Indoor Location with Wi-Fi Fingerprinting

Noah Pritt
Walkersville, Maryland
noahpritt@gmail.com

***Abstract*—There are many applications for indoor location determination, from the navigation of hospitals, airports, parking garages and shopping malls, for example, to navigational aids for the blind and visually impaired, targeted advertising, mining, and disaster response. GPS signals are too weak for indoor use, however, making it necessary to investigate other means of navigation. Most approaches such as ultrasound and RFID tags require special hardware to be installed and remain expensive and inconvenient. The solution proposed in this paper makes use of commonly available Wi-Fi networks and runs on ordinary smart phones and tablets without the need to install special hardware. It comprises a calibration stage and a navigation stage. The calibration stage creates a "Wi-Fi fingerprint" for each room of a building. It minimizes the calibration time through the use of waypoints. The navigation stage matches Wi-Fi signals to the fingerprints to determine the user's most likely location. It uses maximum likelihood classification for this matching and takes the building's topology into account through the use of Bayes' Theorem. The system is implemented as a mobile Android app and is easy to use. In testing, it took only an hour to calibrate a home or shopping mall, and the navigation stage yielded the correct location 97.5% of the time in a home and 100% of the time in a mall.**

Keywords*—*indoor location; navigation; wi-fi; wlan; wireless; fingerprinting; gps

I. Introduction

Despite intensive research, the problem of developing a reliable indoor location system remains largely unsolved. GPS is widely used for outdoor navigation where signals are unobstructed, but these signals are attenuated and nearly useless indoors. GPS satellites orbit the earth at an altitude of 20,000 km. Upon reaching the earth's surface, the signal strength is -130 dBm due to path loss, which is just strong enough to be used for location determination. After passing through building materials, the signals undergo an additional loss of 10-30 dBm, rendering them too weak to be used for location determination [1].

Google offers a service called Indoor Maps, but it is generally limited to the display of floor plans and does not provide indoor location in most buildings. When it does, however, it can be extremely inaccurate or even nonfunctional. For example, a recent test by the author at Columbia Mall, a large shopping mall in Maryland, showed excellent GPS-based navigation performance when outside the mall. Upon entering, however, the system deteriorated almost immediately. The "you are here" blue dot icon wandered aimlessly hundreds of meters from the true location and did not recover until the author returned outdoors where GPS was once again accessible.

There are many applications for indoor location determination, from consumer use—navigating hospitals, airports, parking garages, and shopping malls—to targeted advertising, navigational aids for the blind and visually impaired [2], mining [3], and disaster response [4]. With a reliable indoor location system, emergency responders would be able to locate not just the right street address but also the right floor and room. Businesses would improve their targeted advertising by presenting special offers to users depending on their proximity to products in a store, and manufacturers would be able to track inventory inside warehouses and factories.

The solution proposed in this paper makes use of commonly available wireless networks and runs on ordinary tablets and smart phones. Implemented as an Android app, the system indicates the user's location indoors by measuring the received signal strengths of Wi-Fi signals and matching them to a list of stored fingerprints. The system is fast, accurate, and works in both residential and business environments.

The paper is organized as follows. Section II reviews prior approaches to the problem of indoor location and their limitations. After a presentation of the characteristics of Wi-Fi signals and methods that utilize them for location in Section III, Sections IV-VI describe the system proposed in this paper. Section VII presents experimental results, and Section VIII concludes with a discussion of the system's advantages and disadvantages.

II. Prior Approaches

A. Augmented GPS

Augmented or assisted GPS systems have been devised to increase the signal strength indoors. Some systems consist of networks of GPS transmitters on towers. Because they are much closer to users, their signal strengths are strong enough for indoor location determination. The main disadvantages of these systems are their great cost, limited coverage, and relative inaccuracy of around 50 meters [5, 6].

B. Cell Phone Localization

Cell phone localization uses mobile phone signals to determine a user's position. The advantage of this approach is the presence of an already existing cell tower infrastructure. The disadvantage is an extreme inaccuracy of hundreds of meters, rendering it unsuitable for indoor location [7].

C. RFID Tags

Radio frequency identification (RFID) systems use a network of radio beacons and tags. The advantages of these systems are their accuracy and reliability. The disadvantage is

Authorized licensed use limited to: ESCUELA POLITECNICA DEL LITORAL (ESPOL). Downloaded on February 18,2022 at 05:20:30 UTC from IEEE Xplore. Restrictions apply.

the requirement for numerous tags to be installed, along with a central network server and transmitters [8].

D. Ultrasound

Ultrasound techniques use sound waves instead of radio waves. Unlike radio waves, sound waves are less sensitive to interference by walls and objects. Ultrasound transmitters are installed at numerous locations around a building. The system measures the distance between a receiver and the transmitters by calculating the time-of-flight of the signals from each transmitter. Trilateration calculations then determine the location of the receiver. This technique is extremely accurate and can determine a user's location to within several centimeters. However, it requires the installation of numerous ultrasound transmitters [9].

E. Magnetic Fields

Other indoor location systems detect variations in the earth's magnetic field [10]. These variations are caused by ferrous objects in a building's structure such as steel beams. Each location in the building has a unique pattern of magnetic variations. Because many smart phones have magnetic field sensors, this approach is convenient and does not require special hardware. The disadvantage is that these magnetic variations are not necessarily stable over time. For example, moving a metal filing cabinet or computer will change the nearby field and impact the performance of the localization system.

F. Image Processing

Some systems for indoor navigation are based on image processing. One approach uses a camera pointed towards the ground and software that detects changes in the user's position based on the camera images [11]. It has a number of restrictions including the fast accumulation of errors, rendering it unsuitable for practical use. Another technique navigates by matching the camera photographs to a database of images using the SIFT algorithm [12]. It requires numerous reference images, however. Both of these systems also suffer from the requirement for high computing power, which makes them unsuitable for use on a smart phone or tablet.

A simpler image processing technique that does not require such high computing power uses fiduciary markers. These markers are special tags that are installed throughout a building. When a user photographs one of them, the system determines the user's location by matching the tag to a database of stored tags and locations. The main disadvantage of this technique is the need to install numerous fiduciary markers [13].

G. Inertial Navigation

Inertial navigation techniques use gyroscopes and accelerometers to detect movement. These movements are integrated to compute changes in position. Many cell phones and tablets contain inertial sensors based on low-cost Micro-Electro-Mechanical Systems (MEMS) technology, prompting much research into this type of navigation for pedestrians. The disadvantage of this approach, however, is that errors accumulate quickly, especially given the low accuracy of the MEMS sensors. Because of this error accumulation, inertial navigation cannot be used alone and must be supplemented with a second navigation technique, such as GPS, to correct and remove the errors [14].

III. Wi-Fi Signals

Most smart phones and tablets contain a Wi-Fi adapter for connecting to wireless networks. Wi-Fi signals are transmitted by network routers, which are plentiful in home and business environments. This situation presents an intriguing possibility. Can these signals be used for location determination?

In considering this possibility, it is important to understand the behavior of wireless signals indoors. A number of factors influence the strength of a received Wi-Fi signal. These include spatial as well as temporal effects. *Path loss* is the dissipation of power as the distance between receiver and transmitter increases as shown by the straight line in the log-log plots of Fig. 1. It is defined by the equation

$$P_R = P_T G_R G_T \left(\frac{\lambda}{4\pi d}\right)^2,$$

where P_R is the received power, P_T is the transmit power, G_R and G_T are the gains of the receive and transmit antennas, respectively, λ is the wavelength, and d is the distance between the receiver and transmitter [15, 16].

Another cause of variation in signal strength is *shadowing*, which is graphed in Fig. 1(a). Walls, objects, and even people cause the Wi-Fi signal strength to vary due to absorption, reflection, scattering, and diffraction. For example, radio signals are absorbed by some walls and reflected by others. They can also diffract around corners or scatter off surfaces.

Still other variations are caused by the constructive and destructive interference of radio waves as they reflect off objects, as shown by the graph of Fig. 1(b). When a Wi-Fi signal reflects off a wall and interferes with the direct path signal, the received signal can be strengthened or attenuated as shown in Fig. 2 [17]. Such variations occur on the order of the wavelength, which for a 2.4 GHz Wi-Fi signal is 12.5 cm.

In addition to these spatial effects, a Wi-Fi signal can undergo temporal variation. This occurs when the signal is influenced by time-varying factors, such as people moving about, cars driving by, or doors opening and closing. The graphs in Fig. 3 show signal strengths over time as measured by a stationary receiver. They vary by as much as 10 dBm. The histograms in Fig. 4 show that the distributions of these signal strengths are approximately normal.

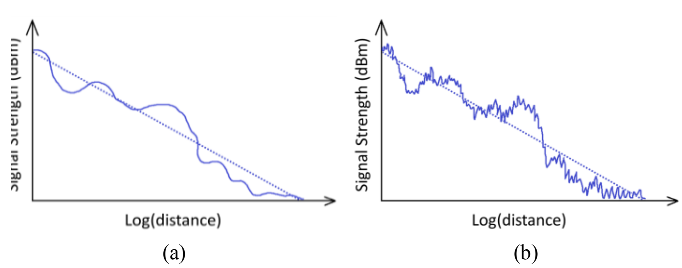


Fig. 1. Log-log plots of signal strength with respect to distance. The straight lines show the path loss, which causes a steady decrease in signal strength. (a) Variations due to shadowing. (b) Variations due to wave interference.

Authorized licensed use limited to: ESCUELA POLITECNICA DEL LITORAL (ESPOL). Downloaded on February 18,2022 at 05:20:30 UTC from IEEE Xplore. Restrictions apply.

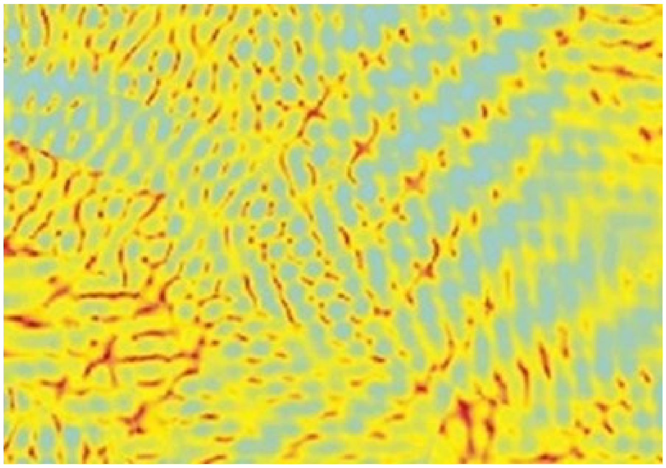


Fig. 2. This color plot shows the wave interference of Wi-Fi signals. The strongest signals (red) are due to constructive interference, while the weakest signals (blue) are caused by destructive interference. (Source: [17])

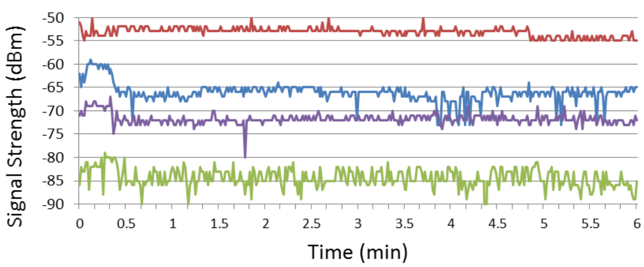


Fig. 3. Variations of Wi-Fi signal strengths at a fixed location from four different APs over a 6-min time period.

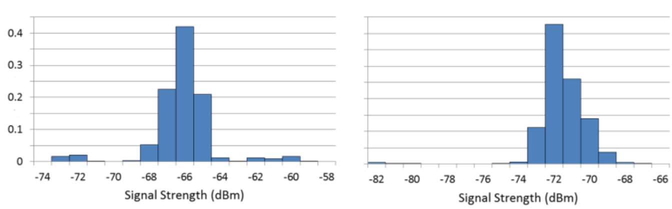


Fig. 4. Histograms of Wi-Fi signal strengths from two different APs over a 6-min time period. They are approximately normal distributions.

Several systems have been published that attempt to achieve indoor location from Wi-Fi signals.

A. RADAR

The RADAR system requires a number of laptop "base stations" with Wi-Fi adaptors to be installed throughout a building [18]. The user carries a device equipped with a Wi-Fi router to broadcast signals. The base stations receive these signals and triangulate the user's position. The disadvantage of this system lies in the fact that it requires the installation of special hardware and a Wi-Fi router on the user's device.

B. Horus

Horus is a laptop-based system that uses Wi-Fi fingerprinting to determine a user's location [19]. It is difficult to calibrate, however, because it requires an accurately measured floor plan with a dense set of calibration points spaced 1.5-2 m apart. Furthermore, one hundred Wi-Fi measurements must be collected at each of these many points, making calibration times excessive.

C. WiFi-SLAM

WiFi-SLAM employs Gaussian process latent variable models to build an indoor map as the user moves throughout a building [20]. Unlike RADAR and Horus, it does not require a calibration stage. However, it only works with very simple, rectangular floor plans and makes restrictive assumptions about user movements. It also requires integration with additional sensors to determine the direction and distance of movement.

IV. System Design

Our system for indoor navigation utilizes Wi-Fi signals and runs on a smart phone or tablet. Because these devices have Wi-Fi adapters, and because Wi-Fi routers are so prevalent, the system has the advantage that it requires no special hardware to be installed. It consists of a calibration stage and a navigation stage. In the calibration stage, the system creates a Wi-Fi fingerprint for each room of a building, where the received signal strengths of multiple signals are measured in dBm and stored as normal distributions. Knowledge of the locations of the APs (i.e., "access points" or Wi-Fi routers) is not required or used. To overcome the variations that plague Wi-Fi signals discussed in Section III, these measurements are collected over time and space. During navigation, the system determines the user's position by measuring the strengths of the ambient Wi-Fi signals and matching them to the stored fingerprints.

Unlike many approaches to indoor location determination, such as ultrasound and RFID, our system is convenient and economical because it does not require the installation of special equipment or sensors. It is also simpler and easier to calibrate, because it determines position based on discrete waypoints. Many indoor location algorithms attempt to achieve sub-meter accuracy, but this is unnecessary for most indoor navigation applications. Our system also achieves a very high level of reliability through its use of rigorous probabilistic techniques that take full advantage of all of the information available, including the statistical distributions of Wi-Fi signals and a user's most likely movements through a building.

V. Calibration Stage

During the calibration stage, the system stores Wi-Fi fingerprints at selected locations called waypoints. It also stores the name of each waypoint and which ones are adjacent to each other. Optionally, the user can specify the waypoints on a floor plan. The floor plan does not need to be measured or scaled, and waypoint coordinates need not be entered. This greatly simplifies and speeds the calibration stage. For example, it requires only about $1/10^{th}$ the calibration time of the Horus system [19].

A. Wi-Fi Fingerprinting

To form a calibration fingerprint at a fixed location in a building, the system measures the Wi-Fi signal strengths of each AP. It then stores the means and standard deviations of these measurements as shown in Fig. 5. We will denote such a fingerprint by $F = \{\mu_i, \sigma_i\}$, where μ_i is the mean of the signals from the ith AP and σ_i is the standard deviation. This approach

Authorized licensed use limited to: ESCUELA POLITECNICA DEL LITORAL (ESPOL). Downloaded on February 18,2022 at 05:20:30 UTC from IEEE Xplore. Restrictions apply.

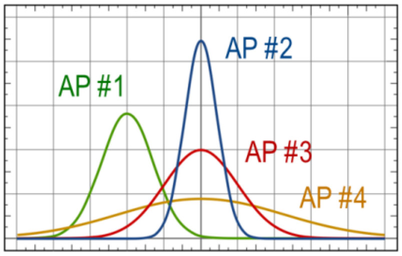


Fig. 5. A Wi-Fi fingerprint at a fixed location (waypoint) consists of a collection of normal distributions, one for each AP.

averages the signals over time and space to overcome the variations that characterize Wi-Fi signals discussed in Section III. During the averaging process, the individual calibrating the system turns in slow circles for a fixed period of time. To determine the optimal amount of time, we performed a comparative study of the system's effectiveness for calibration times of 15, 30, and 60 sec. As will be shown in Section VII, the optimum calibration time is 60 sec.

Given a set of locations at which fingerprints have been defined, the calibration file stores these fingerprints and their locations. The latter are represented as coordinates on a map or floor plan of the building along with a textual description such as "Living Room" or "JC Penney." During the navigation stage, the system uses these fingerprints to identify the location with the highest probability given the measured Wi-Fi signals.

B. *Waypoints*

The system is designed so that each calibration fingerprint represents a specific waypoint in a given building. In a suburban home, for example, a waypoint would be placed in the middle of each room as shown in Fig. 6(a). In a shopping mall or parking garage, on the other hand, the waypoints would be placed every 20 m or so along a walkway or lane. The use of waypoints simplifies and speeds the calibration procedure, because there are a minimal number of locations where Wi-Fi signals must be measured. During the navigation stage, the system returns the waypoint that is closest to the user's location. The system does not attempt to determine the exact position by interpolation, as this is unnecessary information for most indoor navigation applications.

C. *Building Topology*

The system also takes the topology of a building into account when determining a user's location. Topology is important because it indicates where a user is likely to move, thus providing important information to the indoor navigation algorithm. For example, it is more likely that a user will move to a neighboring location rather than a location on the opposite side of the building.

The topology indicates which waypoints are connected without specifying the exact distance between them. For example, the simple floor plan of Fig. 6(a) has a topology that is represented by the network graph in Fig. 6(b). Our system allows the user to define the topology very quickly during the calibration stage on a smart phone. It is accomplished by means of pull down menus that list the rooms or waypoints and a pushbutton to link them. The software then creates an n x n matrix of 0's and 1's, called the *link matrix* L, where n is the number of waypoints and a value of 1 in the *(i, j)* entry indicates that waypoints i and j are linked. The link matrix is symmetric, and the diagonal consists of 1's because each room is linked to itself. The floor plan and topology of Fig. 6 would have the following link matrix:

$$L = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 1 & 0 & 0 & 1 & 1 \end{bmatrix}.$$

VI. NAVIGATION STAGE

During the navigation stage, the system uses the calibration results to determine the user's location. It does this by measuring the Wi-Fi signals and using Bayes' Theorem to calculate the most probable waypoint. It matches these measurements to the stored fingerprints using maximum likelihood classification and uses the link matrix, which encodes the building topology, to factor in the user's movements from one waypoint to the next. The system uses all of the available Wi-Fi signals, even the weakest ones.

As the user moves throughout a building, the system averages the last 3-5 signals to determine the location in a continuous manner. The current location is shown as a red dot on the floor plan. For navigating to a desired goal, the system executes Dijkstra's shortest-path algorithm [21] on the topology graph (Fig. 6b) and shows the route from the current location to the goal on the floor plan. Optionally, the waypoint names can be spoken aloud by voice synthesis software, making it suitable for navigational use by the blind or visually impaired.

A. *Bayes' Theorem*

The navigation stage is based on Bayes' Theorem. If W denotes the event that the user is at waypoint W (i.e., in room W) and F denotes the event that the measured Wi-Fi fingerprint at this location is F, then the system must compute the probability $P(W|F)$. In fact, the system must compute this probability for every waypoint (or room) W in the building. It is computed using Bayes' Theorem:

$$P(W|F) = \frac{P(F|W)P(W)}{P(F)}.$$

The probability $P(F|W)$ is the probability of measuring the Wi-Fi fingerprint F at the waypoint W. It can be computed

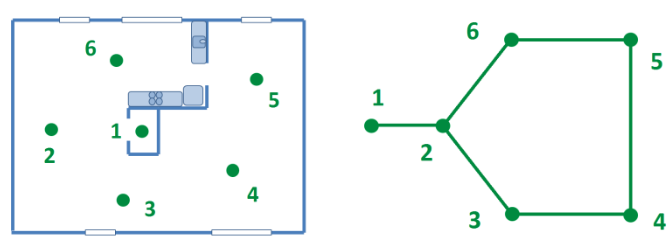


Fig. 6. The simple floorplan on the left has six waypoints (rooms) marked by green dots. It can be represented by the graph on the right, where the nodes are the waypoints and the edges link neighboring waypoints.

Authorized licensed use limited to: ESCUELA POLITECNICA DEL LITORAL (ESPOL). Downloaded on February 18,2022 at 05:20:30 UTC from IEEE Xplore. Restrictions apply.

from the stored fingerprints as explained in Section B below. $P(W)$ is the probability that the user is at waypoint W. Most Wi-Fi location algorithms assume this probability is 1, but our system uses the building topology to calculate it. If a given waypoint is linked to n other waypoints (including itself), then the probability of moving to one of these waypoints is defined to be $1/n$. The probability of moving to any other waypoint is 0. These transition probabilities are stored in a non-symmetric matrix T whose *(i, j)* entry is the probability of moving from waypoint i to waypoint j. The software calculates it by counting the number n of 1's in each row of the link matrix and replacing each of these 1's with $1/n$. Thus the transition probability matrix L for the floor plan of Fig. 6 would be

$$T = \begin{bmatrix} 1/2 & 1/2 & 0 & 0 & 0 & 0 \\ 1/4 & 1/4 & 1/4 & 0 & 0 & 1/4 \\ 0 & 1/3 & 1/3 & 1/3 & 0 & 0 \\ 0 & 0 & 1/3 & 1/3 & 1/3 & 0 \\ 0 & 0 & 0 & 1/3 & 1/3 & 1/3 \\ 0 & 1/3 & 0 & 0 & 1/3 & 1/3 \end{bmatrix}.$$

The 0's are replaced with small non-zero probabilities in practice to allow for recovery from blunders. Finally, the denominator $P(F)$ is a normalizing sum calculated as

$$P(F) = \sum_i P(F|W_i)P(W_i),$$

which is evaluated over the waypoints W_i.

B. *Maximum Likelihood Classification*

Many fingerprint algorithms assume $P(W|F) = P(F|W)$, i.e., $P(W) = 1$ in Bayes' Theorem for every waypoint W. Many algorithms also use a method called nearest neighbor classification. This method does not use the distributions of the Wi-Fi measurements. In fact, it does not even calculate probabilities. Instead it selects the calibration fingerprint—in this case only the means $\{\mu_i\}$—that most closely matches the measured means $\{\bar{x}_i\}$ by minimizing the Euclidian distance

$$\sqrt{\sum (\bar{x}_i - \mu_i)^2},$$

where the sum is taken over all the APs. This quantity is computed for each stored fingerprint $\{\mu_i\}$ and the minimum is selected as the most likely location. Its main advantage is that it is fast to calculate in smart phone software.

The problem with nearest neighbor classification is that it does not use all of the information available, namely the standard deviations. Some Wi-Fi signals have a broader spread than others as shown in Fig. 5, and this information should be used during classification. Furthermore, it is not clear how to combine this method with knowledge of the building topology, since Euclidean distance is not a probability measure that can be inserted in Bayes' Theorem.

Our system uses maximum likelihood classification to select the fingerprint that most likely produces the measured Wi-Fi signals. If the distributions of the signals are really normal, then maximum likelihood is in fact the optimal classifier [22]. Our research has confirmed this by showing that maximum likelihood classification gives better results than nearest neighbor classification [23].

Assuming the Wi-Fi signal strengths from one AP are independent of those from another, maximum likelihood classification computes the probability

$$P(F|W) = \prod \frac{1}{\sigma_i \sqrt{2\pi}} \, e^{-(\bar{x}_i - \mu_i)^2 / 2{\sigma_i}^2} \, ,$$

where F denotes the measured signal strength means $\{\bar{x}_i\}$, W is the waypoint or room with the stored Wi-Fi fingerprint $\{\mu_i, \sigma_i\}$, and the product is evaluated over all the APs. This probability is used in Bayes' Theorem to compute the probability $P(W|F)$ that the current location is waypoint W, as explained in Section A above. Note that the probability above simplifies to

$$P(F|W) = \frac{e^{-\sum (\bar{x}_i - \mu_i)^2 / 2{\sigma_i}^2}}{(2\pi)^{n/2} \prod \sigma_i},$$

which can be evaluated quickly in smart phone software. The exponential needs to be evaluated only once per stored fingerprint, and the denominator need not be calculated at all during the navigation stage. It only needs to be calculated once per stored fingerprint during the calibration stage and saved along with each fingerprint for use in the navigation stage.

C. *Weak Signal Handling*

Many algorithms do not use all of the available Wi-Fi signals. Typically they use a "cluster" of only the strongest signals [19]. Ignoring the weaker signals, however, discards useful information.

Our system uses all of the Wi-Fi signals, including the weakest ones. To do this, it must deal with a great deal of uncertainty due to the periodic "dropping" of signals. For example, a weak -90 dBm signal will drop out quite frequently. These dropped signals must be handled in a way that estimates their distributions without penalizing the fingerprint matching results due to uncertainties in these distributions.

When a signal becomes too weak to be detected by the system, it is assigned a very weak strength of -95 dBm and a large standard deviation of 4 dBm. Because most tablets and smart phones cannot detect signals weaker than -90 dBm, -95 dBm is a good estimate for the actual signal strength of the dropped signal. The standard deviation is large enough to avoid matching penalties. As a result, dropped signals do not negatively affect the system.

VII. RESULTS

The system was implemented as an Android app and evaluated on a Samsung Galaxy Tab 2. This tablet has an internal Wi-Fi adaptor that samples signal strengths from all detectable APs at an approximate rate of once per second. Fig. 7(a) shows the calibration stage being used in a shopping mall, and Fig. 7(b) shows the navigation stage.

We performed three sets of experiments. The first was a comparative study of system performance for different calibration times and showed that 60-sec times were optimal. The second set of experiments measured the system's location determination capability and compared it with two other

Authorized licensed use limited to: ESCUELA POLITECNICA DEL LITORAL (ESPOL). Downloaded on February 18,2022 at 05:20:30 UTC from IEEE Xplore. Restrictions apply.

algorithms: maximum likelihood classification without the use of building topology and nearest neighbor classification. The third set of experiments measured navigation performance under realistic conditions as a user roamed throughout a building. Each set of experiments was performed in a suburban home and a shopping mall.

Suburban Home: Fig. 8 shows the floor plan of a two-story home in Walkersville, Maryland. Calibrations were performed at the 18 waypoints marked with green dots, and tests were performed at the 100 locations marked with red dots. The system detected 23 Wi-Fi APs, with signal strengths varying from -90 to -25 dBm. Two of the APs were wireless routers located in the home, while the other 21 were routers located in other homes in the neighborhood.

Shopping Mall: Experiments were also performed at the Francis Scott Key Shopping Mall in Frederick, Maryland [24], which is shown in Fig. 9. During calibration, 176 APs were present. About 30 were strong enough to be detected at any one time. Calibration fingerprints were collected at the 27 waypoints marked with green dots in the figure, and tests were performed at the 100 points marked with red dots.

A. Calibration Time

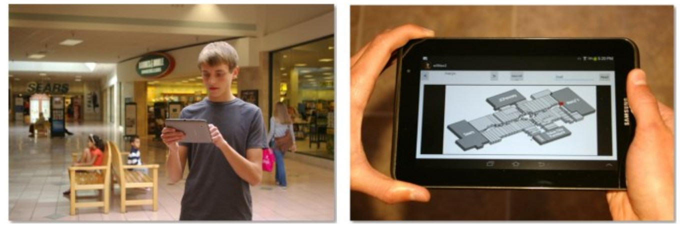
The purpose of the first set of experiments was to determine the optimal time that should be spent on the calibration stage. The testing procedure consisted of performing the calibration stage three times. In the first calibration, Wi-Fi signals were measured at each waypoint for 60 sec and stored in a fingerprint file. In the second calibration, they were measured for 30 sec and stored in a separate file. The third calibration collected the signals for 15 sec. We then measured the performance of each calibration stage by running the navigation stage at each of the 100 test points. The system determined the most likely location after each Wi-Fi measurement (i.e., after each second), averaging the signals over time. As time elapsed, the performance improved due to signal averaging. The amount of time that elapsed in each case before the system determined the correct location was recorded.

Fig. 10 shows the results for the home test site. The navigation time refers to the amount of time for which test data was collected before determining location. Performance improved significantly as the calibration time increased from 15 to 30 to 60 sec. Fig. 11 shows the results for the shopping mall. There was little difference between calibration times of 15 and 30 sec, but significant improvement for 60 sec. Thus, 60 sec appears to be the optimal calibration time.

B. Location Performance

In the second set of experiments we compared the location performance with that of two other algorithms. Neither of these other algorithms used the building topology. In other words, they had no knowledge of which waypoints were linked and thus which were more likely for the user to move to. The second of these other algorithms used nearest neighbor classification instead of maximum likelihood.

After calibrating each test site with a 60-sec calibration time per waypoint, we measured the performance of each algorithm by running the navigation stage at the test points. As



(a) (b)

Fig. 7. Using the Android app. (a) Calibration stage. (b) Navigation stage.

Fig. 8. Floor plan of two-story home used for testing. The green dots mark the locations of the 18 waypoints where calibration fingerprints were defined, and the red dots mark the 100 test locations.

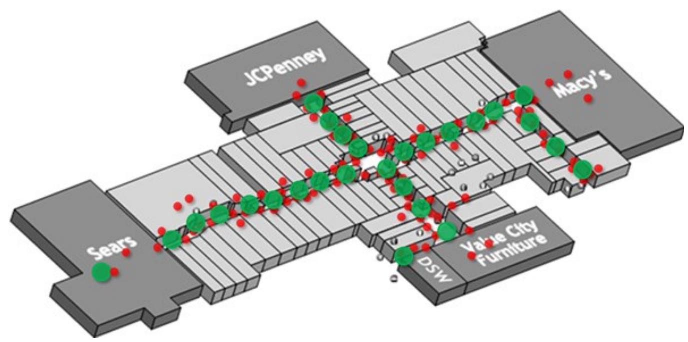


Fig. 9. Indoor map of shopping mall. The green dots mark the 27 waypoints where calibrations were performed. The red dots mark the 100 test locations.

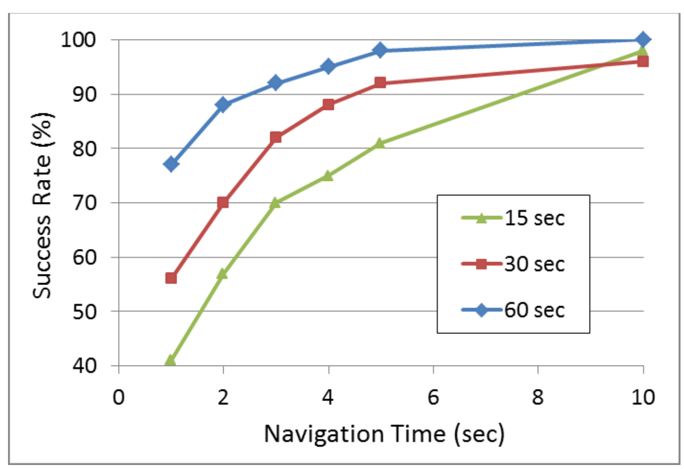


Fig. 10. Success rate of the system in the suburban home for the three calibration times of 15, 30, and 60 sec. The 60-sec calibration time yielded the best performance.

Authorized licensed use limited to: ESCUELA POLITECNICA DEL LITORAL (ESPOL). Downloaded on February 18,2022 at 05:20:30 UTC from IEEE Xplore. Restrictions apply.

in the first set of experiments, the system determined the most likely location after each 1-Hz Wi-Fi measurement, with performance improving as time elapsed.

Fig. 12 shows the results for the home test site. The system (denoted TOP in the figure) performed significantly better than the other two algorithms (denoted MAX for maximum likelihood and NN for nearest neighbor). After 1 sec, it identified the correct location 76% of the time, while the other algorithms had lower success rates of 60% and 55%. After 5 sec, the system achieved a 98% success rate.

Fig. 13 shows the results for the shopping mall. The system (TOP) achieved an 86% success rate after 1 sec, compared with 82% for the non-topological algorithm (MAX) and 76% for the nearest neighbor algorithm (NN). It achieved a 100% success rate after 5 sec.

The system performed much better than the other two algorithms in the home, but in the mall the difference was not as significant. This is probably due to the fact that the home had two stories. Waypoints that were on two different floors could have similar Wi-Fi fingerprints because of their spatial proximity and thus appear very similar to the non-topological algorithms. Because the system uses the building topology, however, these similar waypoints were not linked and thus were less likely to be confused.

C. Navigation Performance

The third set of experiments measured navigation performance under realistic conditions. We tested each algorithm by roaming throughout a building, recording the correctness or incorrectness of each location. The software averaged the last 5 Wi-Fi measurements to determine location continuously. Whenever a wrong location was recorded, the distance to the correct location in terms of number of waypoints was also recorded.

Fig. 14 shows a walking tour of the home, which started in the kitchen, covered the first floor, continued to the second floor, returned to the first floor for another circuit, and finally terminated in the powder room. The tour lasted 9 min. Fig. 15 shows the navigation performance. Our system (TOP) yielded the correct location 97.5% of the time compared with 91% for the non-topological algorithm (MAX). When it yielded the incorrect location, the software recovered with the correct location within seconds.

During a 30-min walking tour of the shopping mall, the system yielded the correct location 100% of the time.

VIII. Conclusion

In this paper, we have presented a reliable indoor positioning system that runs on a smart phone or tablet and takes advantage of the many Wi-Fi signals that are present in home and commercial environments. Its use of waypoints shortens the calibration time and renders the navigation stage more robust. Its use of maximum-likelihood classification improves the location performance over other methods. It also improves navigation by using Bayes' Theorem to incorporate the building topology and the user's most likely movements. During testing, the system yielded success rates of 97.5% in a suburban home and 100% in a shopping mall.

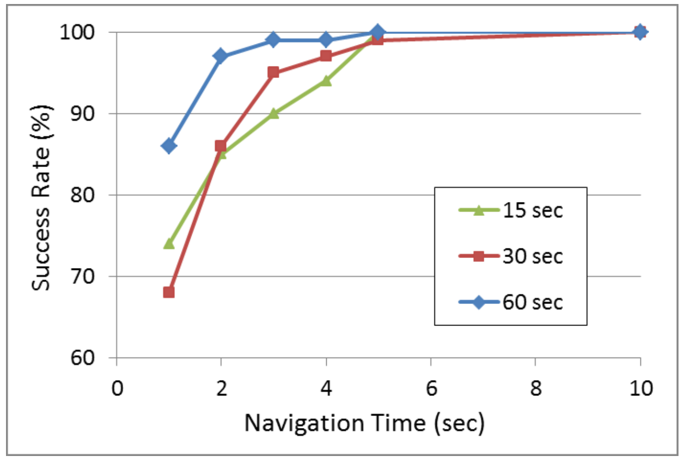


Fig. 11. Success rate of the system in the shopping mall for the three calibration times. The 60-sec calibration time yielded the best performance. The 15 and 30-sec calibration times had nearly the same results, indicating these times were insufficient to estimate the Wi-Fi signal distributions accurately.

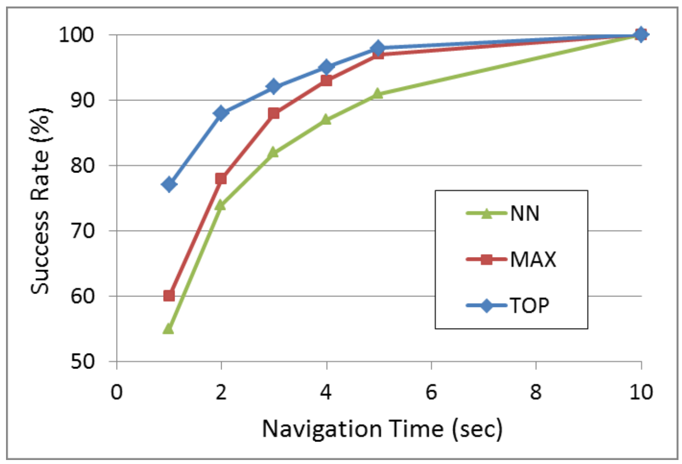


Fig. 12. Success rate of the system (TOP) compared with the two other algorithms (MAX and NN). Results are from the suburban home experiment. The system performance was significantly better than the other two algorithms after only 1 or 2 sec. This was probably due to the multiple stories.

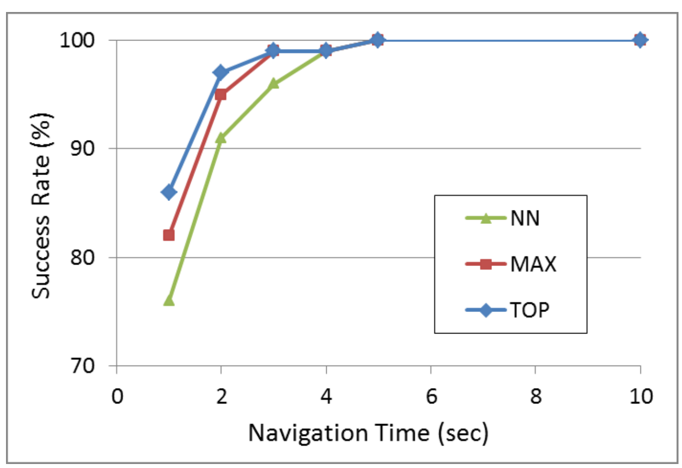


Fig. 13. Success rate of the system (TOP) compared with the two other algorithms (MAX and NN). Results are from the shopping mall experiment.

Authorized licensed use limited to: ESCUELA POLITECNICA DEL LITORAL (ESPOL). Downloaded on February 18,2022 at 05:20:30 UTC from IEEE Xplore. Restrictions apply.

Fig. 14. Walking tour of the home for the test of navigation performance.

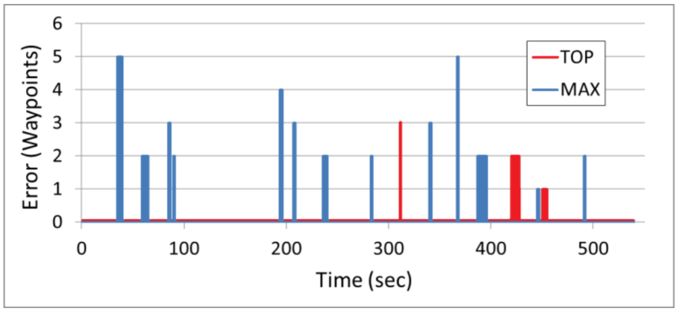


Fig. 15. Navigation performance of the system (TOP) compared with the non-topological algorithm (MAX). The system yielded the correct location 97.5% of the time compared with 91% for the non-topological algorithm. Results are from the suburban home.

In addition to testing the navigation performance under realistic conditions, we also tested the calibration stage and determined the optimal calibration time to be 60 sec. Finally, we compared the success rates for location determination with two other algorithms.

As currently implemented, the system uses all of the available Wi-Fi signals. If there are not more than a few hundred such signals, tablets and smart phones can handle the processing load. Initial experiments at a larger shopping mall with 600 signals overloaded the Samsung tablet used for testing, making it clear that the system needs to be modified to limit the number of signals it uses in signal-rich environments.

Another limitation of the system is that it has only been tested on one device. Initial experiments have shown that different devices have different sensitivities to Wi-Fi signals and sample these signals at different rates. Published results on device sensitivity are contradictory. Some research indicates that the difference in sensitivity is merely an additive term in dBm [25], while other results show that the differences are more complicated [26, 27]. Further research will be needed before the system can be extended to other devices.

REFERENCES

[1] K. Ozsoy, A. Bozkurt, and I. Tekin, "Indoor positioning based on global positioning system signals," Microwave and Optical Technology Letters, vol. 55, no. 5, pp. 1091–1097, 2013.

[2] E. Wise, B. Li, T. Gallagher, A.G. Dempster, C. Rizos, E. Ramsey-Stewart, and D. Woo, "Indoor navigation for the blind and vision impaired: Where are we and where are we going?" Int. Conf. Indoor Positioning and Indoor Navigation, 13-15 Nov 2012.

[3] S. Dayekh, S. Affes, N. Kandil, and C. Nerguizian, "Cooperative geo-location in underground mines: a novel fingerprinting positioning technique exploiting spatio-temporal diversity," 2011 IEEE 22nd Int. Symposium on Personal, Indoor and Mobile Radio Comm., 2011.

[4] S.R. Dandhi and A. Ganz, "Fireguide: firefighter guide and tracker," 32nd Annual Int. Conf. of the IEEE EMBS, 2010.

[5] NextNav LLC, Dec 6, 2013, http://www.nextnav.com.

[6] "Indoor location test bed report," Working Group 3, Communications Security, Reliability and Interoperability Council III, Mar 14 2013.

[7] Y. Gu, A. Lo, and I. Niemegeers, "A survey of indoor positioning systems for wireless personal networks," IEEE Communications Surveys & Tutorials, vol. 11, 2009.

[8] S.P. Subramanian, J. Sommer, S. Schmitt, and W. Rosenstiel, "INR - indoor navigation with RFID locator," 2009 Third Int. Conf. on Next Generation Mobile Applications, Services and Technologies, 2009.

[9] S. Holm, "Ultrasound positioning based on time-of-flight and signal strength," 2012 Int. Conf. Indoor Positioning and Indoor Navigation, 13-15 Nov 2012.

[10] S. Kim, Y. Kim, J. Yoon, and E.S. Kim, "Indoor positioning system using geomagnetic anomalies for smartphones," 2012 Int. Conf. Indoor Positioning and Indoor Navigation, 13-15 Nov 2012.

[11] C. Hide, T. Botterill, and M. Andreotti, "Low cost vision-aided IMU for pedestrian navigation," Journal of Global Positioning Systems, vol. 10, no. 1, 2011.

[12] J.C. Ching, C. Domingo, K. Iglesia, C. Ngo, and N. Chua, "Mobile indoor positioning using Wi-Fi localization and image processing," Proceedings of the 2nd Workshop on Computation: Theory and Practice, Manila, The Philippines, Sep 2012.

[13] A. Mulloni, D. Wagner, D. Schmalstieg, and I. Barakonyi, "Indoor positioning and navigation with camera phones," IEEE Pervasive Computing, vol. 8, pp. 22-31, Apr-Jun 2009.

[14] C. Lukianto and H. Sternberg, "Overview of current indoor navigation techniques and implementation studies," FIG Working Week, Bridging the Gap between Cultures, Marrakech, Morocco, 18-22 May 2011.

[15] A. Goldsmith, Wireless Communications, New York: Cambridge University Press, pp. 27-28, 2009.

[16] T. S. Rappaport, Wireless Communications: Principles and Practice, 2nd ed., Upper Saddle River, NJ: Prentice Hall PTR, pp. 105-106, 2002.

[17] H.J. Ohlbach, M. Rosner, B. Lorenz, and E.P. Stoffel, "NL navigation commands from indoor WLAN fingerprinting position data," Technical Report of REWERSE-Project, Munich, Germany, 30 Sep 2006.

[18] P. Bahl and V.N. Padmanabhan, "RADAR: an in-building RF-based user location and tracking system," INFOCOM, pp. 775-784, 2000.

[19] M. Youssef and A. Agrawala, "The Horus WLAN location determination system," 3rd Int. Conf. Mobile Systems, Applications, and Services, Applications, and Services, 6-8 Jun 2005.

[20] B. Ferris, D. Fox, and N. Lawrence, "WiFi-SLAM using Gaussian process latent variable models," in Proc. of the International Joint Conference on Artificial Intelligence (IJCAI), 2007.

[21] S. Dasgupta, C. Papadimitriou, and U. Vazirani, Algorithms, Boston: McGraw-Hill, pp. 119-124, 2008.

[22] J.D. Paola and R.A. Schowengerdt, "A detailed comparison of backpropagation neural network and maximum-likelihood classifiers for urban land use classification," IEEE Trans. Geoscience & Remote Sensing, vol. 33, July 1995.

[23] N. Pritt, "Indoor positioning with maximum likelihood classification of Wi-Fi signals," IEEE Sensors, Baltimore, Maryland, 4-6 Nov 2013.

[24] Francis Scott Key Mall, Frederick, Maryland, http://shopfskmall.com/.

[25] F. Dong, Y. Chen, J. Liu, Q. Ning and S. Piao, "A calibration-free localization solution for handling signal strength variance," in Mobile Entity Localization and Tracking in GPS-less Environnments, Lecture Notes in Computer Sci., vol. 5801, Berlin: Springer, pp. 79-90, 2009.

[26] J. Park, D. Curtis, S. Teller and J. Ledlie. "Implications of device diversity for organic localization," Proc. of the 30th IEEE Int. Conf. on Computer Communications, pp. 3182-3190, 2011.

[27] K. Kaemarungsi, "Distribution of WLAN received signal strength indication for indoor location determination," 1st International Symposium on Wireless Pervasive Computing, 16-18 Jan 2006.

Authorized licensed use limited to: ESCUELA POLITECNICA DEL LITORAL (ESPOL). Downloaded on February 18,2022 at 05:20:30 UTC from IEEE Xplore. Restrictions apply.