Indoor Positioning with Maximum Likelihood Classification of Wi-Fi Signals

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***Abstract*—There are many applications for indoor positioning, from navigating hospitals, airports and shopping malls, to mining and disaster response. Despite intensive research, the problem of developing an accurate indoor location system remains largely unsolved. GPS is widely used for outdoor navigation, but its signals are attenuated and useless indoors. Augmented GPS, ultrasound, and inertial navigation systems have been proposed but remain impractical. The solution presented in this paper makes use of commonly available Wi-Fi networks. Implemented as an Android app on an ordinary smart phone, it comprises 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 power of multiple signals are collected over time and space and stored as multivariate Gaussian distributions. During the navigation stage, the system determines its position by matching Wi-Fi signal strengths to the fingerprints with maximum-likelihood classification. Evaluation results in home and commercial environments show that this classification method outperforms the more conventional nearest neighbor algorithm. The resulting system can determine its position in only a few seconds.**

I. INTRODUCTION

There are many potential uses for indoor positioning. The average person would benefit from a GPS-like system for navigating shopping malls, hospitals, airports, museums, and parking garages. Businesses could improve their targeted advertising by presenting special offers to users depending on their proximity to products in a store. Manufacturers would be able to track inventory inside warehouses and factories. The blind and visually impaired would benefit from indoor navigation aids [1]. The level of safety would increase in mining operations [2] and firefighting [3]. Emergency responders would be able to find not just the right street address but also the right floor and room.

Despite intensive research, the problem of developing a reliable indoor positioning system remains largely unsolved. GPS is widely used for outdoor navigation where signals are unobstructed, but these signals are weak and nearly useless indoors. NextNav attempts to overcome this problem with beacon transmitters spread across a geographical area, while Polaris Wireless employs RF pattern matching on cell tower signals. Qualcomm uses a combination of both. However, the accuracies of these systems are on the order of hundreds of meters, rendering them ineffective for indoor positioning [4]. Other approaches use radio frequency identification (RFID) tags [5], fiduciary markers [6], and ultrasound transducers [7]. These techniques all require specialized equipment to be installed and remain generally impractical. Still other approaches use inertial navigation techniques, where a user's movement is determined by frequent measurements of acceleration and direction. However, most smartphones lack the gyro sensors required to make this approach work. In addition, it must be complemented with a location technique such as GPS to prevent the accumulation of errors [8]. Still other approaches measure the strengths of Wi-Fi signals in the environment, but they are still immature [9-11].

There is a great need for an indoor positioning system that is reliable and easily fielded. The solution proposed in this paper makes use of commonly available wireless networks and runs on ordinary smart phones. Implemented as an Android app, the system displays an indoor map of a building—for example, a shopping mall—and a red "You are here" dot to indicate the user's location. It accomplishes this by measuring the received signal power of Wi-Fi APs (access points) and matching them to a list of stored fingerprints. The system is fast, accurate, and works in both residential and business environments.

II. WI-FI SIGNALS

Many smart phones have a Wi-Fi adapter that can be accessed by means of software. The primary API for accessing this adapter on an Android phone is the WifiManager class. Calling the method getScanResults returns a list of all APs including their unique identifiers (BSSIDs) and received signal strengths in dBm. A fresh scan can be performed about once per second.

In developing a Wi-Fi navigation system, it is important to understand the behavior of wireless signals indoors. A number of factors influence the strength of a received signal. These include large- and small-scale propagation effects [12] as well as temporal variations. *Large scale* propagation causes

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variations over large distances (10-100 meters or more) and includes two phenomena called path loss and shadowing. *Path loss* is the dissipation of power as the distance between receiver and transmitter increases. 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 transmitter antennas, respectively, λ is the wavelength, and d is the distance between the receiver and transmitter [13].

If path loss were the only phenomenon that affected Wi-Fi signal strength, location could be determined by trilateration, which is the method employed by GPS. However, the many objects that exist in indoor environments cause *shadowing*, which is the variation of signal strength due to absorption, reflection, scattering, and diffraction. For example, Wi-Fi signals can be absorbed by some walls and reflected by others. They can also diffract around corners. These effects cause nearly unpredictable variations in signal strength, rendering trilateration impossible.

Small-scale propagation effects occur over much smaller distances (less than one meter). They are caused by the constructive and destructive interference of radio waves as they reflect off objects. When a Wi-Fi signal reflects off a wall and interferes with the direct path signal, the received signal can be strengthened or attenuated. Such “multipath” variations occur on the order of the wavelength, which for a 2.4 GHz Wi-Fi signal is 12.5 centimeters.

Fig. 1 illustrates these large- and small-scale propagation effects. Path loss and shadowing cause smooth variations in the signal, while small-scale variations cause unpredictable fluctuations. The two-dimensional color plot in Fig. 1 shows Wi-Fi signal variation in a room [14]. Note the small-scale propagation effects due to wave interference.

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. 2 show signal strengths over time as measured by a stationary receiver. They vary by as much as 10 dBm. Fig. 2 also shows that the distributions of these signals are approximately normal.

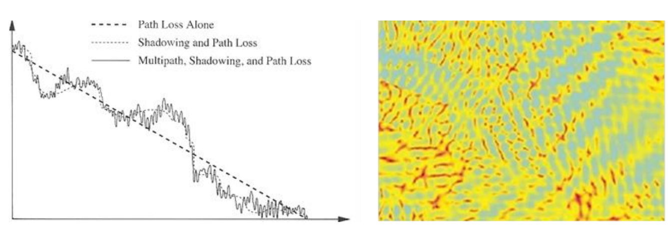

Figure 1. The graph on the left [12] is a log-log plot of signal strength with respect to distance from the transmitter. Path loss causes a steady decrease in signal strength, shadowing causes large-scale variations, and interference from multipath effects causes small-scale variations. The color plot on the right [14] shows signal strength over a 2-D area. Note the wave interference.

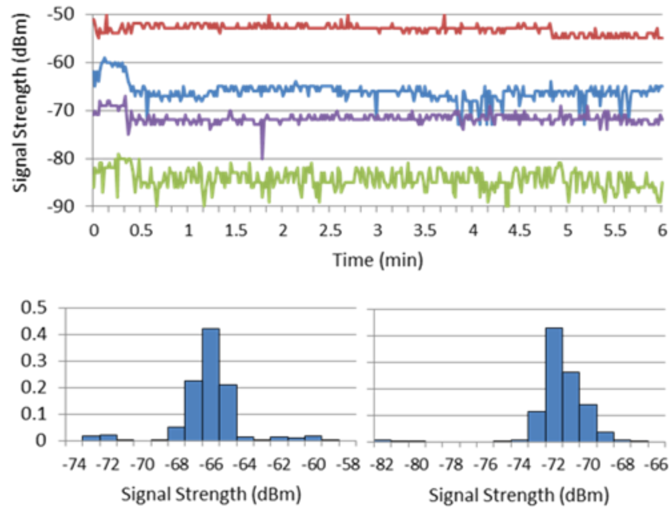

Figure 2. The upper graph shows the variations of Wi-Fi signal strengths at a stationary receiver from four APs over a 6-minute time period. The lower graphs show the distributions of the signal strengths of two of these APs.

III. System Design

A. Calibration and Navigation Stages

Our system for indoor navigation 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 power of multiple signals are measured in dBm and stored as multivariate Gaussian distributions. To overcome the variations that plague Wi-Fi signals discussed in section 2, these measurements are collected over time and space as the user turns slowly or walks in circles. During the navigation stage, the system determines the user’s position by measuring the strengths of the Wi-Fi signals and matching them to the fingerprints by means of maximum-likelihood classification. After describing the fingerprinting, we will present the method of classification.

B. Wi-Fi Fingerprinting

To form a calibration fingerprint at a fixed location, the system records m measurements of the signal strengths from n Wi-Fi APs. Denoting the jth measurement from AP i by x_i^j, the means and standard deviations are calculated by

$$\bar{x}_i = \frac{1}{m}\sum_{j=1}^{m} x_i^j, \qquad s_i = \sqrt{\frac{1}{m-1}\sum_{j=1}^{m}\left(x_i^j - \bar{x}_i\right)^2}.$$

The fingerprint is defined to be $\boldsymbol{F} = (\bar{\boldsymbol{x}}, \boldsymbol{s})$, where $\bar{\boldsymbol{x}}$ and $\boldsymbol{s}$ are the n-dimensional vectors $(\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_n)$ and $(s_1, s_2, \ldots, s_n)$, respectively.

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 acquires the fingerprint of an unknown location and then finds the calibration fingerprint that best matches it. This classification step is described in the next section.

C. Maximum Likelihood Classification

Nearest neighbor classification is a common technique for matching fingerprints [9,11]. It finds the calibration fingerprint whose signal means $(\bar{x}_1, \bar{x}_2, \dots, \bar{x}_n)$ minimize the Euclidian distance to the signal means $(\bar{x}'_1, \bar{x}'_2, \dots, \bar{x}'_n)$ at an unknown location:

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

The problem 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. 3.

The standard deviations of the signal strengths can be taken into account with the method of maximum-likelihood classification, which is often used in image processing to classify the pixels of a satellite image [15]. The probability of obtaining a Wi-Fi measurement x from a normal distribution with mean μ and standard deviation σ is

$$p(x|\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}.$$

Because the signals from different Wi-Fi APs are independent, their probabilities can be multiplied. Thus, the probability of obtaining the navigation fingerprint $\boldsymbol{F}'$ at a location whose calibration fingerprint is $\boldsymbol{F}$, is given by

$$p(\boldsymbol{F}'|\boldsymbol{F}) = \frac{1}{(\prod s_i)(2\pi)^{n/2}} e^{-\frac{1}{2}\sum\left(\frac{\bar{x}_i' - \bar{x}_i}{s_i}\right)^2}.$$

The computational cost of evaluating this function can be reduced by taking its natural log:

$$-\ln\left(\prod s_i\right) - \frac{n}{2}\ln 2\pi - \frac{1}{2}\sum\left(\frac{\bar{x}_i' - \bar{x}_i}{s_i}\right)^2.$$

Multiplying this expression by –1, ignoring the second term because it is constant, and defining $r = \ln \Pi\, s_i$ to be the first term, which only needs to be computed once for each calibration fingerprint, we define the following discriminant function to be minimized:

$$g(\bar{\boldsymbol{x}}') = r + \frac{1}{2}\sum\left(\frac{\bar{x}_i' - \bar{x}_i}{s_i}\right)^2.$$

Given the Wi-Fi signal means $\bar{\boldsymbol{x}}'$ measured at an unknown location, the calibration fingerprint $\boldsymbol{F} = (\bar{\boldsymbol{x}}, \boldsymbol{s})$ that yields the minimum value of this discriminant function determines the most likely location.

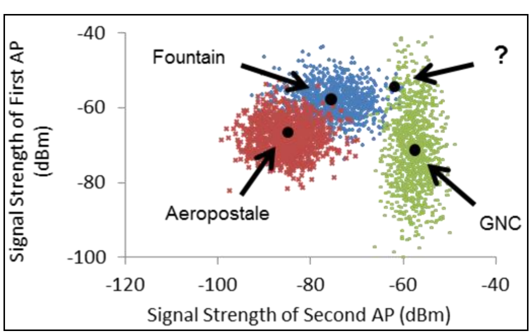

Figure 3. These scatter plots show signal strengths from two APs at three locations in a shopping mall. The dot labeled with the question mark is to be classified into a location. The nearest neighbor method incorrectly classifies it as "Fountain", but maximum likelihood correctly classifies it as "GNC".

IV. Results

Both stages were implemented as a mobile Android app and tested on a Samsung Galaxy Tab 2. There were two test sites: a suburban home and a shopping mall. Fig. 4 shows the floor plan of the home. The system detected 23 Wi-Fi APs, with signal strengths varying from -95 to -25 dBm. Two of the APs were wireless routers located in the home, while the other 21 were located elsewhere in the neighborhood. Calibrations were performed at the 18 locations marked with green dots in Fig. 4. Each calibration consisted of the collection of signal strengths from each of the APs at a rate of 1 Hz for 60 seconds. These measurements were stored as a fingerprint of means and standard deviations as described in section 2.

The testing procedure consisted of collecting Wi-Fi signals at 75 points throughout the home. After each second the classification results of the nearest neighbor and maximum likelihood algorithms were recorded. The success rates with standard error bars are presented in Fig. 5. After one second (i.e., one measurement of each of the AP signals) the algorithms correctly identified the location 72% and 63% of the time, respectively. Within only 5 seconds, the maximum likelihood algorithm achieved a 100% success rate on the 75 trials, and within 10 seconds the nearest neighbor algorithm also achieved 100%.

We repeated this testing procedure at the Francis Scott Key Shopping Mall in Frederick, Maryland, which is shown in Fig. 6. During calibration, 176 APs were detected. About 30 were strong enough to be detected at any one time. Calibration fingerprints were collected at the 27 locations marked with green dots in the figure. The total calibration required about an hour to complete. Tests were performed at the 100 points marked with red dots. After one second, the nearest neighbor algorithm identified the correct location 86% of the time, and the maximum likelihood algorithm 94% of the time, as shown

Figure 4. Floor plan of home used for testing. The green dots mark the locations of the 18 calibration fingerprints, which were about 3 m apart.

in Fig. 7. After only 5 seconds, the maximum likelihood algorithm achieved a 100% success rate on these 100 trials.

V. Conclusion

The indoor positioning system proposed in this paper runs on an ordinary smart phone and takes advantage of the many Wi-Fi signals that are present in home and commercial environments. Its use of maximum-likelihood classification instead of the nearest neighbor method results in location determination within only five seconds. By depicting the user's location as a red "You are here" marker on a map, it renders indoor navigation easier and faster, removing the need for the user to seek and decipher a building directory.

It is not yet clear how often the system needs to be recalibrated. Although the calibration stage is relatively fast, it would be advantageous if it could be completed more quickly. Future research will include studying the effects of shorter calibration times on the success rate of the system. The effect of removing Wi-Fi APs, due to a store closing in a shopping mall, for example, will also be studied. The system will also be combined with other positioning techniques, such as inertial navigation, in order to achieve more precision. This could result in the need for fewer calibration fingerprints, and thus a system that is more maintainable.

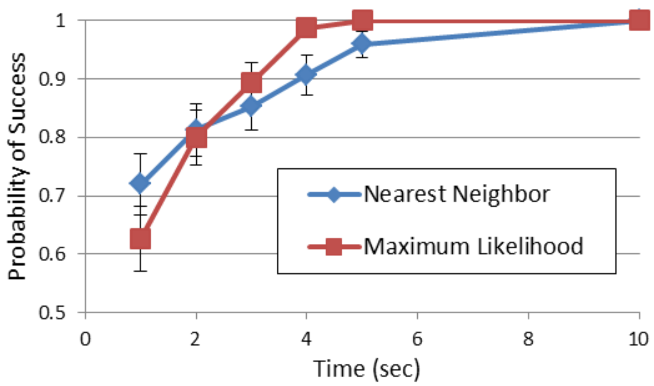

Figure 5. Probability of success with standard error bars for the home test. The maximum likelihood algorithm achieved a 100% success rate within 5 seconds, while the nearest neighbor method required 10 seconds.

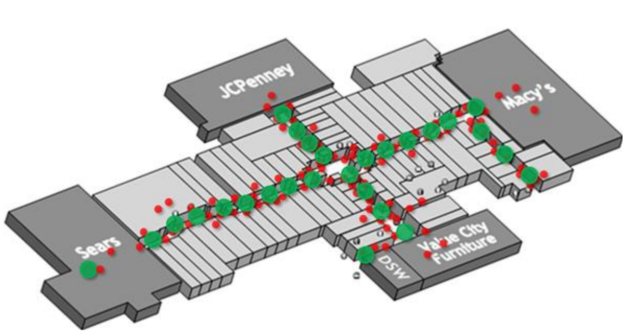

Figure 6. Indoor map of shopping mall. The green dots mark the 27 calibration locations, which were spaced about 20 m apart. The red dots mark the 100 test points, which were scattered throughout the mall.

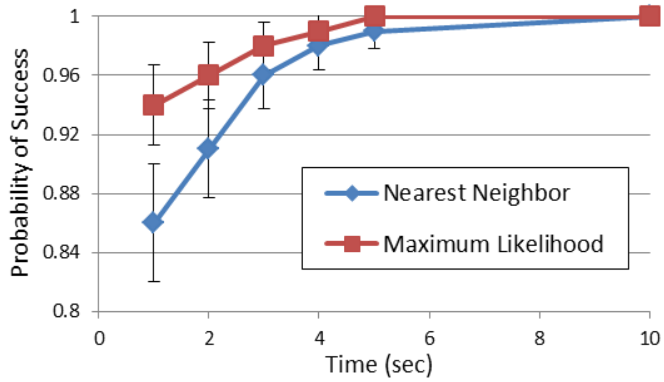

Figure 7. Probability of success with standard error bars for the shopping mall test. As in the home test, the maximum likelihood algorithm achieved a 100% success rate within 5 seconds.

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