This section briefly describes our examination of the pre-processing convolution edge filter. Two different edge filters were compared. The learning model assumed 250 sub-windows, a sub-window size of 20x20 pixels, scale sub-window appearance mode, and a RBG (3 bytes) colour model. We used and varied the pre-processing convolution edge filter. The results are seen in Table 4-9.

The Two Different Edge Filters Examined

$$\begin{matrix} 0 & -3 & 0 \\ -3 & 12 & -3 \\ 0 & -3 & 0 \end{matrix} \qquad\qquad \begin{matrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{matrix}$$

Edge Filter 1 Edge Filter 2

Different Edge Filters	Results (% Misclassified)
Edge 1	21.5%
Edge 2	21.8%
No Filter	21.5%

Table 4-9: Results from Different Edge Filters, with Scale Mode

This test showed that there was no significant difference using the pre-processing convolution edge filter.

Variation in Number of Random Tree Tests in Model Construction

This test examined the results of the image classifier, when altering the number (35, 105, and 210) of randomized tree tests used to create the classifier learning model. The learning model assumed 250 sub-windows, a sub-window size of 16x16 pixels, scale sub-window appearance mode, a HSV colour model, and no pre-processing filters. We varied the number of randomized tree tests used during classifier model creation. The results are seen in Table 4-10.

Number of Randomized Tests	Results (% Misclassified)
35	20.5%
105	18.7%
210	17.1%

Table 4-10: Result from Varying the Number of Randomized Tree Tests

The test results show that using more random tests does improve results. This classifier obtained the best results thus far and therefore, these parameters are used to create the classifiers for the Scene Analysis system.

Additional Tests on Optimal Classifier

Some additional tests were performed on the classifier with the best combination of parameter settings. These tests examined more randomized tree tests used during model creation and the number of sub-windows extracted during classification testing. The learning model assumed 250 sub-windows, a sub-window size of 16x16 pixels, scale sub-window appearance mode, a HSB colour model, and no pre-processing filters. We increased and varied the number of randomized tree tests used during classifier model creation, and the number of sub-windows extracted during classification. The results are seen in Table 4-11.

Number of Randomized Tests	Results (% Misclassified)
420 – 250 Windows during classification	16.008%
840 – 250 Windows during classification	16.424%
420 – 100 Windows during classification	17.879%
840 – 100 Windows during classification	15.385%

Table 4-11: Results from Additional Tests on Optimal Classifier

Sometimes decreasing the number of sub-windows during testing classification does result in slightly better classification results, but this is not a usual occurrence. This abnormal increase is due to an optimal random selection of sub-windows from the images being classified. Secondly, it should be noted that increasing the number of sub-windows selected during testing classification results in an increase in the amount of time it takes to classify a random image.

4.3.3 PIXIT Remarks and Conclusions

When creating a classifier, each learning dataset scene needs to have the same number of images to prevent the classifier model from applying more weight on one scene than another.

At least one third of the initially gathered scene images were randomly extracted from the image data collection to be used for the testing model.

When testing the classifying model, having fewer sub-windows extracted from the image almost always resulted in poorer performance or increased error rate.

Due to a large image size and somewhat large training dataset, it was impossible to create a classifier with more than 300 sub-windows using the PIXIT software due to memory issues. Theoretically, the more sub-windows there are, the better the classifier is at correctly classifying the correct scene. Nevertheless, the developer of the software stated that "similar results can be obtained with fewer sub-windows; however, you need to increase the number of randomized tests when creating the classifier tree".

Possible future trials could include using lower resolution images for the training dataset so that there are more images used when creating the scene classifier. Other work could investigate the use of a completely different multi-class image classifier that would look at edges (vertical and horizontal), and colour, separately, before classifying the image.

4.4 Altimeter Sensor

The altimeter sensor is extremely sensitive, not only to changes in elevation, but to other conditions such as local pressure variations and changes in weather. Long-term altitude readings fluctuate considerably due to the varying atmospheric conditions. This is illustrated in Figure 4-10.

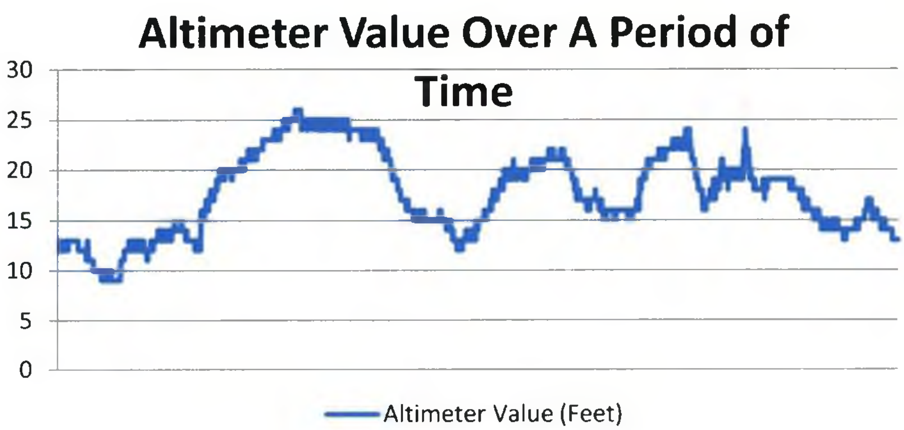


Figure 4-10: Graph Displaying Fluctuations in Altimeter Value

To help overcome the issue of fluctuating atmospheric pressure, which either increases or decreases over time, the investigation of measuring relative altitude changes was examined. The addition of a floor value was added to the system, which only changes when there is an extreme increase or decreases in altitude over a short period of time. A sliding window of three previous altitude readings was kept to prevent gradual fluctuations in atmospheric pressure over time, and the user's activity from influencing the floor value. An example can be seen in Figure 4-11. Over a period of time, there is a significant decrease in atmospheric pressure. However, the floor value remains consistent over this period of time.

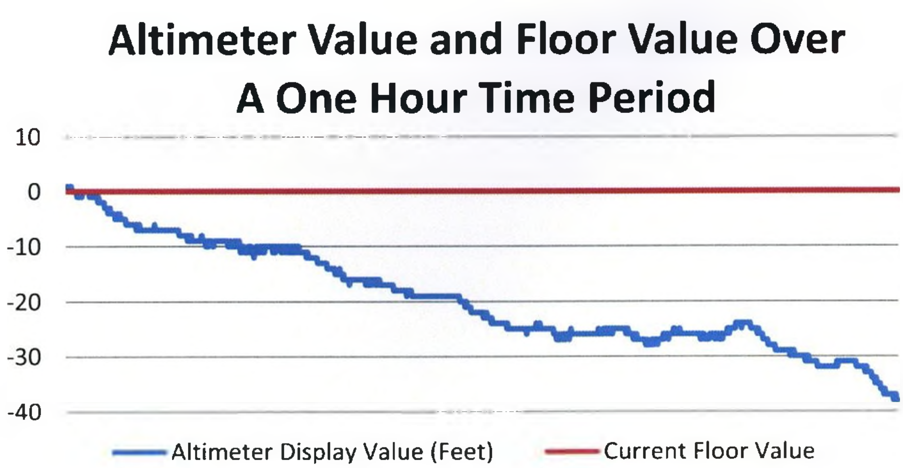


Figure 4-11: Altimeter with Brief History to Maintain Current Floor Results

4.5 Summary

This chapter presented the algorithms used for the Wi-Fi components, the configuration of parameters, the use of the PIXIT software for scene analysis, and how the use of relative altitude data from the altimeter sensor can be utilized.

Chapter 5
Implementation

The following chapter provides detailed explanation regarding the implementation of the hybrid indoor location system.

5.1 Overview of Design

This section discusses the Wi-Fi Signalling, Scene Analysis, and Sensor System implementations in detail. The system prototype consists mostly of off-the-shelf hardware and software. This has proven to speed up development, however, it created many hurdles in migrating them into a single system. The entire system prototyping was developed on an IBM X41 1.5GHZ notebook, with 760 MB Ram, running Windows XP Tablet PC Edition, with SP2 installed. A notebook was chosen over other portable options because many different types of peripherals could be affixed, and its capacity and capability to utilize complete language libraries.

5.1.1 Wi-Fi Signalling Positioning System

The Wi-Fi signalling positioning system was developed using Microsoft's C# language. This language was selected for its fast Graphic User Interface (GUI) prototyping abilities. The Wi-Fi System queries the Windows Management Instrumentation (WMI), to obtain a list of detected access points MAC address, RSSI values, and Network Names at specified time intervals. The installation of Intel's PROSet/Wireless Software is needed to provide WMI support, as this technique is not possible when Windows is managing the wireless adapter. A MySQl database was used to store and retrieve collected fingerprint information. The developed system is capable of using several different location estimation algorithms as discussed in the previous chapter.

5.1.2 Scene Analysis Positioning System

The implementation of this system requires multiple elements. To begin, the user wears a camera to periodically capture images as they move throughout their surroundings. For our purposes, we used Microsoft's LifeCam NX-6000 Webcam. This camera is capable of capturing 2.0 megapixel images. Furthermore, it is small and compact, which allowed us to easily create a device to hold the camera and worn around the user's neck. Once the image is obtained, it is then classified under a particular scene type using a single generic multi-class classifier. A percentage of confidence, or probability, is calculated for all of the possible classes. This was accomplished using PIXIT software [71], an off-the-shelf image classifier created by Raphaël Marée and discussed in Chapter 4. The classification techniques used are based on combining random sub-window extraction, and a machine learning decision tree [54]. The PIXIT software and API are written in Java. The API requires the creation of a scene classifier using the PIXIT software and learning image dataset. Once the scene classifier is created and loaded, the user's location would be determined by the scene that the captured image is classified as. Since this system is not written in the same language as the others, the hybrid system parses the data file generated by this system using the same time interval used for detecting access points.

The Wi-Fi system first estimates the user's location by providing a location likelihood, and its associated scene, for each possible location. The results of the Scene Analysis system are examined and compared to the scenes associated with each of the possible locations. For each possible location, if its associated scene matches the classified scene, then its location probability is increased by the following:

(1 – Wi-Fi location likelihood) * .5 = new location likelihood

Secondly, for each possible location, if its associated scene is one of the scenes in the bottom quarter of the scene classification results, then it likelihood is multiplied by 0.25.

Furthermore, due to the less than ideal scene classifier performance, the only time when these formulas are implemented in the decision component is when the Scene Analysis system has classified three consecutive images as being of the same particular scene. This reduces the possibility of increasing the likelihood of a location matching a scene that has been misclassified by the Scene Analysis system.

5.1.3 Sensor Positioning System

The sensor positioning system periodically polls, every second, generated altimeter information from the ZLog MOD4 Recording Altimeter [75]. This tiny altimeter, normally used for radio controlled models, has an altitude resolution of either one foot or one meter. The interface for the ZLog Module was developed in C#. It provides continuous serial output of altitude data and is powered through its USB interface connector. The Zlog is a barometric pressure sensor that is able to detect changes in air pressure, occurring due to changes in altitude and is extremely sensitive as observed in Section 4.4. Using absolute altitude information, the system would not be able to determine the correct floor the user is on without additional information. It would require having altimeters on every floor, as reference points, to cancel out the fluctuations in atmospheric pressure.

Chapter 6
Experiments

This chapter discusses the experiments that were used to demonstrate the effectiveness of the hybrid indoor location system over single technology indoor location systems. Each component of the hybrid system; Wi-Fi signals, Scene Analysis, and Altimeter Sensor Systems were tested individually to provide a baseline for location accuracy. Different combinations of systems were tested to demonstrate that involving additional system components to create a hybrid indoor locations system does indeed increase location accuracy and precision.

6.1 Experimental Environment

The following section provides details about the environments used for the experiments.

6.1.1 Experimental Environments

All the systems were tested in two distinct environments: a public building, Middlesex College, located on the University of Western Ontario's campus, and a residential property which is the townhouse where I currently reside. In both environments, there was little to no control over the access points and their installed locations. The selection of two almost completely different environments shows that the system is both adaptable and scalable. Furthermore, at each environment, there were several different scene types with a similar number of each type within its corresponding environment.

Middlesex College

This environment is the largest test area spanning multiple floors (second and third) of the north wing of the building. This testing area detects anywhere from seven to ten APs of the fourteen installed in the building, with each location fingerprint detecting an average of three or four APs. This environment contains a wide variety of possible location scenes (classroom, computing lab, office, hallway, stairwell, group office, and conference room) with similar number of each type. The floors are approximately fourteen feet apart.

Townhouse

This environment covers ground and upper floors of a home located in a highly populated urban neighborhood. There is only one access point located in the home, however, there are many additional APs in the neighboring homes that can be detected. Each location fingerprint can consist of five to ten APs. This environment contains one type of each possible scene (living room, hallway, dining room, kitchen, master bedroom, and spare bedroom). The two floors are approximately ten feet apart

6.1.2 Fingerprint Data Collection

This section outlines how data was collected for the Wi-Fi and Scene Analysis singleton systems. The only requirement that needed to be satisfied was the ability to quickly and easily collect this information.

Wi-Fi Fingerprints

There are several possible approaches that can be used to collect this data. The first possibility is to collect a single fingerprint in each room. This means that the best possible location accuracy would be room level. A second approach would be to take fingerprints at a specified distance apart from each other, say every three to five meters. The best possible location accuracy would be three to five meters, which is achievable in ideal, controlled environments using previously developed Wi-Fi systems [14, 19, 20, 25]. The second approach was used, as it provides better location accuracy. It also takes less time to gather the location fingerprints every three to five meters than every meter, which is one of the reasons for gathering every three to five meters. Stairwell and hallway fingerprints are gathered slightly farther apart, as users are usually moving in these areas, and location accuracy is not as important.

Fingerprints were collected such that they create zones as demonstrated in Figure 6-1, option A below. The other option is to have fingerprints overlap each other as demonstrated in option B. However, this configuration takes longer to gather and configure. Furthermore, option B leads to more locations, making it difficult to create meaningful relative location names. This configuration may also lead to reduced location determination accuracy as there will be quite a few relative locations with very similar fingerprints.

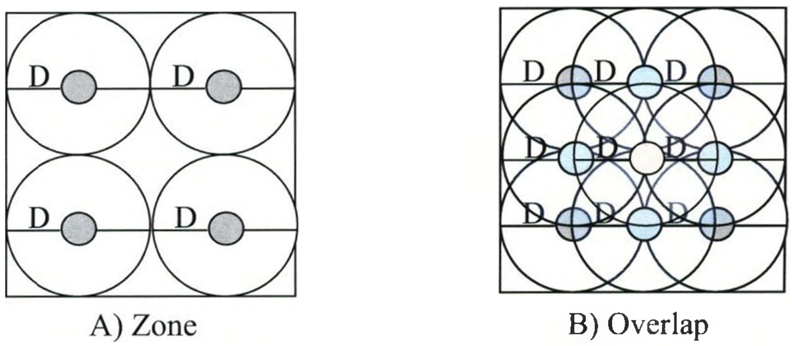


Figure 6-1: Fingerprint Options

For stairwells in Middlesex College, fingerprint locations points were taken at every landing, resulting in three points for every two floors. One at second floor landing X_1, one at the landing in-between the second and third floor X_2, and one at the third floor landing X_3. This configuration is demonstrated in Figure 6-2.

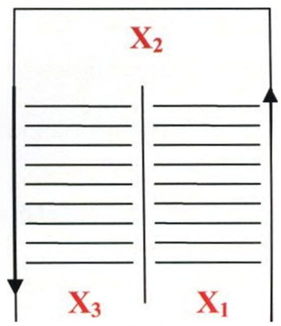


Figure 6-2: Stairwell Fingerprint Layout

Fingerprint scans are parameterized by the number of scans, the time in-between consecutive scans and what networks to look for when generating the fingerprints. A fingerprint represents the average value of signals monitored over the period of time selected. If more than one fingerprint is collected at the same location, the scan stores the continual average, maximum high and minimum low signal strength values.

For testing purposes, two fingerprint scans were collected at every location. The fingerprint data was collected at least one month before any testing was performed to ensure that the data was usable over a significant amount of time.

Scene Analysis

Images are captured wearing a Microsoft LifeCam Webcam. Images are captured every 10 seconds as the user moves throughout the building. These images are then categorized into different scene class folders based on where the images were captured, to be used by the PIXIT image classification software. Each scene folder is then split into learning images and testing images at random. The testing images are at least 25 percent of the total scene images stored in the scene folders. The PIXIT software selects image features for classification by adjusting variables, such as, the number of sub-windows, sub-window size, sub-window mode (normal, scale, shear and rotate), colour coding (B/W, HSB, and RBG), and selection of image filters (grayscale, threshold, invert colour and edges). Adjusting these variables increases or decreases the number of possible features that are used for scene classification. A discussion of the parameters that can be adjusted and how this impacts accuracy was discussed in Chapter 4.

6.1.2.1 Middlesex College Fingerprint Locations

The fingerprint locations collected, and their relative names for Middlesex College, are shown in Figure 6-3. For the entire environment, there were a total of 84 fingerprints collected.

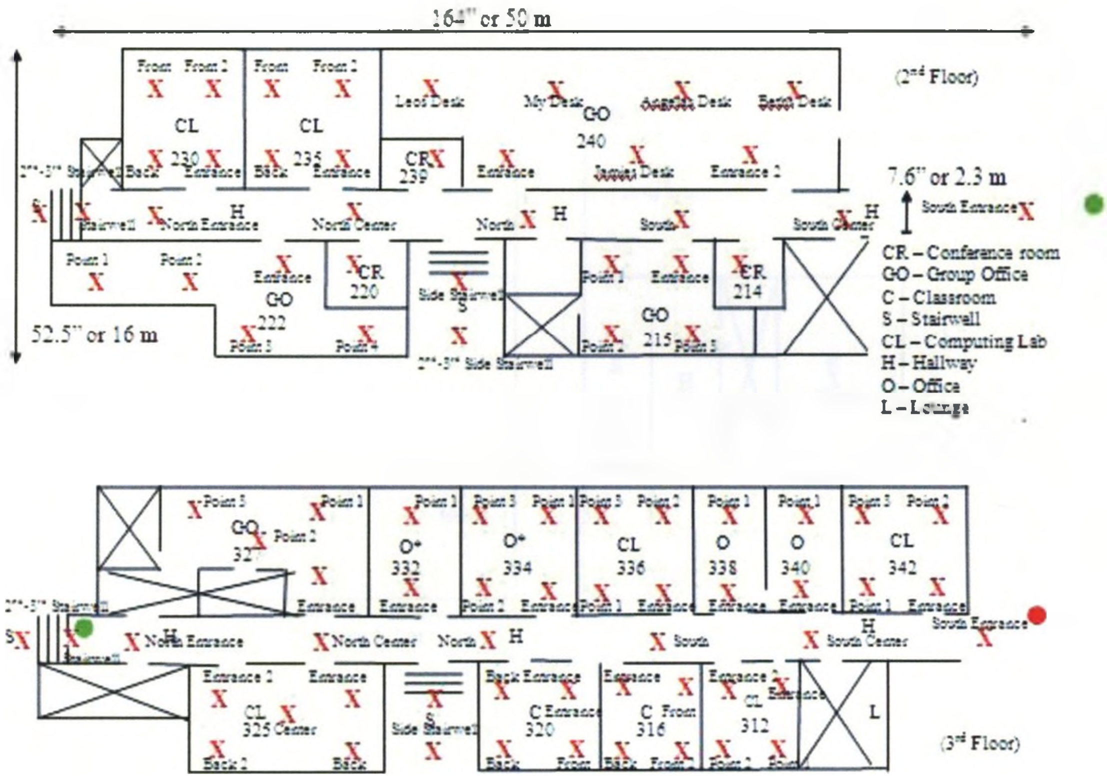


Figure 6-3: Middlesex College Map with Fingerprint Locations and Names

6.1.2.2 Townhouse Fingerprint Locations

The fingerprint locations collected, and their relative names for the townhouse, are shown in Figure 6-4. For the entire environment, there were a total of 14 fingerprints collected.

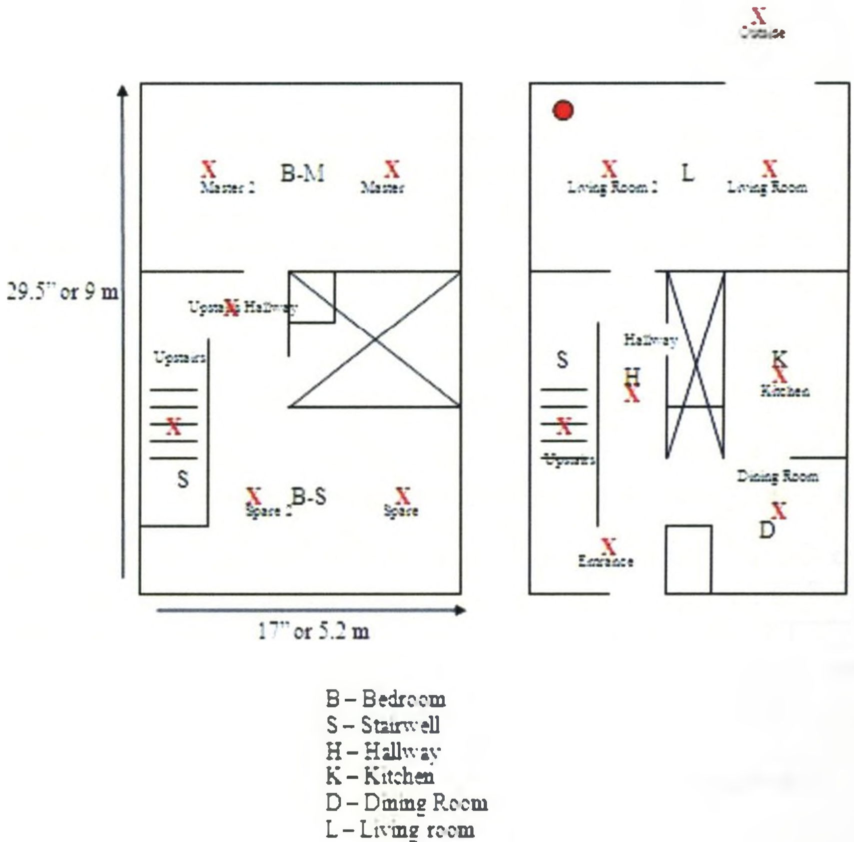


Figure 6-4: Townhouse Map with Fingerprint Locations and Names

6.1.3 Test Paths

Once the fingerprint scans are collected, the next step is to determine a testing path that crosses a large subset of fingerprint points and different scenes. The path covers multiple floors and must inspect locations within the close proximity of each other with the same scene type. The testing paths for Middlesex College and the Townhouse can be seen in Figure 6-5 and Figure 6-6 respectfully. For testing purposes, the user stopped at every fingerprint location landmark along the test path, and let the system determine the user's location for a period of time (i.e., 50 location scans or about 8 minutes). Information was gathered for the three different fingerprint algorithms (1AP, 2AP and 3AP), and the different techniques, either using Real Time (RT) or History (H) AP scans, with either

Real Time (RT) or History (H) location likelihoods were examined. Each test path was traversed three times.

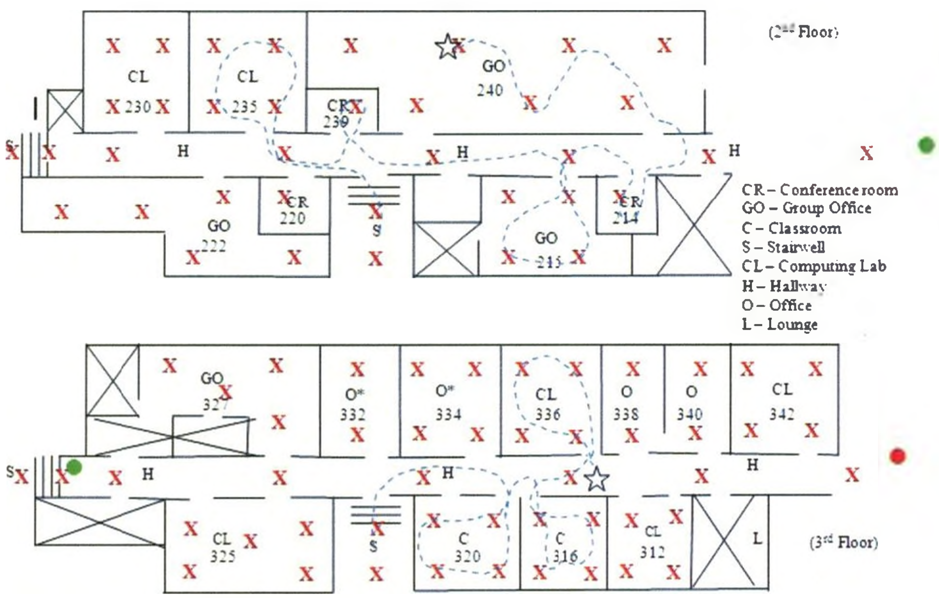


Figure 6-5: Middlesex College Map with Testing Path

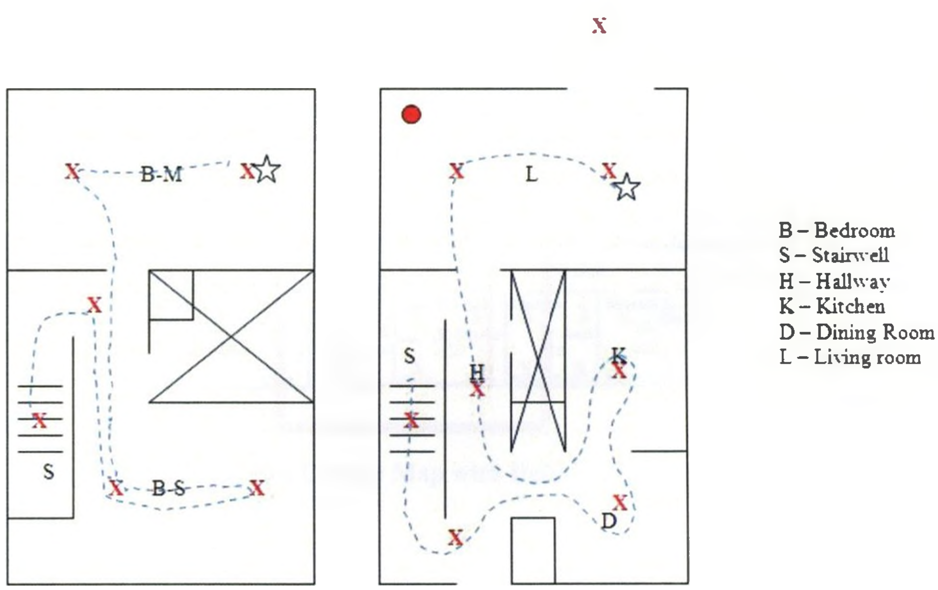


Figure 6-6: Townhouse Map with Testing Path

6.1.4 Defining Adjacent Locations

To demonstrate the accuracy and precision of the location system, the definition of an adjacent location needed to be defined. If the system did not return the user's correct location, how close was its estimation to the user's actual location. Due to the large size and lower density of APs, Middlesex College's adjacent location definitions cover a larger area. The general description of being within one fingerprint and within two fingerprints is shown in Figure 6-7. Since the Townhouse was a small environment and there is a high density of AP's, its adjacent location definition covers a smaller area. The general description of being within one fingerprint is shown in Figure 6-8.

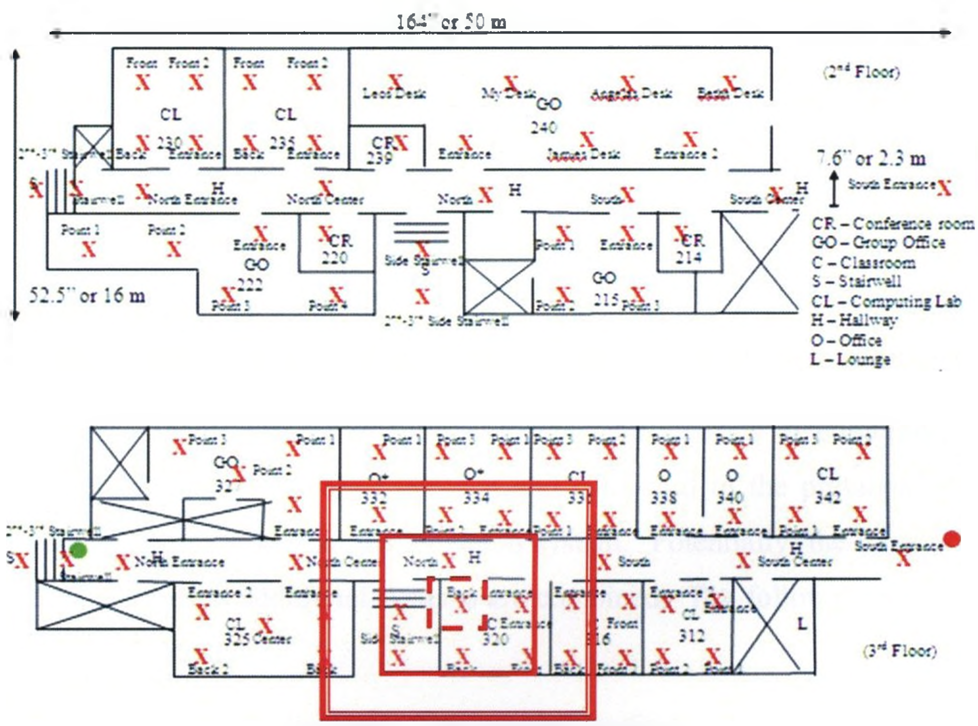


Figure 6-7: Middlesex College Map with Definition of Adjacent Locations

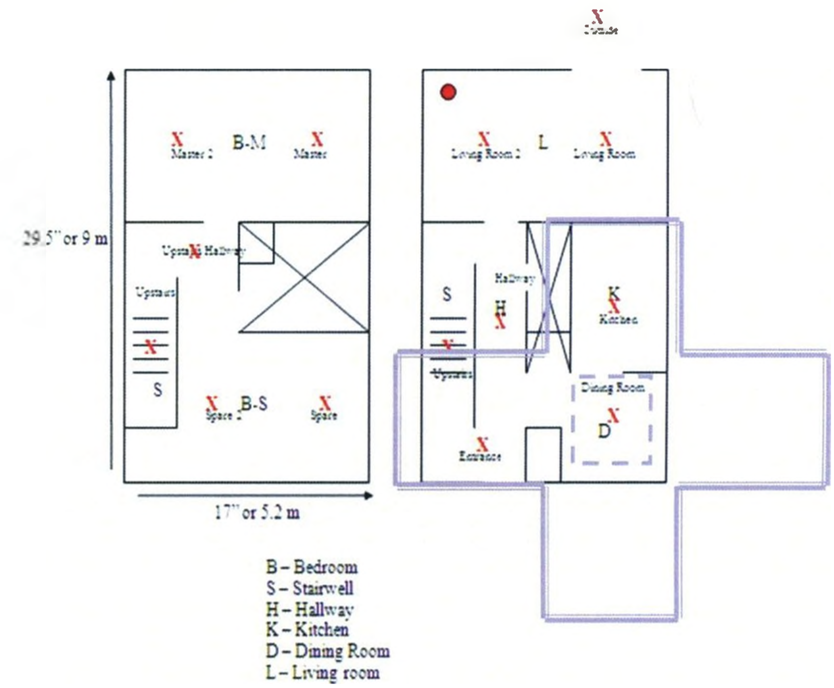


Figure 6-8: Townhouse Map with Definition Adjacent Locations

6.1.5 System Configurations

This section outlines the different singleton systems that were developed to be used in the hybrid system. Once this information is known, the analysis of combining singleton systems into hybrid systems are examined and compared to the previous measures of location accuracy of the user in the singleton system. Potentially, the location accuracy of the user increases as additional systems are combined. The following system configurations were examined:

Wi-Fi Signals (Single System): This system configuration determines the user's location by analyzing Wi-Fi access point signals. The fingerprinting technique was applied on the detected MAC addresses and corresponding RSSI values obtained from Wi-Fi AP signals.

Scene Analysis (Single System): This system configuration extracts low level features from captured images to determine the user's location based on the landscape. These images become input to a machine learning program which classifies the image as a particular scene type. When collecting Wi-Fi fingerprint data, the corresponding scene type must be stored.

Altimeter Sensor (Single System): This system configuration uses an altimeter sensor to determine the user's location based on the particular floor. When collecting Wi-Fi fingerprint data, the corresponding floor value must be stored.

Wi-Fi Signals and Altimeter Sensor (Hybrid System): This system configuration combines Wi-Fi signal and altimeter sensor data. The Wi-Fi component uses the detected MAC addresses and RSSI information to create a list of possible locations. This list is further reduced by eliminating locations from the list with a different floor value than what was determined by the altimeter sensor.

Wi-Fi Signals, Altimeter Sensor, and Scene Analysis (Hybrid System): This system configuration combines all three systems: Wi-Fi signals, altimeter sensor and scene analysis to determine the user's location. The Wi-Fi component uses the detected MAC addresses and RSSI information to create a list of possible locations. This list is reduced by eliminating locations from the list with a different floor value than what was determined by the altimeter sensor. The scene analysis system classifies the captured image as a particular scene and modifies the likelihoods of the possible locations list using this information.

The combination of scene analysis and altimeter sensor was not investigated as the hybrid system, as the system had difficulty in determining an initial starting position. Likewise, the combination of Wi-Fi signals and scene analysis was removed as a possible configuration during the observation and implementation phases. The reason for this is that the results of the scene analysis component were not overwhelmingly positive, and the improvement in location accuracy and precision using this combination would have been marginal. By combining the altimeter sensor information before the scene analysis result, the Location Decision component can filter out all possible locations on incorrect floors. Thus leaving a smaller set of possible locations before filtering based on the scene data.

Each system was tested using the different fingerprint algorithms (1AP, 2AP and 3AP). These each examine the different techniques, either using Real Time (RT) or History (H) AP scans with either Real Time (RT) or History (H) location likelihoods. Table 6-1 outlines the system test table setup for the different combinations of tests performed.

RT/RT: The location likelihood value is calculated based on the most recent Scan. The location likelihood returned is the calculated location likelihood estimation.

RT/H: The location likelihood value is calculated based on the most recent AP Scan. The location likelihood returned is the continual average of the last three location likelihood estimations.

H/RT: The location likelihood value is calculated based on the average of the last three AP Scans. The location likelihood returned is the last calculated location likelihood estimation.

H/H: In this combination, the location likelihood value is calculated based on the average of the last three access point scans. The location likelihood returned is the average of the last three likelihood estimations.

1AP Algorithm	RT/RT	RT/H	H/RT	H/H
2AP Algorithm	RT/RT	RT/H	H/RT	H/H
3AP Algorithm	RT/RT	RT/H	H/RT	H/H

Table 6-1: System Tests Table Setup (Scan/Likelihood)

6.2 Singleton System Testing

In this section, the testing results from the three different singleton indoor positioning systems are presented.

6.2.1 Wi-Fi Signalling Positioning System

The results from the Wi-Fi Signalling system are summarized in the tables below. For more detailed information about the location results for each fingerprint landmark along the testing path, refer to Appendix A.

6.2.1.1 Middlesex College – Wi-Fi System

The location accuracy of the Wi-Fi positioning system testing in Middlesex College is presented in Table 6-2. The table shows the results of the location accuracies of estimation algorithms (1AP, 2AP and 3AP), the precision (actual location, within 1 fingerprint, within 2 fingerprints) and the examination of adding history to either the AP scan and/or the location estimation. The 3AP algorithm using history AP scans and history location likelihood estimations had the highest accuracy and precision.

	RT/RT			RT/H			H/RT			H/H		
	AL	1 FP	2 FP	AL	1 FP	2FP	AL	1 FP	2FP	AL	1 FP	2FP
Totals (Average) 1AP	0.04	0.13	0.25	0.03	0.14	0.27	0.03	0.12	0.23	0.04	0.12	0.23
Totals (Average) 2AP	0.07	0.25	0.38	0.07	0.28	0.42	0.07	0.26	0.40	0.06	0.28	0.43
Totals (Average) 3AP	0.12	0.37	0.50	0.15	0.41	0.55	0.13	0.41	0.55	0.15	0.44	0.57

Table 6-2: Middlesex College Wi-Fi System Results

6.2.1.2 Townhouse – Wi-Fi System

The location accuracy of the Wi-Fi positioning system testing in the Townhouse is presented in Table 6-3. The table shows the results of the different location accuracy of estimation algorithms (1AP, 2AP and 3AP), the precision (actual location and within 1 fingerprint) and the examination of adding history to either the AP scan and/or the location estimation. The 3AP algorithm using history AP scans and history location likelihood estimations had the highest accuracy and precision.

	RT/RT		RT/H		H/RT		H/H	
	AL	1 FP	AL	1 FP	AL	1 FP	AL	1 FP
Totals (Average) 1AP	0.27	0.47	0.28	0.48	0.3	0.51	0.32	0.52
Totals (Average) 2AP	0.32	0.6	0.36	0.59	0.36	0.62	0.37	0.6
Totals (Average) 3AP	0.35	0.66	0.41	0.67	0.4	0.67	0.41	0.68

Table 6-3: Townhouse Wi-Fi System Results

6.2.2 Scene Analysis Positioning System

This section presents the detailed testing phase results of the scene classifiers, created for both testing environments, generated by the PIXIT software. The results demonstrate the Scene Analysis system's ability to determine the current scene the user is in.

6.2.2.1 Middlesex College – Scene Analysis System

The results from the Middlesex College scene classifier are shown below. The classifier that was selected used the following parameters. Further information about different classifier parameters tested can be found in Section 4.3.

- HSV – Colour Model , 16x16 Pixel Sub-Window Dimension
- Scale Window Mode, Number of Sub-Windows: 250 per image
- 10 – Trees , 420 – Randomized Tests

Table 6-4 and Figure 6-9 provide a detailed overview of the scene classifier's ability to detect different scene types. Using the testing dataset and every image in all the labelled scene classes, the PIXIT application shows what scene the classifier defined the image as.

	Classifier Output								
Scene Class	classroom	comp_lab	conf_room	group_office	hallway	office	outside	stairwell	**Total**
classroom	63	1	0	1	1	3	0	1	**70**
comp_lab	6	75	0	2	2	14	0	0	**99**
conf_room	1	0	24	0	0	1	0	0	**26**
group_office	7	7	1	74	0	9	1	0	**99**
hallway	0	0	0	1	33	0	1	1	**36**
office	6	6	0	4	0	83	0	0	**99**
outside	0	0	0	0	0	0	22	0	**22**
stairwell	2	1	0	1	4	1	1	20	**30**

Table 6-4: Summary of Middlesex College PIXIT Classifier Results

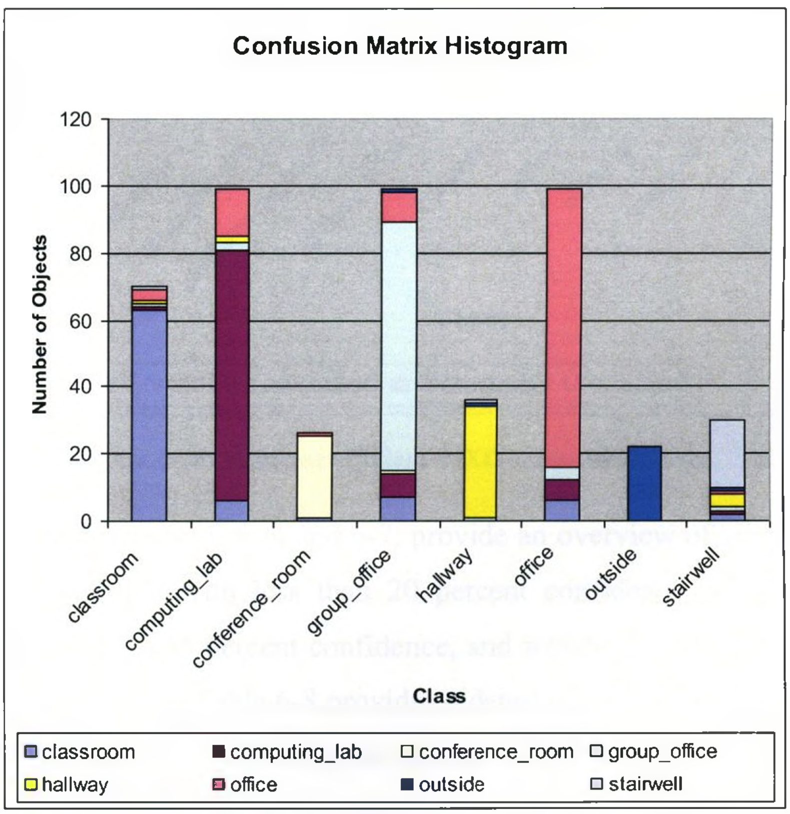


Figure 6-9: Middlesex College PIXIT Classifier Matrix Histogram

Figure 6-10 shows the overall classifier's ability to classify scene types correctly by each scene type. The chosen classifier has a classification error rate of approximately

16% using 250 sub-window extraction, and 18% using 100 sub-window extraction, during image classification. Again, an increased number of sub-windows extracted during image classification increases the amount of time the classifier takes to classify a random image. For the hybrid system, a 125 sub-window extraction is used, taking the system approximately 4 seconds to classify a random image.

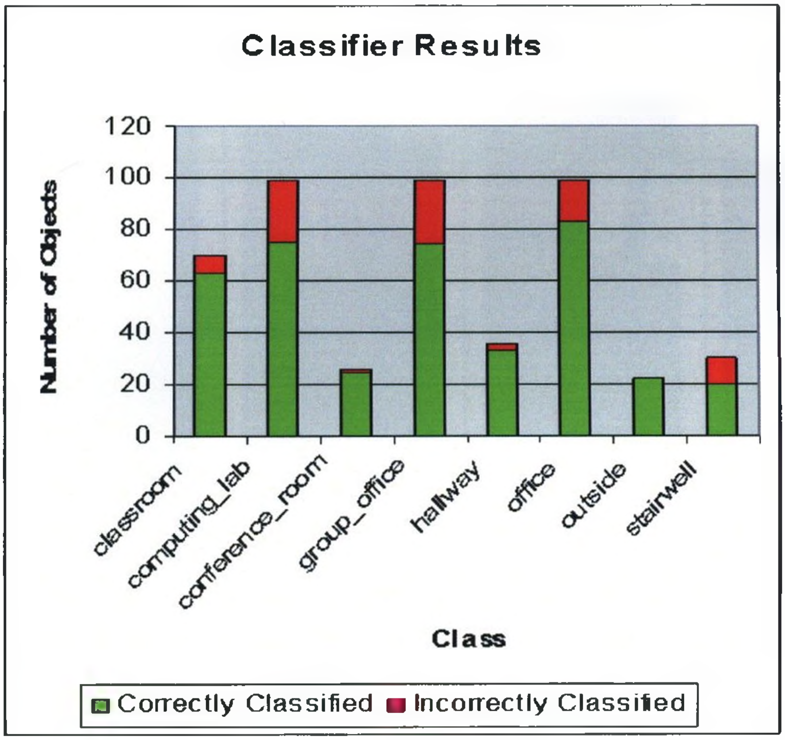


Figure 6-10: Middlesex College PIXIT Classifier Results

The next three Tables, 6-5, 6-6, and 6-7, provide an overview of which images were misclassified or classified with less than 20 percent confidence, which images were classified between 20 and 35 percent confidence, and which images were classified with over 35 percent confidence. Table 6-8 provides a detailed overview of the scene classifiers confidence for each scene, providing the average confidence when classified correctly and the max/min confidence over all the testing images.

Classroom				
Computing Lab				
Conference Room				
Group Office				
Hallway				
Office				
Stairwell				

Table 6-5: Middlesex Scenes Below 20 Percent Confidence or Misclassified

Classroom				
Computing Lab				
Conference Room				
Group Office				
Hallway				
Office				
Stairwell				

Table 6-6: Middlesex Scenes Between 20 and 35 Percent Confidence

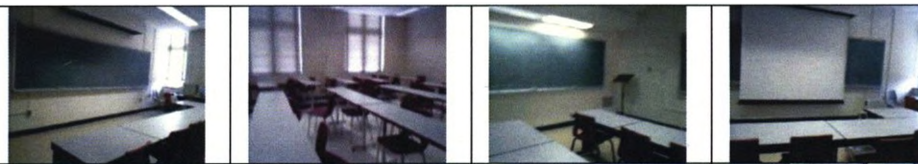
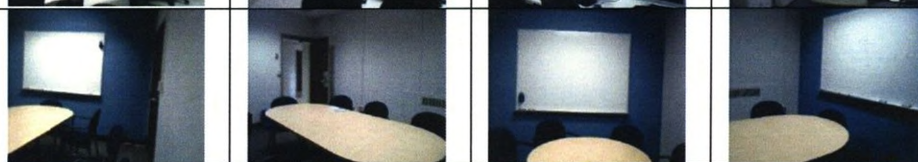
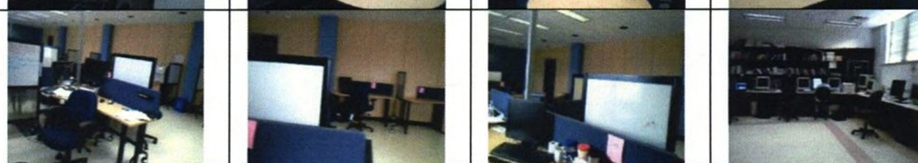
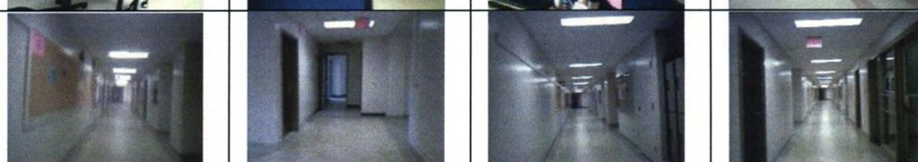
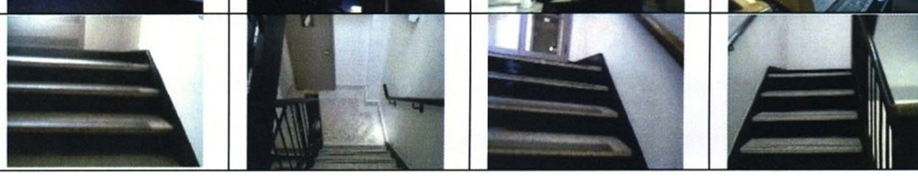
Classroom	
Computing Lab	
Conference Room	
Group Office	
Hallway	
Office	
Stairwell	

Table 6-7: Middlesex Scenes Above 35 Percent Confidence

Classification Class	Average Confidence	Max Confidence	Min Confidence
Classroom	26.805	42.64	14
Computing Lab	27.367	46.92	14
Conference Room	40.014	81.72	12.75
Group Office	28.573	58.52	11
Hallway	52.187	76.8	6
Office	27.324	56.651	12
Stairwell	23.335	47.16	9
Outside	60.882	80.64	27.8

Table 6-8: Summary of Average Middlesex College Classifier Scene Confidence

6.2.2.2 Townhouse – Scene Analysis System

The results from the Townhouse scene classifier are shown below. The classifier that was selected used the same parameters that were used with Middlesex College.

	Classifier Output							
Scene Class	bedroom_m	bedroom_s	dining_room	hallway	kitchen	living_room	stairwell	**Total**
bedroom_m	32	0	0	0	1	1	1	**35**
bedroom_s	1	32	0	1	1	0	0	**35**
dining_room	0	4	19	7	4	1	0	**35**
hallway	0	1	7	32	0	1	2	**43**
kitchen	0	0	0	1	26	0	2	**29**
living_room	3	1	1	2	0	34	0	**41**
stairwell	1	0	1	2	0	0	21	**25**

Table 6-9: Summary of Townhouse PIXIT Classifier Results

Table 6-9 and Figure 6-11 provide a detailed overview of the scene classifier's ability to detect different scene types. Using the testing dataset, every image in all the labelled classes, the application shows what scene the classifier believed the image to be.

Figure 6-12 shows the overall classifier's ability to classify scene types correctly by each scene type. The chosen classifier has a classification error rate of approximately 19% using 250 sub-window extraction, and 20% using 100 sub-window extraction, during image classification.

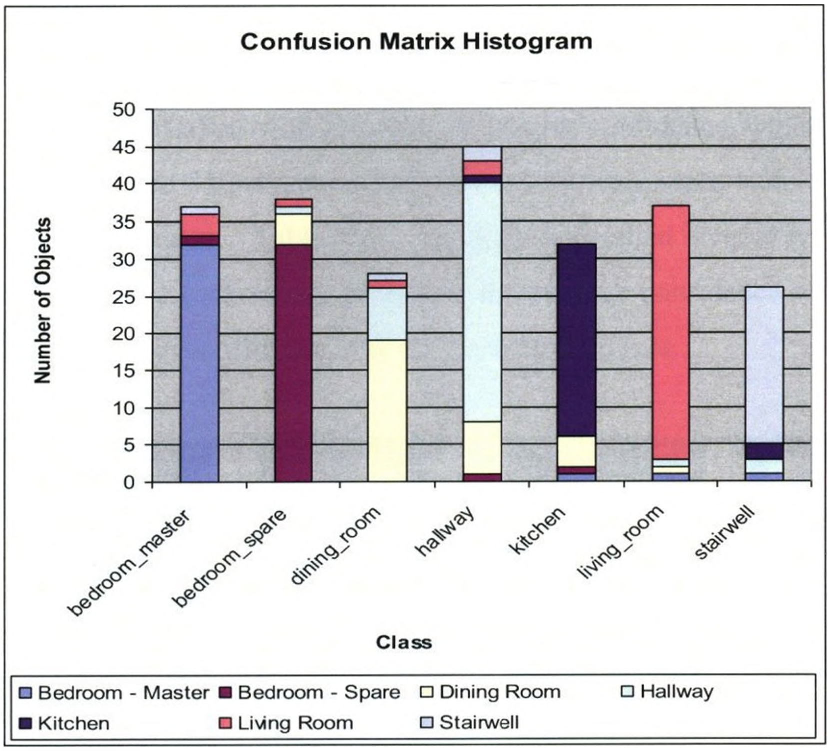


Figure 6-11: Townhouse PIXIT Classifier Matrix Histogram

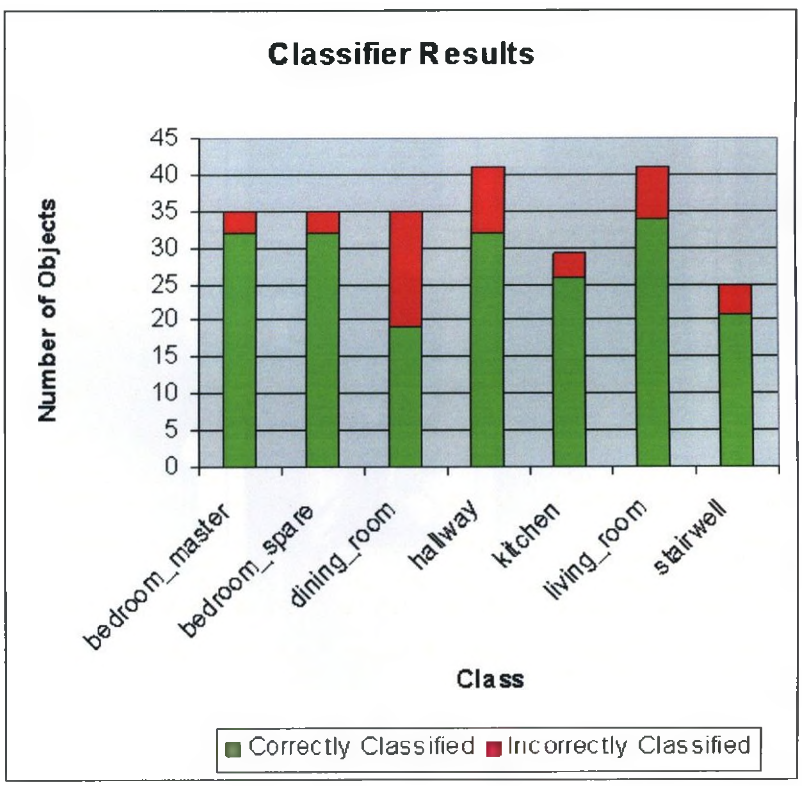


Figure 6-12: Townhouse PIXIT Classifier Results Graph

The next three Tables, 6-10, 6-11, and 6-12, provide an overview of which images were misclassified or classified with less than 20 percent confidence, which images were classified between 20 and 35 percent confidence, and which images were classified with over 35 percent confidence. Table 6-13 provides a detailed overview of the scene classifiers confidence for each scene, providing the average confidence when classified correctly and the max/min confidence over all the testing images.

Bedroom – Master				
Bedroom – Spare				
Kitchen				
Dining Room				
Hallway				
Living Room				
Stairwell				

Table 6-10: Townhouse Scenes Below 20 Percent Confidence or Misclassified

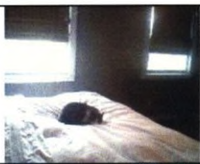
Bedroom – Master				
Bedroom – Spare				
Kitchen				
Dining Room				
Hallway				
Living Room				
Stairwell				

Table 6-11: Townhouse Scenes Between 20 and 35 Percent Confidence

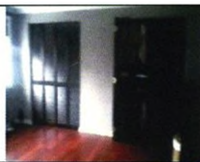
Bedroom – Master				
Bedroom – Spare				
Kitchen				
Dining Room				
Hallway				
Living Room				
Stairwell				

Table 6-12: Townhouse Scenes Above 35 Percent Confidence

Classification Class	Average Confidence	Max Confidence	Min Confidence
Bedroom – Master	45.36	64.82	6
Bedroom – Spare	35.44	58.84	10
Kitchen	46.65	69.6	8
Dining Room	34.98	68.88	6
Hallway	36.99	77.08	4
Living Room	38.08	59.8	6
Stairwell	53.83	88.44	12

Table 6-13: Summary of Average Townhouse Scene Confidence

Table 6-5 and Table 6-10 show images that were misclassified, or had a low confidence value by the scene classifier. There are images which demonstrate that lighting conditions, minimum features in a scene, similar scene features, and transitional scene type images can all be cause for misclassification. The time of day and interior lighting can also play a factor in whether the image is classified correctly. In Middlesex College, this is not as prevalent, as the lighting is recessed in the ceiling and lighting conditions are fairly consistent throughout the day. However, in the Townhouse, lighting conditions change from room to room, and the time of day determined whether the lights were on or off. These factors significantly affected whether the image was classified correctly.

6.2.3 Sensor Positioning System

This section provides the results of testing the sensor positioning system. The main purpose of the experiments was to test the altimeter sensor's ability to determine the correct floor of the user. The sensor system maintains a short history of previous altimeter data and examines it for a rapid change to determine if the user changed floors. Using relative change in altimeter data was implemented because of the altimeter's sensitivity to constant fluctuations in atmospheric pressure. Figure 6-13 demonstrates the sensor system's ability to determine the user's correct floor, when moving up and down between floors, even though there are regular changes in altimeter readings.

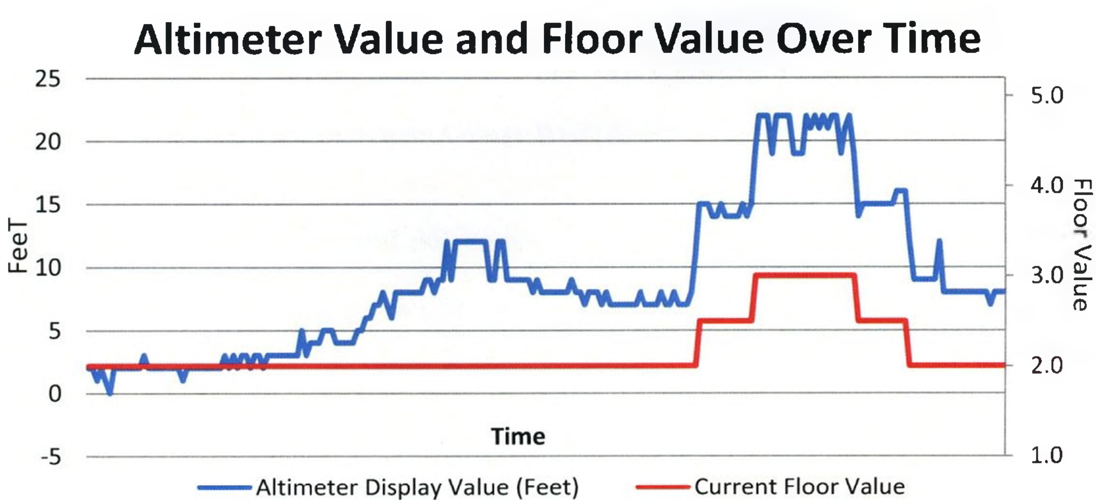


Figure 6-13: Zlog Altimeter Testing, Floor Determination Results

6.3 Hybrid System Testing

The following section gives details about the testing completed on the hybrid indoor positioning systems.

6.3.1 Wi-Fi and Altimeter Sensor System

The results from the Wi-Fi and Altimeter positioning system are summarized below. For more detailed information about the location results for each fingerprint landmark along the testing path, refer to Appendix A.

6.3.1.1 Middlesex College – Wi-Fi and Altimeter

The location accuracy of the Wi-Fi and Altimeter positioning system testing in Middlesex College is presented in Table 6-14. The table shows the results of the location accuracies of estimation algorithms (1AP, 2AP and 3AP), the precision (actual location and within one fingerprint), and the examination of adding history to either the AP scan and/or the location estimation. The 3AP algorithm, using history AP scans and history location likelihood estimations, had the highest accuracy and precision.

	RT/RT			RT/H			H/RT			H/H		
	AL	1 FP	2 FP	AL	1 FP	2FP	AL	1 FP	2FP	AL	1 FP	2FP
Totals (Average) 1AP	0.11	0.29	0.49	0.12	0.33	0.50	0.12	0.31	0.50	0.11	0.31	0.52
Totals (Average) 2AP	0.18	0.50	0.69	0.20	0.57	0.75	0.18	0.54	0.73	0.20	0.59	0.77
Totals (Average) 3AP	0.25	0.62	0.79	0.27	0.67	0.84	0.29	0.69	0.86	0.31	0.71	0.87

Table 6-14: Middlesex College Wi-Fi & Altimeter System Results

6.3.1.2 Townhouse – Wi-Fi and Altimeter

The location accuracy of the Wi-Fi and Altimeter positioning system testing in the Townhouse is presented in Table 6-15. The table shows the results of the location accuracies of estimation algorithms (1AP, 2AP and 3AP), the precision (actual location and within one fingerprint), and the examination of adding history to either the AP scan and/or the location estimation. The 3AP algorithm, using history AP scans and history location likelihood estimations, had the highest accuracy and precision.

	RT/RT		RT/H		H/RT		H/H	
	AL	1 FP	AL	1 FP	AL	1 FP	AL	1 FP
Totals (Average) 1AP	0.38	0.68	0.39	0.7	0.39	0.7	0.42	0.71
Totals (Average) 2AP	0.45	0.76	0.46	0.77	0.48	0.76	0.48	0.77
Totals (Average) 3AP	0.59	0.88	0.65	0.91	0.63	0.9	0.66	0.91

Table 6-15: Townhouse Wi-Fi & Altimeter System Results

6.3.2 Wi-Fi, Altimeter Sensor and Scene Analysis System

The results from the Wi-Fi, Altimeter, and Scene Analysis positioning system are summarized below. For more detailed information about the location results for each fingerprint landmark along the testing path, refer to Appendix A.

6.3.2.1 Middlesex College – Wi-Fi, Altimeter and Scene Analysis

The location accuracy of the Wi-Fi, Altimeter, and Scene Analysis positioning system testing in Middlesex College is presented in Table 6-16. The table shows the results of the location accuracies of estimation algorithms (1AP, 2AP and 3AP), the precision (actual location and within one fingerprint), and the examination of adding history to either the AP scan and/or the location estimation. The 3AP algorithm, using history AP scans and history location likelihood estimations, had the highest accuracy and precision.

	RT/RT			RT/H			H/RT			H/H		
	AL	1 FP	2 FP	AL	1 FP	2FP	AL	1 FP	2FP	AL	1 FP	2FP
Totals (Average) 1AP	0.10	0.29	0.49	0.15	0.42	0.61	0.09	0.28	0.49	0.14	0.42	0.61
Totals (Average) 2AP	0.21	0.56	0.73	0.25	0.66	0.80	0.23	0.60	0.76	0.26	0.66	0.80
Totals (Average) 3AP	0.28	0.69	0.83	0.32	0.76	0.88	0.31	0.73	0.86	0.32	0.76	0.88

Table 6-16: Middlesex College Wi-Fi, Altimeter & Scene System Results

6.3.2.2 Townhouse – Wi-Fi, Altimeter and Scene Analysis

The location accuracy of the Wi-Fi, Altimeter, and Scene Analysis positioning system testing in the Townhouse is presented in Table 6-17. The table shows the results of the location accuracies of estimation algorithms (1AP, 2AP and 3AP), the precision (actual location and within one fingerprint), and the examination of adding history to either the AP scan and/or the location estimation. The 3AP algorithm, using history AP scans and history location likelihood estimations, had the highest accuracy and precision.

	RT/RT		RT/H		H/RT		H/H	
	AL	1 FP	AL	1 FP	AL	1 FP	AL	1 FP
Totals (Average) 1AP	0.47	0.79	0.58	0.8	0.57	0.8	0.59	0.81
Totals (Average) 2AP	0.69	0.9	0.79	0.93	0.72	0.9	0.75	0.91
Totals (Average) 3AP	0.78	0.97	0.87	0.98	0.84	0.98	0.88	0.98

Table 6-17: Townhouse Wi-Fi, Altimeter & Scene System Results

6.4 Summary

The system testing examines and compares the different fingerprint techniques and combinations. The results showed that for both environments there was an increase in both location accuracy and precision as fingerprinting techniques become more complex. The use a single AP in determining the location of the user was not as effective as using two APs. The use of three APs in determining the location of the user showed an improvement over using two APs. In all cases, the use of the three AP algorithm using history AP scans and history location likelihood estimations had the highest accuracy and precision. Furthermore, using history location likelihood estimates (i.e. the average of three consecutive likelihood values) yielded little improvement when using history AP scans versus real-time AP scans. The reader can refer to Figures 6-14 and 6-15 for a comparison of all system testing completed for each testing environment.

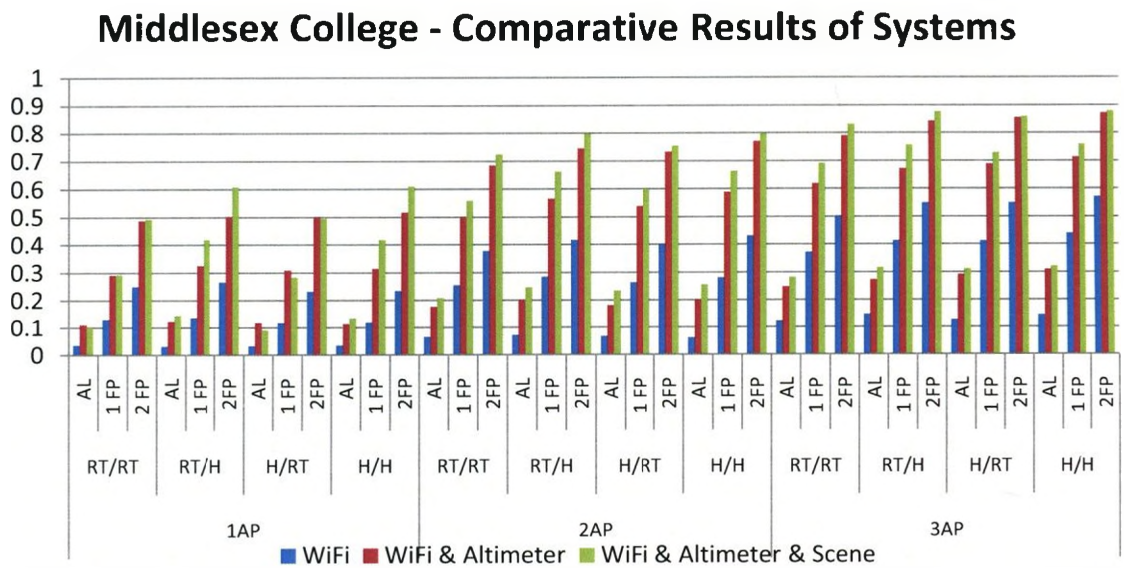


Figure 6-14: Middlesex College System Comparison Graph

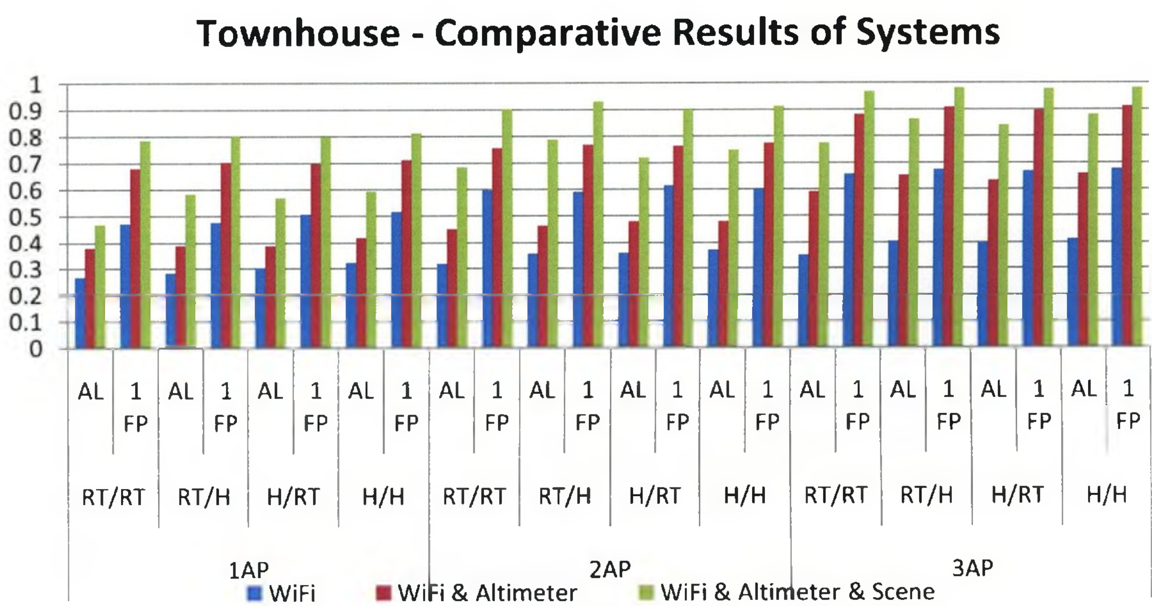


Figure 6-15: Townhouse System Comparison Graph

Chapter 7
Conclusions

The research presented in this thesis examines the use of multiple technologies, Wi-Fi signals, altimeter sensor, and scene analysis for indoor location sensing. These technologies were selected as they are cost effective and readily available. The developed hybrid system heavily relies on Wi-Fi signals, but the use of Wi-Fi signals is augmented with other sources of information. The system allows for different technologies to be incrementally added, something not found in other hybrid systems. The significantly different testing environments represented real-world settings. The testing environments covered multiple floors, with little or no control over the number and position of access points. The test results confirmed that the altimeter is highly valuable since it filters out similar Wi-Fi fingerprints on the incorrect floor. Although there was little improvement in the test results when using image analysis, this technology is promising, but requires more research and experimentation into its different techniques. It should be noted that the most time consuming aspect of this work was the data collection needed to produce the scene classifier. This thesis demonstrated the system's ability to function in uncontrolled environments, and showed that as other technologies are combined, there is an increase in both location accuracy and precision.

7.1 Contributions

The following section outlines the contributions this thesis made:

- This work demonstrated that the hybrid location system has the ability to work effectively in two different, multi-floor environments which there was minimal to no control over the environment. The altimeter sensor provided very useful information to have, as seen from the results.

- This work compared results of the singleton technology location systems to the results of different combinations of hybrid systems. The testing results illustrated that augmenting Wi-Fi signals with other technologies was effective.

- This work demonstrated that location accuracy increases as technologies are combined, and that a small continual history window on both the AP scan and location likelihood estimation improves location estimation precision.

- This work demonstrated that the hybrid system prototype was cost effective using off-the-shelf technologies that are readily available. There are a lot of buildings that have adopted Wi-Fi networks for other purposes, and thus using Wi-Fi for location positioning comes at no extra cost to the organization that deployed the Wi-Fi system. The altimeters, other sensors and webcams, are inexpensive and are increasingly being used in Smartphones.

- The developed prototype system provided the ability to dynamically select different sources of information and Wi-Fi algorithms. This feature will be especially important for future work, where other sources of information will be considered.

- The Wi-Fi system component deals with the issue of signal fluctuations by applying a sliding window of continual averages for both the AP scan and location likelihood estimations. Furthermore, during the location likelihood calculation, different weights are given to the possible relative locations based on how close the detected APs RSSI values are to the stored fingerprint APs RSSI values. Refer to Section 4 for more information regarding Wi-Fi algorithms.

- The prototype system developed uses Wi-Fi algorithms [27, 28, 34, 44] where the off-line phase (i.e. the creation of radio map or fingerprint collections, which can be used to determine location while in the on-line phase) overlaps with the on-line phase. This makes the daunting task of re-calibration easier.

7.2 Future Work

Building on the success of hybrid indoor location prototype, the use of other sources of information and the benefits they could provide will be examined. The design of the software is highly flexible allowing the user to select the desired sources of information. Some other work suggests that Bluetooth [12, 17, 28, 37, 38], RFID [11, 15, 18, 30, 39, 40, 76], and accelerometer sensors [36, 61, 64-66] could be greatly beneficial. Accelerometers can be used to determine a position relative to an initial position based on user movement. Tree-graphs [77] that represent all the possible movements/paths the user can make from a relative location may also be extremely helpful in determining the user's location. The location system could remove locations from the list of possible locations that are realistically impossible to get based on previous location estimations. These graphs could be created at the same time the user collects location fingerprints.

There will be continued work on improving fingerprint collection and Wi-Fi algorithms. Some researchers [41] have observed that the direction and orientation of the mobile device Wi-Fi antenna impacts the signal strengths of detected APs. Further research of other algorithms that use distance measures, (i.e., Euclidian and Manhattan) K-nearest neighbours, and probabilistic techniques will be conducted.

More learning images would have improved the scene classification results, but due to memory constraints in Windows (maximum 1.6GB per process), it was not possible to use more than 150 learning images per scene. One possibility that will be looked at, in order to improve scene classification results, is to reduce the image resolution to get more images per learning set. Another approach to improving the scene classifier system may be to dynamically adjust the weight of importance the scene classifier results has on the location likelihood estimation. This would be based on confidence values returned by the scene classifier for each scene type. A different weight value can be applied for different scene confidence values.

Using Image Classification to determine location provided poor results on its own, and mediocre results as an additional source of information. Additional issues include the time consuming collection of data to build the classifier, and the large computational power to classify images. However, image classification technology and techniques are relatively new, and research gains are being made to both improve image classification performance and image capturing techniques.

One of the reasons for using a notebook was the ability to use peripheral devices, and the ease in finding libraries for these peripheral devices. As Smartphone support, external ports and embedded devices increase, the development of indoor positioning software for Smartphones will be explored in more detail.

Appendix A

Detailed System Testing Results

Wi-Fi System - Townhouse

Location / Test	1AP							
	RT/RT		RT/H		H/RT		H/H	
	AL	1 FP	AL	1 FP	AL	1 FP	AL	1 FP
Dining Room	0.34	0.45	0.25	0.27	0.15	0.27	0.11	0.15
Entrance	0.21	0.47	0.24	0.47	0.33	0.61	0.30	0.59
Kitchen	0.25	0.34	0.12	0.16	0.27	0.34	0.16	0.21
Living Room	0.46	0.89	0.47	0.83	0.41	0.94	0.41	0.92
Living Room 2	0.82	0.91	0.79	0.90	0.94	0.98	0.91	0.97
Main Hallway	0.01	0.25	0.08	0.37	0.00	0.26	0.15	0.37
Master	0.09	0.22	0.21	0.24	0.24	0.29	0.37	0.41
Master 2	0.07	0.14	0.08	0.23	0.14	0.29	0.16	0.49
Spare	0.69	0.89	0.76	0.86	0.69	0.90	0.75	0.89
Spare 2	0.15	0.44	0.26	0.33	0.29	0.63	0.39	0.57
Stairwell	0.10	0.39	0.12	0.46	0.17	0.42	0.14	0.35
Upstairs Hallway	0.03	0.31	0.03	0.59	0.01	0.15	0.01	0.28
Totals	0.27	0.47	0.28	0.48	0.3	0.51	0.32	0.52

Location / Test	2AP							
	RT/RT		RT/H		H/RT		H/H	
	AL	1 FP	AL	1 FP	AL	1 FP	AL	1 FP
Dining Room	0.36	0.65	0.42	0.65	0.43	0.66	0.39	0.57
Entrance	0.20	0.65	0.22	0.63	0.31	0.67	0.31	0.67
Kitchen	0.02	0.07	0.02	0.04	0.00	0.02	0.00	0.01
Living Room	0.47	0.83	0.52	0.87	0.61	0.89	0.62	0.89
Living Room 2	0.64	0.98	0.78	0.97	0.74	0.99	0.89	0.99
Main Hallway	0.23	0.49	0.28	0.43	0.28	0.48	0.28	0.45
Master	0.11	0.19	0.12	0.25	0.11	0.21	0.12	0.22
Master 2	0.20	0.39	0.24	0.33	0.26	0.57	0.28	0.53
Spare	0.89	0.98	0.97	0.99	0.97	1.00	0.99	1.00
Spare 2	0.44	0.70	0.52	0.70	0.36	0.74	0.40	0.75
Stairwell	0.10	0.49	0.06	0.45	0.03	0.46	0.00	0.41
Upstairs Hallway	0.14	0.71	0.13	0.75	0.21	0.70	0.18	0.74
Totals	0.32	0.6	0.36	0.59	0.36	0.62	0.37	0.6

Location / Test	3AP							
	RT/RT		RT/H		H/RT		H/H	
	AL	1 FP	AL	1 FP	AL	1 FP	AL	1 FP
Dining Room	0.46	0.83	0.59	0.84	0.56	0.85	0.59	0.85
Entrance	0.12	0.54	0.12	0.53	0.22	0.65	0.21	0.65
Kitchen	0.30	0.38	0.37	0.40	0.32	0.34	0.39	0.40
Living Room	0.40	0.80	0.51	0.85	0.49	0.90	0.53	0.91
Living Room 2	0.57	0.95	0.65	0.95	0.49	0.94	0.50	0.95
Main Hallway	0.18	0.50	0.19	0.51	0.18	0.50	0.20	0.49
Master	0.27	0.53	0.33	0.51	0.26	0.39	0.27	0.39
Master 2	0.28	0.45	0.34	0.53	0.34	0.50	0.34	0.52
Spare	0.77	0.97	0.84	0.99	0.85	0.99	0.86	0.99
Spare 2	0.38	0.67	0.41	0.63	0.47	0.66	0.53	0.68
Stairwell	0.27	0.53	0.32	0.56	0.27	0.53	0.27	0.54
Upstairs Hallway	0.20	0.73	0.19	0.78	0.34	0.78	0.28	0.74
Totals	0.35	0.66	0.41	0.67	0.4	0.67	0.41	0.68

Wi-Fi System – Middlesex College

Location / Test	1AP											
	RT/RT			RT/H			H/RT			H/H		
	AL	1 FP	2 FP	AL	1 FP	2FP	AL	1 FP	2FP	AL	1 FP	2FP
MC 2nd Floor North	0.01	0.14	0.15	0.02	0.11	0.12	0.00	0.10	0.10	0.10	0.20	0.20
MC 2nd Floor North Center	0.16	0.17	0.18	0.08	0.12	0.14	0.13	0.14	0.14	0.11	0.16	0.23
MC 2nd Floor Side Stairwell	0.05	0.10	0.31	0.03	0.05	0.18	0.02	0.05	0.33	0.01	0.07	0.16
MC 2nd Floor South	0.01	0.27	0.27	0.01	0.23	0.23	0.00	0.24	0.24	0.00	0.12	0.12
MC 2nd-3rd Side Stairwell	0.01	0.06	0.12	0.03	0.20	0.31	0.00	0.08	0.20	0.11	0.29	0.36
MC 3rd Floor North	0.00	0.03	0.03	0.02	0.07	0.08	0.00	0.04	0.08	0.00	0.07	0.08
MC 3rd Floor Side Stairwell	0.21	0.22	0.35	0.05	0.18	0.33	0.14	0.16	0.32	0.03	0.14	0.24
MC 3rd Floor South	0.00	0.00	0.00	0.08	0.08	0.08	0.00	0.00	0.00	0.01	0.01	0.01
MC214	0.08	0.14	0.53	0.06	0.10	0.33	0.06	0.08	0.39	0.05	0.05	0.26
MC215 Entrance	0.12	0.30	0.35	0.04	0.17	0.24	0.15	0.36	0.37	0.04	0.13	0.17
MC215 Point 1	0.06	0.26	0.33	0.01	0.10	0.18	0.06	0.34	0.34	0.01	0.16	0.22
MC215 Point 2	0.06	0.24	0.24	0.04	0.08	0.10	0.06	0.18	0.18	0.07	0.10	0.11
MC215 Point 3	0.07	0.36	0.36	0.03	0.27	0.27	0.07	0.36	0.36	0.01	0.20	0.20
MC235 Back	0.00	0.09	0.25	0.00	0.03	0.20	0.00	0.07	0.19	0.03	0.13	0.25
MC235 Entrance	0.00	0.08	0.45	0.01	0.07	0.50	0.00	0.05	0.39	0.05	0.07	0.41
MC235 Front	0.01	0.01	0.10	0.03	0.07	0.14	0.00	0.00	0.14	0.01	0.04	0.13
MC235 Front 2	0.02	0.05	0.25	0.08	0.14	0.26	0.00	0.01	0.19	0.03	0.10	0.12
MC239	0.03	0.10	0.21	0.01	0.05	0.16	0.01	0.16	0.25	0.00	0.08	0.13
MC240 Angelas Desk	0.06	0.15	0.27	0.05	0.14	0.25	0.10	0.14	0.25	0.09	0.14	0.23
MC240 Entrance 2	0.19	0.23	0.44	0.09	0.12	0.24	0.23	0.25	0.48	0.12	0.14	0.33
MC240 Jamies Desk	0.01	0.16	0.51	0.01	0.13	0.33	0.06	0.15	0.56	0.03	0.08	0.42
MC240 My Desk	0.08	0.29	0.36	0.00	0.22	0.28	0.05	0.25	0.40	0.02	0.19	0.28
MC316 Back	0.00	0.07	0.21	0.01	0.30	0.53	0.00	0.08	0.25	0.00	0.15	0.39
MC316 Entrance	0.00	0.10	0.24	0.07	0.36	0.47	0.00	0.05	0.14	0.10	0.30	0.40
MC316 Front	0.00	0.00	0.21	0.13	0.16	0.49	0.00	0.00	0.01	0.11	0.13	0.22
MC316 Front 2	0.00	0.26	0.32	0.05	0.37	0.52	0.00	0.22	0.24	0.01	0.27	0.44
MC320 Back	0.00	0.08	0.09	0.01	0.10	0.23	0.00	0.06	0.06	0.00	0.05	0.16
MC320 Back Entrance	0.00	0.01	0.23	0.01	0.03	0.34	0.00	0.00	0.23	0.01	0.10	0.43
MC320 Entrance	0.01	0.01	0.26	0.01	0.03	0.31	0.00	0.00	0.29	0.00	0.04	0.27
MC320 Front	0.00	0.26	0.26	0.01	0.23	0.38	0.00	0.21	0.21	0.01	0.17	0.28
MC336 Entrance	0.00	0.00	0.12	0.01	0.14	0.29	0.00	0.00	0.15	0.00	0.05	0.30
MC336 Point 1	0.02	0.15	0.24	0.00	0.07	0.24	0.01	0.18	0.32	0.03	0.10	0.23
MC336 Point 2	0.00	0.03	0.03	0.00	0.09	0.09	0.00	0.00	0.00	0.00	0.02	0.05
MC336 Point 3	0.00	0.10	0.23	0.02	0.07	0.21	0.00	0.03	0.08	0.01	0.09	0.17
Totals (Average)	0.04	0.13	0.25	0.03	0.14	0.27	0.03	0.12	0.23	0.04	0.12	0.23

Location / Test	2AP											
	RT/RT			RT/H			H/RT			H/H		
	AL	1 FP	2FP	AL	1 FP	2FP	AL	1 FP	2FP	AL	1 FP	2FP
MC 2nd Floor North	0.06	0.10	0.11	0.03	0.06	0.06	0.00	0.03	0.03	0.00	0.01	0.01
MC 2nd Floor North Center	0.00	0.27	0.35	0.01	0.27	0.31	0.00	0.36	0.43	0.00	0.40	0.49
MC 2nd Floor Side Stairwell	0.03	0.09	0.29	0.00	0.04	0.31	0.03	0.06	0.26	0.02	0.03	0.29
MC 2nd Floor South	0.04	0.29	0.29	0.02	0.31	0.31	0.00	0.35	0.35	0.00	0.32	0.32
MC 2nd-3rd Side Stairwell	0.02	0.15	0.29	0.03	0.12	0.30	0.05	0.23	0.37	0.06	0.18	0.36
MC 3rd Floor North	0.03	0.30	0.30	0.03	0.19	0.19	0.00	0.34	0.34	0.01	0.28	0.28
MC 3rd Floor Side Stairwell	0.03	0.23	0.32	0.03	0.25	0.34	0.02	0.25	0.40	0.02	0.29	0.43
MC 3rd Floor South	0.34	0.37	0.37	0.41	0.45	0.45	0.37	0.38	0.38	0.37	0.37	0.37
MC214	0.10	0.15	0.41	0.16	0.16	0.50	0.09	0.11	0.41	0.13	0.13	0.56
MC215 Entrance	0.11	0.23	0.25	0.05	0.29	0.33	0.11	0.20	0.26	0.05	0.19	0.24
MC215 Point 1	0.05	0.25	0.26	0.05	0.16	0.16	0.02	0.20	0.20	0.02	0.19	0.20
MC215 Point 2	0.12	0.19	0.19	0.08	0.17	0.18	0.15	0.20	0.24	0.12	0.12	0.13
MC215 Point 3	0.03	0.24	0.24	0.05	0.32	0.32	0.01	0.29	0.29	0.04	0.31	0.31
MC235 Back	0.00	0.39	0.60	0.00	0.40	0.67	0.03	0.32	0.65	0.00	0.40	0.77
MC235 Entrance	0.01	0.22	0.64	0.04	0.20	0.61	0.00	0.29	0.60	0.00	0.33	0.55
MC235 Front	0.04	0.46	0.47	0.06	0.60	0.61	0.02	0.47	0.47	0.04	0.52	0.52
MC235 Front 2	0.28	0.38	0.55	0.34	0.50	0.67	0.49	0.37	0.53	0.35	0.46	0.56
MC239	0.04	0.18	0.35	0.02	0.18	0.38	0.02	0.20	0.35	0.01	0.22	0.47
MC240 Angelas Desk	0.07	0.21	0.42	0.03	0.16	0.31	0.09	0.27	0.43	0.07	0.24	0.39
MC240 Entrance 2	0.16	0.26	0.33	0.12	0.25	0.37	0.10	0.18	0.45	0.08	0.17	0.51
MC240 Jamies Desk	0.08	0.22	0.44	0.07	0.13	0.39	0.15	0.22	0.37	0.14	0.18	0.40
MC240 My Desk	0.03	0.13	0.16	0.00	0.12	0.14	0.09	0.18	0.19	0.03	0.11	0.12
MC316 Back	0.01	0.40	0.61	0.01	0.58	0.88	0.01	0.36	0.64	0.00	0.48	0.84
MC316 Entrance	0.12	0.48	0.61	0.35	0.77	0.84	0.10	0.49	0.59	0.24	0.66	0.75
MC316 Front	0.03	0.38	0.63	0.02	0.39	0.67	0.01	0.29	0.65	0.02	0.27	0.73
MC316 Front 2	0.02	0.23	0.51	0.00	0.25	0.48	0.03	0.28	0.65	0.00	0.33	0.57
MC320 Back	0.08	0.32	0.41	0.07	0.35	0.47	0.04	0.43	0.51	0.02	0.41	0.53
MC320 Back Entrance	0.04	0.10	0.33	0.01	0.06	0.32	0.01	0.08	0.25	0.00	0.05	0.31
MC320 Entrance	0.03	0.25	0.34	0.10	0.43	0.49	0.00	0.25	0.35	0.04	0.33	0.42
MC320 Front	0.10	0.37	0.54	0.09	0.41	0.64	0.14	0.43	0.66	0.08	0.50	0.75
MC336 Entrance	0.01	0.22	0.34	0.02	0.25	0.35	0.00	0.18	0.35	0.01	0.15	0.34
MC336 Point 1	0.04	0.15	0.39	0.05	0.18	0.40	0.05	0.15	0.39	0.04	0.12	0.35
MC336 Point 2	0.03	0.27	0.27	0.04	0.26	0.26	0.00	0.26	0.26	0.00	0.29	0.29
MC336 Point 3	0.04	0.19	0.26	0.07	0.45	0.49	0.09	0.26	0.31	0.08	0.48	0.52
Totals (Average)	0.07	0.25	0.38	0.07	0.28	0.42	0.07	0.26	0.40	0.06	0.28	0.43

Location / Test	3AP											
		RT/RT			RT/H			H/RT			H/H	
	AL	1 FP	2FP	AL	1 FP	2FP	AL	1 FP	2FP	AL	1 FP	2FP
MC 2nd Floor North	0.05	0.20	0.25	0.01	0.15	0.19	0.01	0.09	0.12	0.01	0.04	0.06
MC 2nd Floor North Center	0.01	0.46	0.62	0.01	0.47	0.65	0.00	0.58	0.72	0.00	0.57	0.72
MC 2nd Floor Side Stairwell	0.12	0.23	0.42	0.08	0.12	0.40	0.09	0.19	0.39	0.06	0.12	0.31
MC 2nd Floor South	0.04	0.41	0.41	0.02	0.36	0.36	0.04	0.32	0.32	0.03	0.29	0.29
MC 2nd-3rd Side Stairwell	0.06	0.12	0.26	0.07	0.12	0.25	0.08	0.13	0.26	0.10	0.15	0.26
MC 3rd Floor North	0.02	0.50	0.51	0.00	0.52	0.52	0.00	0.65	0.65	0.00	0.65	0.65
MC 3rd Floor Side Stairwell	0.15	0.37	0.44	0.19	0.45	0.56	0.17	0.40	0.59	0.22	0.50	0.70
MC 3rd Floor South	0.56	0.58	0.58	0.72	0.73	0.73	0.70	0.70	0.70	0.75	0.75	0.75
MC214	0.26	0.29	0.46	0.25	0.27	0.57	0.25	0.27	0.58	0.30	0.32	0.68
MC215 Entrance	0.08	0.36	0.36	0.11	0.43	0.43	0.13	0.44	0.47	0.20	0.50	0.52
MC215 Point 1	0.29	0.35	0.35	0.40	0.41	0.41	0.25	0.28	0.28	0.28	0.31	0.31
MC215 Point 2	0.07	0.32	0.33	0.06	0.31	0.31	0.07	0.24	0.24	0.07	0.24	0.24
MC215 Point 3	0.15	0.50	0.50	0.15	0.49	0.49	0.05	0.49	0.49	0.05	0.51	0.51
MC235 Back	0.27	0.48	0.89	0.29	0.57	0.88	0.31	0.44	0.91	0.45	0.60	0.92
MC235 Entrance	0.07	0.36	0.66	0.23	0.61	0.80	0.12	0.41	0.76	0.24	0.47	0.77
MC235 Front	0.13	0.51	0.51	0.24	0.73	0.73	0.07	0.48	0.48	0.09	0.57	0.57
MC235 Front 2	0.31	0.42	0.60	0.43	0.54	0.68	0.38	0.48	0.73	0.40	0.50	0.73
MC239	0.16	0.35	0.50	0.14	0.33	0.55	0.12	0.45	0.64	0.12	0.47	0.64
MC240 Angelas Desk	0.03	0.07	0.27	0.03	0.06	0.28	0.04	0.07	0.29	0.05	0.05	0.23
MC240 Entrance 2	0.08	0.17	0.21	0.01	0.19	0.25	0.01	0.12	0.14	0.00	0.12	0.16
MC240 Jamies Desk	0.06	0.26	0.51	0.06	0.18	0.43	0.08	0.29	0.64	0.09	0.21	0.59
MC240 My Desk	0.18	0.27	0.30	0.11	0.18	0.22	0.15	0.29	0.30	0.12	0.30	0.33
MC316 Back	0.09	0.57	0.67	0.12	0.74	0.84	0.04	0.57	0.64	0.05	0.77	0.80
MC316 Entrance	0.23	0.53	0.67	0.23	0.63	0.75	0.33	0.67	0.79	0.34	0.69	0.84
MC316 Front	0.15	0.53	0.75	0.27	0.64	0.80	0.23	0.64	0.83	0.26	0.67	0.87
MC316 Front 2	0.01	0.38	0.46	0.01	0.34	0.41	0.01	0.41	0.52	0.01	0.49	0.54
MC320 Back	0.03	0.27	0.58	0.02	0.27	0.61	0.02	0.50	0.74	0.01	0.47	0.71
MC320 Back Entrance	0.06	0.30	0.45	0.09	0.38	0.55	0.03	0.34	0.54	0.08	0.40	0.60
MC320 Entrance	0.02	0.44	0.52	0.05	0.63	0.68	0.00	0.58	0.65	0.00	0.68	0.72
MC320 Front	0.08	0.32	0.54	0.14	0.32	0.63	0.13	0.34	0.52	0.16	0.31	0.59
MC336 Entrance	0.04	0.44	0.72	0.07	0.53	0.84	0.05	0.65	0.87	0.05	0.74	0.90
MC336 Point 1	0.19	0.40	0.67	0.12	0.31	0.72	0.20	0.32	0.63	0.17	0.29	0.63
MC336 Point 2	0.13	0.59	0.65	0.22	0.71	0.74	0.06	0.74	0.77	0.08	0.79	0.82
MC336 Point 3	0.09	0.33	0.49	0.08	0.33	0.43	0.15	0.48	0.51	0.14	0.43	0.52
Totals (Average)	0.12	0.37	0.50	0.15	0.41	0.55	0.13	0.41	0.55	0.15	0.44	0.57

Wi-Fi & Altimeter - Townhouse

Location / Test	1AP							
	RT/RT		RT/H		H/RT		H/H	
	AL	1 FP	AL	1 FP	AL	1 FP	AL	1 FP
Dining Room	0.43	0.97	0.44	0.92	0.49	1.00	0.51	1.00
Entrance	0.21	0.38	0.19	0.52	0.27	0.40	0.31	0.42
Kitchen	0.27	0.68	0.27	0.70	0.30	0.70	0.32	0.70
Living Room	0.42	0.98	0.40	0.95	0.36	0.98	0.36	0.97
Living Room 2	0.92	0.97	0.92	0.96	1.00	1.00	1.00	1.00
Main Hallway	0.00	0.22	0.19	0.36	0.00	0.15	0.18	0.32
Master	0.50	0.54	0.48	0.52	0.42	0.65	0.40	0.62
Master 2	0.55	0.97	0.55	0.95	0.50	0.99	0.51	0.99
Spare	0.39	0.64	0.41	0.66	0.40	0.63	0.41	0.64
Spare 2	0.25	0.47	0.27	0.55	0.20	0.48	0.23	0.51
Stairwell	0.51	0.51	0.51	0.51	0.57	0.57	0.57	0.57
Upstairs Hallway	0.16	0.83	0.06	0.83	0.16	0.82	0.24	0.80
Totals	0.38	0.68	0.39	0.7	0.39	0.7	0.42	0.71

Location / Test	2AP							
	RT/RT		RT/H		H/RT		H/H	
	AL	1 FP	AL	1 FP	AL	1 FP	AL	1 FP
Dining Room	0.22	0.99	0.18	0.99	0.09	0.97	0.08	1.00
Entrance	0.21	0.47	0.18	0.34	0.38	0.54	0.34	0.52
Kitchen	0.39	0.64	0.59	0.81	0.53	0.66	0.61	0.72
Living Room	0.54	0.92	0.60	0.95	0.56	0.94	0.57	0.94
Living Room 2	0.85	0.99	0.96	0.99	0.89	1.00	0.99	1.00
Main Hallway	0.13	0.55	0.08	0.50	0.11	0.50	0.07	0.46
Master	0.41	0.45	0.38	0.44	0.35	0.37	0.32	0.39
Master 2	0.57	0.74	0.57	0.71	0.61	0.74	0.59	0.72
Spare	0.60	0.86	0.53	0.92	0.62	0.92	0.58	0.97
Spare 2	0.37	0.70	0.45	0.73	0.37	0.71	0.44	0.75
Stairwell	0.91	0.91	0.91	0.91	0.95	0.95	0.95	0.95
Upstairs Hallway	0.24	0.86	0.13	0.93	0.28	0.85	0.22	0.88
Totals	0.45	0.76	0.46	0.77	0.48	0.76	0.48	0.77

Location / Test	3AP							
	RT/RT		RT/H		H/RT		H/H	
	AL	1 FP	AL	1 FP	AL	1 FP	AL	1 FP
Dining Room	0.70	0.99	0.77	0.97	0.67	0.98	0.71	0.99
Entrance	0.43	0.85	0.39	0.73	0.47	0.84	0.48	0.77
Kitchen	0.44	0.88	0.66	0.93	0.66	0.93	0.77	0.97
Living Room	0.65	0.96	0.77	0.99	0.66	1.00	0.72	0.99
Living Room 2	0.78	0.95	0.88	0.99	0.80	0.97	0.80	0.97
Main Hallway	0.24	0.77	0.31	0.89	0.26	0.81	0.30	0.81
Master	0.44	0.79	0.46	0.82	0.39	0.68	0.41	0.79
Master 2	0.58	0.87	0.64	0.91	0.64	0.96	0.67	0.97
Spare	0.72	0.90	0.73	0.96	0.74	0.93	0.71	0.98
Spare 2	0.63	0.82	0.84	0.92	0.82	0.89	0.90	0.93
Stairwell	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
Upstairs Hallway	0.48	0.80	0.40	0.80	0.51	0.78	0.44	0.78
Totals	0.59	0.88	0.65	0.91	0.63	0.9	0.66	0.91

Wi-Fi & Altimeter - Middlesex College

Location / Test	1AP											
	RT/RT			RT/H			H/RT			H/H		
	AL	1 FP	2 FP	AL	1 FP	2FP	AL	1 FP	2FP	AL	1 FP	2FP
MC 2nd Floor North	0.11	0.17	0.19	0.05	0.10	0.10	0.04	0.23	0.23	0.03	0.14	0.14
MC 2nd Floor North Center	0.32	0.62	0.66	0.17	0.33	0.38	0.36	0.70	0.73	0.14	0.38	0.42
MC 2nd Floor Side Stairwell	0.15	0.32	0.61	0.03	0.27	0.54	0.12	0.28	0.54	0.00	0.19	0.47
MC 2nd Floor South	0.00	0.13	0.13	0.08	0.19	0.19	0.03	0.20	0.20	0.11	0.27	0.27
MC 2nd-3rd Side Stairwell	0.65	0.65	0.65	0.66	0.66	0.66	0.71	0.71	0.71	0.72	0.72	0.72
MC 3rd Floor North	0.00	0.29	0.32	0.04	0.27	0.29	0.00	0.23	0.30	0.01	0.23	0.30
MC 3rd Floor Side Stairwell	0.15	0.20	0.67	0.16	0.23	0.62	0.10	0.14	0.67	0.12	0.21	0.68
MC 3rd Floor South	0.10	0.12	0.18	0.09	0.15	0.16	0.11	0.12	0.17	0.07	0.11	0.12
MC214	0.12	0.19	0.41	0.05	0.08	0.32	0.03	0.09	0.34	0.01	0.05	0.37
MC215 Entrance	0.10	0.27	0.33	0.02	0.23	0.27	0.08	0.21	0.26	0.01	0.23	0.28
MC215 Point 1	0.03	0.40	0.41	0.10	0.35	0.40	0.01	0.37	0.37	0.08	0.27	0.32
MC215 Point 2	0.42	0.71	0.72	0.32	0.55	0.56	0.60	0.85	0.85	0.37	0.58	0.58
MC215 Point 3	0.40	0.63	0.63	0.50	0.68	0.68	0.61	0.73	0.73	0.65	0.74	0.74
MC235 Back	0.00	0.23	0.70	0.01	0.28	0.75	0.00	0.15	0.68	0.01	0.18	0.69
MC235 Entrance	0.00	0.24	0.68	0.02	0.16	0.72	0.00	0.26	0.78	0.03	0.25	0.68
MC235 Front	0.04	0.06	0.35	0.10	0.13	0.27	0.04	0.05	0.35	0.11	0.15	0.30
MC235 Front 2	0.00	0.19	0.36	0.14	0.59	0.67	0.00	0.22	0.35	0.16	0.66	0.67
MC239	0.23	0.28	0.49	0.04	0.07	0.46	0.22	0.35	0.34	0.01	0.13	0.76
MC240 Angelas Desk	0.09	0.15	0.30	0.10	0.22	0.43	0.08	0.15	0.28	0.05	0.13	0.34
MC240 Entrance 2	0.12	0.15	0.39	0.09	0.17	0.22	0.11	0.12	0.44	0.05	0.08	0.29
MC240 Jamies Desk	0.21	0.26	0.86	0.23	0.26	0.75	0.30	0.31	0.90	0.34	0.34	0.85
MC240 My Desk	0.19	0.38	0.52	0.19	0.31	0.43	0.12	0.31	0.47	0.11	0.30	0.53
MC316 Back	0.00	0.31	0.63	0.45	0.78	0.82	0.00	0.52	0.74	0.28	0.74	0.79
MC316 Entrance	0.00	0.26	0.46	0.05	0.41	0.59	0.00	0.26	0.46	0.04	0.38	0.61
MC316 Front	0.16	0.32	0.68	0.20	0.49	0.83	0.23	0.36	0.76	0.23	0.43	0.89
MC316 Front 2	0.00	0.35	0.50	0.04	0.55	0.66	0.00	0.41	0.57	0.00	0.49	0.73
MC320 Back	0.02	0.25	0.29	0.01	0.33	0.48	0.06	0.18	0.21	0.01	0.19	0.32
MC320 Back Entrance	0.04	0.38	0.44	0.04	0.38	0.53	0.02	0.36	0.41	0.00	0.41	0.52
MC320 Entrance	0.00	0.17	0.57	0.01	0.38	0.61	0.00	0.26	0.55	0.00	0.33	0.59
MC320 Front	0.02	0.38	0.41	0.01	0.32	0.55	0.01	0.43	0.48	0.01	0.45	0.64
MC336 Entrance	0.03	0.23	0.65	0.12	0.35	0.63	0.01	0.26	0.61	0.03	0.28	0.56
MC336 Point 1	0.00	0.12	0.53	0.05	0.07	0.50	0.00	0.15	0.49	0.01	0.03	0.37
MC336 Point 2	0.00	0.45	0.49	0.01	0.58	0.59	0.00	0.52	0.55	0.00	0.55	0.56
MC336 Point 3	0.03	0.05	0.42	0.09	0.17	0.46	0.03	0.03	0.49	0.05	0.09	0.48
Totals (Average)	0.11	0.29	0.49	0.12	0.33	0.50	0.12	0.31	0.50	0.11	0.31	0.52

Location / Test	2AP											
	RT/RT			RT/H			H/RT			H/H		
	AL	1 FP	2FP	AL	1 FP	2FP	AL	1 FP	2FP	AL	1 FP	2FP
MC 2nd Floor North	0.05	0.35	0.49	0.02	0.36	0.36	0.05	0.54	0.54	0.01	0.41	0.42
MC 2nd Floor North Center	0.05	0.55	0.65	0.03	0.57	0.65	0.04	0.50	0.65	0.10	0.53	0.67
MC 2nd Floor Side Stairwell	0.01	0.23	0.42	0.00	0.36	0.55	0.00	0.33	0.49	0.00	0.43	0.60
MC 2nd Floor South	0.15	0.81	0.81	0.10	0.86	0.86	0.08	0.93	0.93	0.03	0.95	0.95
MC 2nd-3rd Side Stairwell	0.97	0.97	0.97	0.98	0.98	0.98	0.99	0.99	0.99	0.99	0.99	0.99
MC 3rd Floor North	0.04	0.38	0.39	0.06	0.38	0.39	0.03	0.44	0.44	0.04	0.47	0.48
MC 3rd Floor Side Stairwell	0.16	0.33	0.67	0.13	0.29	0.74	0.12	0.30	0.80	0.16	0.33	0.85
MC 3rd Floor South	0.24	0.49	0.53	0.34	0.58	0.61	0.36	0.71	0.72	0.46	0.78	0.79
MC214	0.14	0.24	0.78	0.08	0.15	0.87	0.06	0.14	0.91	0.05	0.11	0.87
MC215 Entrance	0.41	0.56	0.69	0.49	0.77	0.89	0.41	0.57	0.67	0.43	0.72	0.80
MC215 Point 1	0.12	0.50	0.50	0.17	0.69	0.69	0.07	0.45	0.45	0.12	0.64	0.64
MC215 Point 2	0.35	0.80	0.80	0.36	0.96	0.96	0.42	0.89	0.89	0.38	0.95	0.95
MC215 Point 3	0.31	0.69	0.69	0.49	0.88	0.88	0.38	0.72	0.72	0.50	0.87	0.87
MC235 Back	0.09	0.42	0.69	0.22	0.41	0.74	0.08	0.29	0.71	0.16	0.31	0.67
MC235 Entrance	0.02	0.18	0.45	0.01	0.19	0.34	0.00	0.33	0.50	0.00	0.39	0.50
MC235 Front	0.19	0.63	0.74	0.21	0.66	0.75	0.19	0.68	0.75	0.20	0.80	0.83
MC235 Front 2	0.24	0.54	0.68	0.27	0.56	0.70	0.31	0.63	0.70	0.34	0.66	0.71
MC239	0.01	0.25	0.55	0.04	0.31	0.67	0.02	0.26	0.60	0.01	0.28	0.62
MC240 Angelas Desk	0.07	0.24	0.43	0.08	0.21	0.39	0.12	0.30	0.59	0.12	0.29	0.58
MC240 Entrance 2	0.45	0.52	0.88	0.39	0.51	0.90	0.49	0.53	0.87	0.45	0.49	0.94
MC240 Jamies Desk	0.33	0.45	0.93	0.26	0.51	0.97	0.33	0.53	0.99	0.31	0.40	0.99
MC240 My Desk	0.17	0.33	0.46	0.19	0.34	0.41	0.23	0.39	0.53	0.24	0.41	0.54
MC316 Back	0.27	0.56	0.72	0.50	0.81	0.88	0.28	0.65	0.82	0.42	0.80	0.92
MC316 Entrance	0.22	0.58	0.84	0.38	0.84	0.98	0.25	0.59	0.87	0.30	0.72	0.95
MC316 Front	0.03	0.62	0.90	0.00	0.73	0.93	0.01	0.59	0.96	0.00	0.68	0.99
MC316 Front 2	0.10	0.73	0.82	0.12	0.88	0.89	0.03	0.73	0.83	0.13	0.85	0.91
MC320 Back	0.03	0.62	0.77	0.06	0.74	0.85	0.04	0.70	0.77	0.11	0.78	0.87
MC320 Back Entrance	0.39	0.70	0.86	0.36	0.78	0.89	0.35	0.70	0.92	0.37	0.79	0.96
MC320 Entrance	0.05	0.92	0.96	0.00	0.92	0.96	0.04	0.91	0.95	0.02	0.90	0.90
MC320 Front	0.09	0.40	0.64	0.15	0.57	0.84	0.14	0.49	0.73	0.14	0.69	0.84
MC336 Entrance	0.16	0.51	0.86	0.20	0.49	0.91	0.10	0.49	0.93	0.09	0.52	0.90
MC336 Point 1	0.08	0.27	0.78	0.10	0.25	0.80	0.13	0.29	0.82	0.11	0.28	0.79
MC336 Point 2	0.02	0.56	0.57	0.02	0.63	0.64	0.02	0.57	0.57	0.02	0.63	0.63
MC336 Point 3	0.03	0.13	0.38	0.03	0.12	0.45	0.00	0.19	0.30	0.00	0.18	0.29
Totals (Average)	0.18	0.50	0.69	0.20	0.57	0.75	0.18	0.54	0.73	0.20	0.59	0.77

Location / Test	3AP											
	RT/RT			RT/H			H/RT			H/H		
	AL	1 FP	2FP	AL	1 FP	2FP	AL	1 FP	2FP	AL	1 FP	2FP
MC 2nd Floor North	0.17	0.68	0.73	0.14	0.74	0.75	0.20	0.75	0.85	0.16	0.79	0.81
MC 2nd Floor North Center	0.17	0.63	0.65	0.08	0.60	0.61	0.26	0.70	0.73	0.21	0.66	0.68
MC 2nd Floor Side Stairwell	0.11	0.33	0.51	0.12	0.33	0.65	0.15	0.46	0.63	0.14	0.41	0.70
MC 2nd Floor South	0.22	0.78	0.78	0.19	0.77	0.77	0.30	0.73	0.73	0.27	0.72	0.72
MC 2nd-3rd Side Stairwell	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
MC 3rd Floor North	0.16	0.54	0.65	0.11	0.73	0.75	0.12	0.77	0.77	0.11	0.81	0.81
MC 3rd Floor Side Stairwell	0.32	0.61	0.73	0.39	0.64	0.85	0.34	0.68	0.82	0.42	0.70	0.81
MC 3rd Floor South	0.60	0.79	0.79	0.64	0.84	0.85	0.61	0.89	0.89	0.63	0.94	0.94
MC214	0.60	0.64	0.96	0.57	0.59	0.93	0.63	0.64	0.99	0.68	0.68	1.00
MC215 Entrance	0.29	0.90	0.92	0.37	0.97	0.97	0.47	0.99	0.99	0.50	1.00	1.00
MC215 Point 1	0.45	0.83	0.86	0.56	0.87	0.87	0.56	0.91	0.95	0.57	0.95	0.96
MC215 Point 2	0.19	0.91	0.91	0.06	0.97	0.97	0.17	0.95	0.95	0.08	0.98	0.98
MC215 Point 3	0.40	0.80	0.80	0.51	0.94	0.94	0.52	0.99	0.99	0.56	0.99	0.99
MC235 Back	0.21	0.38	0.85	0.34	0.47	0.92	0.32	0.48	0.92	0.47	0.57	0.97
MC235 Entrance	0.07	0.38	0.69	0.11	0.49	0.78	0.04	0.43	0.76	0.04	0.52	0.75
MC235 Front	0.18	0.67	0.74	0.21	0.84	0.85	0.11	0.73	0.77	0.09	0.84	0.84
MC235 Front 2	0.35	0.69	0.79	0.42	0.83	0.89	0.32	0.73	0.87	0.30	0.81	0.87
MC239	0.05	0.14	0.63	0.01	0.14	0.70	0.01	0.18	0.68	0.00	0.15	0.70
MC240 Angelas Desk	0.06	0.22	0.53	0.08	0.17	0.50	0.07	0.21	0.56	0.08	0.21	0.57
MC240 Entrance 2	0.12	0.72	0.90	0.13	0.73	0.94	0.09	0.73	0.98	0.10	0.73	1.00
MC240 Jamies Desk	0.17	0.34	0.91	0.18	0.36	0.93	0.21	0.34	0.99	0.21	0.34	1.00
MC240 My Desk	0.13	0.36	0.48	0.13	0.41	0.52	0.19	0.54	0.61	0.17	0.56	0.63
MC316 Back	0.47	0.79	0.88	0.61	0.88	0.95	0.54	0.89	0.98	0.59	0.87	0.99
MC316 Entrance	0.37	0.76	0.90	0.44	0.87	0.97	0.60	0.93	0.97	0.66	0.97	0.99
MC316 Front	0.11	0.68	0.82	0.17	0.59	0.87	0.10	0.72	0.84	0.12	0.78	0.86
MC316 Front 2	0.17	0.79	0.89	0.21	0.86	0.93	0.20	0.71	0.94	0.33	0.84	0.96
MC320 Back	0.36	0.76	0.86	0.40	0.86	0.90	0.42	0.88	0.91	0.50	0.93	0.96
MC320 Back Entrance	0.39	0.62	0.78	0.49	0.73	0.89	0.59	0.76	0.85	0.61	0.74	0.87
MC320 Entrance	0.01	0.84	0.95	0.00	0.87	0.93	0.00	0.93	0.96	0.00	0.93	0.94
MC320 Front	0.21	0.54	0.85	0.24	0.59	0.98	0.31	0.61	1.00	0.36	0.57	1.00
MC336 Entrance	0.11	0.36	0.70	0.14	0.46	0.81	0.14	0.45	0.79	0.21	0.52	0.85
MC336 Point 1	0.17	0.63	0.94	0.21	0.71	0.95	0.28	0.63	0.94	0.30	0.67	0.97
MC336 Point 2	0.02	0.63	0.66	0.02	0.63	0.65	0.06	0.67	0.67	0.05	0.65	0.65
MC336 Point 3	0.03	0.34	0.85	0.02	0.37	0.91	0.03	0.39	0.86	0.01	0.44	0.88
Totals (Average)	0.25	0.62	0.79	0.27	0.67	0.84	0.29	0.69	0.86	0.31	0.71	0.87

Wi-Fi, Altimeter & Scene Analysis - Townhouse

Location / Test	1AP							
	RT/RT		RT/H		H/RT		H/H	
	AL	1 FP	AL	1 FP	AL	1 FP	AL	1 FP
Dining Room	0.64	0.88	0.72	0.85	0.79	0.90	0.80	0.90
Entrance	0.45	0.81	0.44	0.78	0.48	0.85	0.44	0.89
Kitchen	0.24	0.56	0.35	0.65	0.22	0.50	0.21	0.52
Living Room	0.64	0.88	0.73	0.88	0.63	0.91	0.64	0.91
Living Room 2	0.97	0.98	0.97	0.98	1.00	1.00	1.00	1.00
Main Hallway	0.26	0.43	0.30	0.44	0.43	0.53	0.44	0.54
Master	0.00	0.87	0.68	0.90	0.79	0.94	0.81	0.97
Master 2	0.64	0.78	0.72	0.80	0.61	0.76	0.65	0.77
Spare	0.20	0.89	0.22	0.95	0.19	0.87	0.22	0.87
Spare 2	0.39	0.89	0.57	0.94	0.43	0.91	0.57	0.94
Stairwell	0.64	0.64	0.64	0.64	0.60	0.60	0.59	0.59
Upstairs Hallway	0.56	0.83	0.65	0.84	0.66	0.85	0.73	0.85
Totals	0.47	0.79	0.58	0.8	0.57	0.8	0.59	0.81

Location / Test	2AP							
	RT/RT		RT/H		H/RT		H/H	
	AL	1 FP	AL	1 FP	AL	1 FP	AL	1 FP
Dining Room	0.74	0.98	0.80	0.99	0.77	0.97	0.77	0.99
Entrance	0.67	0.97	0.87	0.98	0.65	0.99	0.72	0.99
Kitchen	0.72	0.88	0.77	0.91	0.75	0.87	0.80	0.94
Living Room	0.81	0.96	0.89	0.96	0.84	0.97	0.87	0.97
Living Room 2	0.90	0.99	0.97	0.99	0.93	0.99	0.96	0.99
Main Hallway	0.27	0.39	0.45	0.47	0.23	0.25	0.25	0.25
Master	0.30	0.88	0.32	0.94	0.32	0.94	0.26	0.98
Master 2	0.87	0.93	0.99	0.99	0.96	0.99	0.99	1.00
Spare	0.61	1.00	0.68	1.00	0.73	1.00	0.76	1.00
Spare 2	0.71	0.96	0.82	0.97	0.70	0.93	0.74	0.91
Stairwell	0.96	0.96	0.96	0.96	0.95	0.95	0.95	0.95
Upstairs Hallway	0.67	0.96	0.96	1.00	0.80	0.98	0.92	0.99
Totals	0.69	0.9	0.79	0.93	0.72	0.9	0.75	0.91

Location / Test	3AP							
	RT/RT		RT/H		H/RT		H/H	
	AL	1 FP	AL	1 FP	AL	1 FP	AL	1 FP
Dining Room	0.83	0.99	0.86	0.99	0.83	1.00	0.87	1.00
Entrance	0.65	1.00	0.73	1.00	0.64	1.00	0.65	1.00
Kitchen	0.72	0.96	0.83	0.98	0.81	0.98	0.84	0.98
Living Room	0.77	0.96	0.88	0.96	0.83	0.99	0.89	0.99
Living Room 2	0.86	1.00	0.96	1.00	0.89	1.00	1.00	1.00
Main Hallway	0.58	0.82	0.71	0.93	0.76	0.88	0.81	0.89
Master	0.66	0.99	0.62	1.00	0.78	0.99	0.73	1.00
Master 2	0.91	0.99	0.99	0.99	0.90	1.00	0.96	1.00
Spare	0.62	1.00	0.92	1.00	0.87	1.00	0.92	1.00
Spare 2	0.87	1.00	0.97	1.00	0.93	1.00	0.98	1.00
Stairwell	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98
Upstairs Hallway	0.85	0.91	0.93	0.95	0.89	0.93	0.96	0.96
Totals	0.78	0.97	0.87	0.98	0.84	0.98	0.88	0.98

Wi-Fi, Altimeter & Scene Analysis - Middlesex College

Location / Test	1AP											
	RT/RT			RT/H			H/RT			H/H		
	AL	1 FP	2 FP	AL	1 FP	2FP	AL	1 FP	2FP	AL	1 FP	2FP
MC 2nd Floor North	0.04	0.30	0.31	0.03	0.17	0.18	0.02	0.27	0.28	0.02	0.26	0.27
MC 2nd Floor North Center	0.11	0.61	0.64	0.12	0.61	0.64	0.12	0.70	0.71	0.09	0.69	0.69
MC 2nd Floor Side Stairwell	0.16	0.16	0.36	0.22	0.24	0.52	0.19	0.19	0.49	0.22	0.22	0.60
MC 2nd Floor South	0.01	0.45	0.45	0.01	0.42	0.42	0.00	0.36	0.36	0.00	0.34	0.34
MC 2nd-3rd Side Stairwell	0.76	0.76	0.76	0.76	0.76	0.76	0.75	0.75	0.75	0.75	0.75	0.75
MC 3rd Floor North	0.07	0.41	0.41	0.06	0.64	0.64	0.01	0.40	0.40	0.00	0.39	0.39
MC 3rd Floor Side Stairwell	0.16	0.19	0.79	0.17	0.32	0.84	0.14	0.15	0.83	0.11	0.23	0.89
MC 3rd Floor South	0.15	0.19	0.21	0.22	0.25	0.27	0.12	0.13	0.14	0.20	0.21	0.22
MC214	0.07	0.18	0.44	0.17	0.24	0.46	0.11	0.18	0.40	0.18	0.21	0.52
MC215 Entrance	0.11	0.26	0.28	0.06	0.28	0.42	0.18	0.32	0.32	0.09	0.45	0.48
MC215 Point 1	0.09	0.31	0.37	0.12	0.41	0.46	0.06	0.31	0.38	0.06	0.41	0.48
MC215 Point 2	0.04	0.28	0.28	0.03	0.39	0.39	0.01	0.24	0.24	0.02	0.39	0.39
MC215 Point 3	0.27	0.38	0.38	0.54	0.64	0.64	0.23	0.30	0.30	0.44	0.51	0.51
MC235 Back	0.01	0.21	0.80	0.14	0.38	0.88	0.01	0.22	0.68	0.27	0.60	0.97
MC235 Entrance	0.01	0.16	0.60	0.03	0.24	0.68	0.01	0.10	0.68	0.04	0.26	0.61
MC235 Front	0.02	0.28	0.40	0.01	0.70	0.77	0.02	0.32	0.43	0.01	0.66	0.72
MC235 Front 2	0.01	0.17	0.34	0.15	0.36	0.60	0.00	0.39	0.55	0.15	0.61	0.76
MC239	0.16	0.24	0.41	0.15	0.24	0.42	0.13	0.33	0.49	0.08	0.29	0.51
MC240 Angelas Desk	0.14	0.17	0.32	0.07	0.17	0.37	0.15	0.19	0.28	0.10	0.15	0.25
MC240 Entrance 2	0.12	0.23	0.62	0.07	0.27	0.53	0.05	0.19	0.53	0.03	0.22	0.47
MC240 Jamies Desk	0.11	0.22	0.83	0.06	0.13	0.76	0.08	0.11	0.77	0.08	0.09	0.80
MC240 My Desk	0.18	0.35	0.45	0.18	0.25	0.36	0.28	0.28	0.39	0.11	0.18	0.30
MC316 Back	0.00	0.38	0.75	0.42	0.76	0.89	0.00	0.53	0.81	0.32	0.82	0.89
MC316 Entrance	0.09	0.30	0.60	0.10	0.53	0.85	0.02	0.24	0.67	0.16	0.53	0.80
MC316 Front	0.03	0.24	0.68	0.06	0.52	0.93	0.04	0.22	0.75	0.04	0.54	0.91
MC316 Front 2	0.00	0.25	0.60	0.06	0.64	0.85	0.00	0.31	0.66	0.00	0.61	0.89
MC320 Back	0.11	0.32	0.48	0.14	0.38	0.71	0.10	0.40	0.54	0.08	0.41	0.76
MC320 Back Entrance	0.15	0.42	0.37	0.14	0.49	0.61	0.07	0.25	0.36	0.12	0.35	0.65
MC320 Entrance	0.18	0.37	0.66	0.16	0.60	0.83	0.13	0.38	0.65	0.09	0.63	0.88
MC320 Front	0.08	0.44	0.46	0.13	0.66	0.75	0.06	0.41	0.48	0.13	0.61	0.77
MC336 Entrance	0.01	0.17	0.34	0.01	0.23	0.37	0.00	0.10	0.37	0.00	0.26	0.33
MC336 Point 1	0.00	0.15	0.51	0.29	0.34	0.55	0.00	0.08	0.45	0.38	0.39	0.72
MC336 Point 2	0.00	0.27	0.35	0.01	0.58	0.61	0.00	0.15	0.21	0.17	0.52	0.57
MC336 Point 3	0.00	0.14	0.52	0.05	0.41	0.72	0.00	0.14	0.48	0.08	0.42	0.63
Totals (Average)	0.10	0.29	0.49	0.15	0.42	0.61	0.09	0.28	0.49	0.14	0.42	0.61

Location / Test	2AP											
	RT/RT			RT/H			H/RT			H/H		
	AL	1 FP	2FP	AL	1 FP	2FP	AL	1 FP	2FP	AL	1 FP	2FP
MC 2nd Floor North	0.17	0.30	0.32	0.14	0.30	0.33	0.10	0.23	0.24	0.09	0.23	0.23
MC 2nd Floor North Center	0.16	0.85	0.92	0.03	0.92	0.96	0.00	0.91	0.96	0.00	0.92	0.97
MC 2nd Floor Side Stairwell	0.17	0.23	0.33	0.27	0.35	0.42	0.17	0.24	0.33	0.17	0.24	0.31
MC 2nd Floor South	0.05	0.66	0.66	0.00	0.60	0.68	0.02	0.79	0.79	0.03	0.82	0.82
MC 2nd-3rd Side Stairwell	0.97	0.97	0.97	0.98	0.98	0.98	0.99	0.99	0.99	1.00	1.00	1.00
MC 3rd Floor North	0.12	0.76	0.76	0.04	0.74	0.74	0.02	0.88	0.88	0.01	0.88	0.88
MC 3rd Floor Side Stairwell	0.41	0.56	0.91	0.58	0.64	0.89	0.45	0.62	0.96	0.58	0.68	0.96
MC 3rd Floor South	0.38	0.52	0.52	0.47	0.55	0.55	0.36	0.45	0.45	0.35	0.40	0.40
MC214	0.26	0.32	0.75	0.31	0.34	0.84	0.32	0.33	0.82	0.32	0.36	0.90
MC215 Entrance	0.12	0.55	0.64	0.13	0.72	0.78	0.18	0.50	0.57	0.20	0.67	0.71
MC215 Point 1	0.10	0.68	0.68	0.12	0.88	0.88	0.05	0.62	0.62	0.11	0.84	0.84
MC215 Point 2	0.11	0.88	0.88	0.05	0.95	0.95	0.08	0.85	0.85	0.06	0.91	0.91
MC215 Point 3	0.46	0.83	0.83	0.68	0.89	0.89	0.44	0.84	0.84	0.69	0.94	0.94
MC235 Back	0.16	0.49	0.96	0.14	0.46	0.97	0.17	0.52	0.97	0.10	0.52	0.99
MC235 Entrance	0.03	0.38	0.69	0.12	0.56	0.76	0.08	0.47	0.68	0.11	0.67	0.71
MC235 Front	0.01	0.84	0.91	0.00	0.96	0.98	0.02	0.85	0.89	0.01	0.88	0.91
MC235 Front 2	0.24	0.40	0.91	0.35	0.48	0.98	0.29	0.44	0.94	0.34	0.50	0.97
MC239	0.20	0.30	0.49	0.30	0.37	0.55	0.27	0.38	0.52	0.33	0.43	0.52
MC240 Angelas Desk	0.05	0.18	0.31	0.05	0.16	0.26	0.11	0.24	0.32	0.08	0.21	0.27
MC240 Entrance 2	0.15	0.54	0.82	0.08	0.71	0.90	0.26	0.61	0.94	0.27	0.67	0.96
MC240 Jamies Desk	0.24	0.42	0.77	0.24	0.51	0.84	0.29	0.52	0.93	0.27	0.56	0.97
MC240 My Desk	0.27	0.33	0.49	0.44	0.46	0.56	0.49	0.50	0.62	0.54	0.55	0.64
MC316 Back	0.38	0.73	0.96	0.65	0.88	0.99	0.51	0.81	0.99	0.64	0.86	0.99
MC316 Entrance	0.27	0.59	0.87	0.32	0.85	0.98	0.34	0.71	0.94	0.43	0.83	0.95
MC316 Front	0.10	0.72	0.82	0.08	0.96	0.96	0.12	0.69	0.75	0.11	0.92	0.94
MC316 Front 2	0.04	0.71	0.81	0.01	0.87	0.92	0.03	0.74	0.87	0.00	0.79	0.92
MC320 Back	0.37	0.61	0.83	0.46	0.57	0.86	0.37	0.65	0.83	0.41	0.71	0.89
MC320 Back Entrance	0.32	0.69	0.80	0.21	0.86	0.92	0.38	0.76	0.89	0.33	0.89	0.96
MC320 Entrance	0.13	0.78	0.98	0.08	0.81	0.99	0.12	0.75	0.96	0.04	0.72	0.97
MC320 Front	0.15	0.75	0.85	0.19	0.86	0.97	0.21	0.71	0.89	0.21	0.73	0.93
MC336 Entrance	0.02	0.29	0.53	0.03	0.57	0.66	0.02	0.35	0.61	0.02	0.52	0.70
MC336 Point 1	0.36	0.45	0.75	0.59	0.68	0.82	0.53	0.57	0.81	0.66	0.70	0.84
MC336 Point 2	0.04	0.32	0.35	0.11	0.58	0.62	0.02	0.39	0.41	0.06	0.48	0.51
MC336 Point 3	0.12	0.39	0.60	0.11	0.53	0.77	0.16	0.50	0.66	0.14	0.55	0.75
Totals (Average)	0.21	0.56	0.73	0.25	0.66	0.80	0.23	0.60	0.76	0.26	0.66	0.80

Location / Test	3AP											
	RT/RT			RT/H			H/RT			H/H		
	AL	1 FP	2FP	AL	1 FP	2FP	AL	1 FP	2FP	AL	1 FP	2FP
MC 2nd Floor North	0.53	0.73	0.73	0.49	0.72	0.72	0.49	0.65	0.65	0.51	0.67	0.67
MC 2nd Floor North Center	0.35	0.79	0.82	0.36	0.90	0.91	0.34	0.74	0.80	0.37	0.81	0.85
MC 2nd Floor Side Stairwell	0.53	0.54	0.66	0.78	0.78	0.81	0.53	0.53	0.60	0.65	0.65	0.69
MC 2nd Floor South	0.09	0.62	0.62	0.15	0.69	0.69	0.13	0.66	0.66	0.13	0.68	0.68
MC 2nd-3rd Side Stairwell	0.99	0.99	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00
MC 3rd Floor North	0.06	0.70	0.70	0.02	0.76	0.76	0.02	0.73	0.73	0.02	0.73	0.73
MC 3rd Floor Side Stairwell	0.57	0.62	0.75	0.56	0.58	0.71	0.63	0.66	0.81	0.58	0.63	0.77
MC 3rd Floor South	0.38	0.63	0.64	0.52	0.76	0.77	0.58	0.81	0.81	0.62	0.83	0.83
MC214	0.47	0.51	0.85	0.47	0.48	0.91	0.49	0.50	0.98	0.48	0.48	0.98
MC215 Entrance	0.09	0.90	0.90	0.05	0.95	0.95	0.09	0.93	0.94	0.06	0.96	0.96
MC215 Point 1	0.43	0.89	0.89	0.49	0.92	0.92	0.37	0.86	0.86	0.43	0.88	0.88
MC215 Point 2	0.11	0.95	0.95	0.11	0.97	0.97	0.12	0.96	0.96	0.11	0.97	0.97
MC215 Point 3	0.35	0.91	0.91	0.45	0.99	0.99	0.39	0.98	0.98	0.40	0.98	0.98
MC235 Back	0.11	0.54	0.91	0.12	0.59	0.98	0.21	0.64	0.96	0.19	0.62	0.99
MC235 Entrance	0.28	0.62	0.89	0.40	0.74	0.96	0.31	0.63	0.88	0.41	0.74	0.89
MC235 Front	0.19	0.90	0.93	0.23	0.99	1.00	0.07	0.93	0.97	0.10	0.98	1.00
MC235 Front 2	0.33	0.71	0.98	0.43	0.81	0.99	0.39	0.72	0.98	0.44	0.76	1.00
MC239	0.31	0.42	0.62	0.43	0.49	0.69	0.39	0.43	0.66	0.44	0.47	0.69
MC240 Angelas Desk	0.10	0.10	0.49	0.10	0.12	0.39	0.14	0.15	0.44	0.15	0.15	0.42
MC240 Entrance 2	0.05	0.76	0.94	0.03	0.80	0.95	0.05	0.79	0.98	0.05	0.81	0.98
MC240 Jamies Desk	0.15	0.50	0.89	0.34	0.55	0.94	0.20	0.44	0.99	0.21	0.60	0.99
MC240 My Desk	0.51	0.63	0.69	0.66	0.74	0.79	0.69	0.83	0.86	0.76	0.88	0.90
MC316 Back	0.53	0.77	0.96	0.72	0.84	0.99	0.61	0.85	0.99	0.66	0.82	0.99
MC316 Entrance	0.42	0.94	0.96	0.14	0.98	0.99	0.47	0.99	0.99	0.46	0.99	0.99
MC316 Front	0.14	0.76	0.86	0.17	0.83	0.85	0.11	0.80	0.91	0.09	0.84	0.90
MC316 Front 2	0.08	0.77	0.84	0.05	0.88	0.92	0.02	0.82	0.90	0.01	0.86	0.91
MC320 Back	0.15	0.55	0.82	0.12	0.60	0.85	0.14	0.64	0.85	0.14	0.64	0.83
MC320 Back Entrance	0.23	0.73	0.87	0.20	0.78	0.83	0.21	0.80	0.92	0.20	0.85	0.90
MC320 Entrance	0.03	0.79	0.99	0.02	0.76	1.00	0.03	0.87	0.99	0.04	0.84	0.99
MC320 Front	0.19	0.82	0.96	0.15	0.84	0.99	0.23	0.75	0.99	0.13	0.76	0.97
MC336 Entrance	0.10	0.65	0.80	0.12	0.78	0.91	0.11	0.70	0.78	0.11	0.79	0.89
MC336 Point 1	0.52	0.63	0.93	0.65	0.78	0.97	0.74	0.67	0.78	0.68	0.76	0.95
MC336 Point 2	0.09	0.67	0.72	0.13	0.78	0.84	0.03	0.78	0.82	0.03	0.83	0.86
MC336 Point 3	0.16	0.53	0.86	0.15	0.58	0.88	0.27	0.57	0.83	0.30	0.56	0.83
Totals (Average)	0.28	0.69	0.83	0.32	0.76	0.88	0.31	0.73	0.86	0.32	0.76	0.88

Appendix B

Hybrid Application Overview

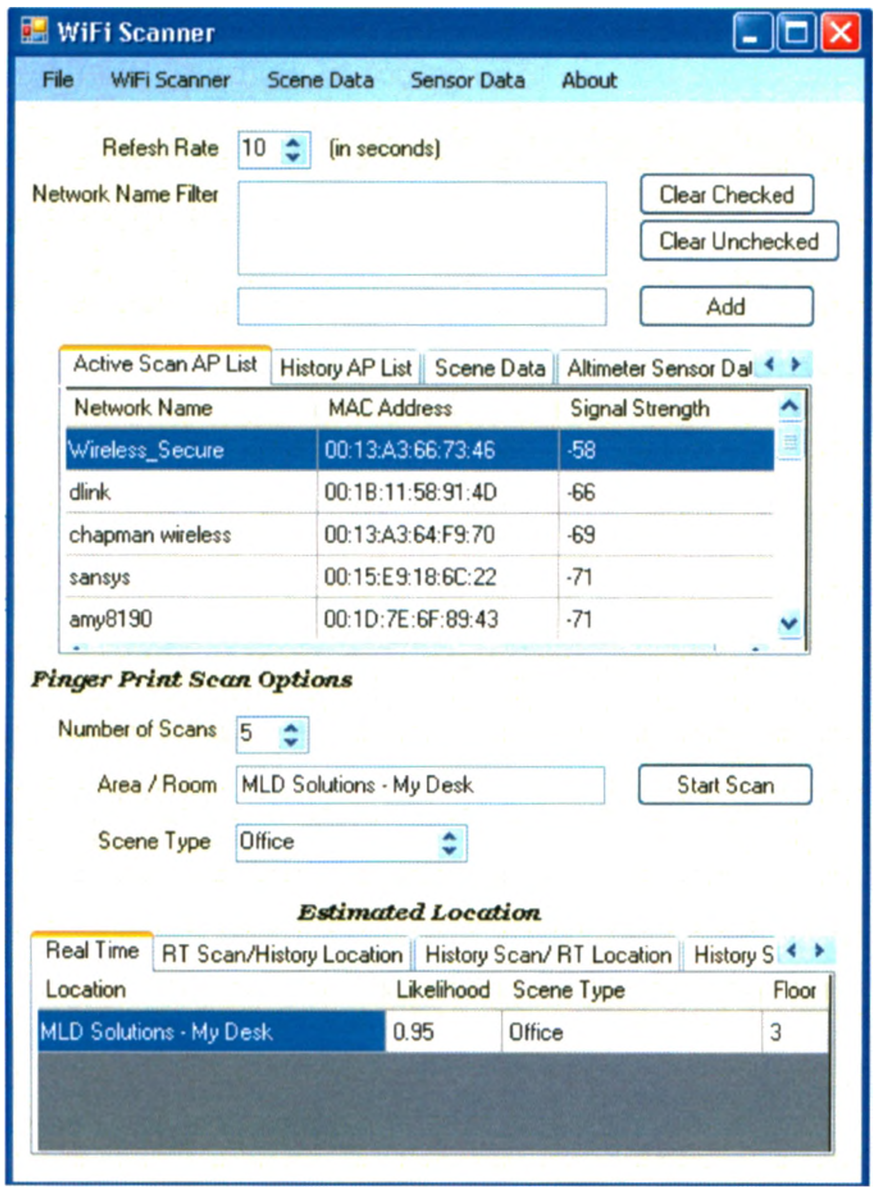


Figure B-1: Screenshot of Developed Application

Wi-Fi System Features

- Capability to turn on/off AP Scan
- Can Vary refresh rate of Wi-Fi AP scan (minimum 5 seconds)
- Ability to filter Access Points based on network name dynamically
- Enable and disable estimated location and AP data logging

- Dynamically change from different location estimation algorithms (CoO, 1AP, 2AP and 3AP fingerprints)
- Ability to perform fingerprint scans. The user can select how many Wi-Fi AP scans to perform to calculate an average received signal strength for each AP. The user also enters a relative location name for the fingerprint scan and its associated scene type. A Floor value is also inserted, however the user must currently edit the DB after by entering the correct floor.
- Additional fingerprint scans can be completed at the same relative location. The repeated scans average, minimum average and maximum average signal values are calculated and updated for each additional fingerprint scans
- Fingerprint Scans add all detected AP's MAC address to the DB. The user has to edit the DB after by entering the installed location of the AP. This is the information used for the Cell of Origin (CoO) algorithm.
- History information is applied to both the AP scan and locations estimates to evaluate the effectiveness at reducing fluctuating signal noise.
    - Real Time Scan / Real Time Location
    - Real Time Scan / History Location
    - History Scan / Real Time Location
    - History Scan / History Location

Scene Analysis System Features

- Ability to turn on/off Scene Analysis
- Reads the scene classification file (scene type and confidence) created by the JAVA application that uses the generated/selected PIXIT Classifier
- Maintains history of the last three scene classifications. If they are all the same then a slight increase in likelihood is applied to those locations with the same scene. Otherwise no increase is applied.
- Ability to reduce location likelihood for estimated locations that have an associated scene type with minimal classification confidence

Java Application – Scene Analysis

- Applies an generated image classifier to a captured images from the webcam
- Outputs the probability of each scene in the images classifier for captured image
- Maintains last classified image results log and history log
- Ability to load different images classifier
- Ability to apply an additional classifier to the same captured image

Altimeter System Features

- Ability to turn on/off Altimeter Scan
- Reads the Altimeter value from a Zlog Altimeter every X seconds
- Currently the user sets the current floor, which is used to filter out locations on the incorrect floor
- A sliding window of three scans is used to detect relative height change in altimeter value. A change in + or – 10 feet determines the user has changed floors and current floor is adjusted accordingly
- History log

Glossary

AP – Access Point

Wireless LAN transmitter/receiver that acts as a connection between wireless clients and wired networks

CCTV – Closed-Circuit Television

CMYK - Cyan, Magenta, Yellow, Black colour space

CoO – Cell of Origin

A fingerprinting technique that uses' the strongest RSSI value from AP to determine location

FP – Fingerprint

One or more identifying characteristics that can be used to infer location

GPS – Global Positioning System

HSV – Hue, Saturation Value colour space or HSB

HSB – Hue, Saturation, Brightness colour space or HSV

INS – Inertia Navigation System

LAN – Local Area Network

MAC – Media Access Control

A unique device identifier

QoS – Quality of Service

RBG – Red, Blue Green colour space

RFID – Radio Frequency IDentification

RSSI – Received Signal Strength Indicator

Is a measurement of the received radio signal strength from an AP

Wi-Fi – Wireless Fidelity

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