Locus: An Indoor Localization, Tracking and Navigation System for Multi-story Buildings Using Heuristics Derived from Wi-Fi Signal Strength

Preeti Bhargava[1], Shivsubramani Krishnamoorthy[1], Aditya Karkada Nakshathri[2], Matthew Mah[1], and Ashok Agrawala[1]

[1] Department of Computer Science
University of Maryland, College Park
{prbharga,shiv,mah,agrawala}@cs.umd.edu
[2] Department of Telecommunications
University of Maryland, College Park
anakshat@umd.edu

Abstract. The holy grail in indoor location technology is to achieve the milestone of combining minimal cost with accuracy, for general consumer applications. A low-cost system should be inexpensive both to install and maintain, requiring only available consumer hardware to operate and its accuracy should be room-level or better. To achieve this, current systems require either extensive calibration or expensive hardware. Moreover, very few systems built so far have addressed localization in multi-story buildings. We explain a heuristics based indoor localization, tracking and navigation system for multi-story buildings called Locus that determines floor and location by using the locations of infrastructure points, and without the need for radio maps or calibration. It is an inexpensive solution with minimum setup and maintenance expenses. Initial experimental results in an indoor space spanning 175,000 square feet, show that it can determine the floor with 99.97% accuracy and the location with an average location error of 7m.

Keywords: Indoor location, Localization, Tracking, Navigation, Context- and location-aware applications and services.

1 Introduction and Related Work

Location is increasingly important for mobile computing, providing the basis for services such as navigation and location-aware advertising. The most popular technology for localization is GPS, which provides worldwide coverage and accuracy of a few meters depending upon satellite geometry and receiver hardware. Its major shortcoming is that it is reliable only in outdoor and environments with direct visibility to at least four GPS satellites. For indoor environments, alternative technologies are required. The holy grail in indoor location technology is to achieve the

K. Zheng, M. Li, and H. Jiang (Eds.): MOBIQUITOUS 2012, LNICST 120, pp. 212–223, 2013.

milestone of combining minimal cost with accuracy, for general consumer applications. A low-cost system should be inexpensive both to install and maintain, requiring only available consumer hardware to operate and its accuracy should be room-level or better. To achieve this level of accuracy, current systems require either extensive calibration or expensive hardware. Most of them are based primarily on either time or signal strength information. A third alternative, angle-of-arrival information is useful in outdoor environments but is not generally helpful indoors due to obstructions and reflections. Time-based systems require hardware support for timestamping that is not available in consumer products.

The use of wireless received signal strength indicators or RSSI values for localization of mobile devices is a popular technique due to the widespread availability of wireless signals and the relatively low cost of implementation.(We use RSSI and signal strength interchangeably in the paper). Its simplest version involves the mobile device measuring the signal strengths of existing infrastructure points such as Wi-Fi access points (APs) or mobile phone base stations and reporting the origin of the strongest signal it can hear as its location. This technique may be applied both to short range communications technologies such as RFID or Bluetooth as well as longer range technologies such as Wi-Fi or mobile phones but its performance is directly linked to the density of reference points. The precision of signal strength approaches is improved to meter-level by fingerprinting techniques, such as those in RADAR [1] or Horus [10], that use pre-measured fingerprinting radio maps. There are commercial solutions available as well such as Ekahau [3] that achieves a high precision of 1 to 3 m but requires proprietary hardware. However, a major drawback of fingerprinting is the cost of recording the radio map; a large amount of human effort is required to record the signal strength at each desired location using a receiver. Also, if the infrastructure or environment changes significantly, for instance the locations of APs are changed, furniture is moved around, the number of people occupying the closed space increases dramatically, or the test site is changed; the radio map must be remeasured to maintain performance [2].

Systems that don't use fingerprinting techniques often suffer from very low precision. These include Active Campus [4], that uses an empirical propagation model and hillclimbing algorithm to compute location with a location error of about 10 meters, and a ratio based algorithm proposed by Li [5], which produces median errors of roughly 20 feet (6.1 m) by predictively computing a map of signal strength ratios. Lim et al [6] proposed an automated system for collection of RSSI values between APs and between a client and an AP to determine the client's location with an error of 3m. They do not create a radio map but require initial AP calibration and its modification for continuous data collection.

However, more important than the raw error in distance is the computation of the correct floor in indoor multi-story environments. Even a most modest error in altitude can result in an incorrect floor leading to a high location error as determined by human walking distance. Identifying the exact floor is also more difficult because there are multiple APs on each floor and a device can receive signals from APs across floors. To address this, we explain a heuristics based indoor localization, tracking and navigation system for multi-story buildings - *Locus* (Section 3), that determines a device's floor and location by using the locations of infrastructure points but without the need of radio maps. As explained in Section 5, it can enable indoor location based services and applications such as a smartphone application that automatically downloads a map of a building when a user enters it, tracks his approximate current position on a floor map, and provides indoor navigation directions for destinations such as restrooms, offices, or conference rooms. It is also essential for situations like search and rescue operations where knowledge of the exact floor and location of a device/person on that floor is crucial for timely assistance.

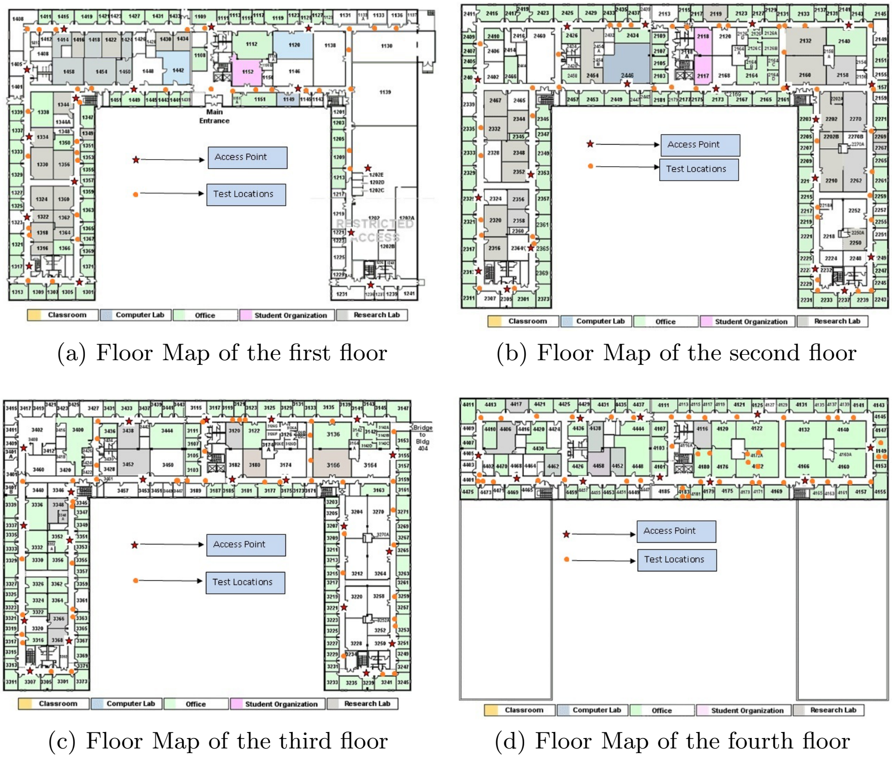
Our system is calibration-free and is an inexpensive solution suitable for localization with minimum setup, deployment or maintenance expenses. By avoiding the dependence on radio maps, it is readily deployable and robust to environmental change. It relies on existing infrastructure and mobile device capabilities, and requires no proprietary hardware to be installed. Initial experimental results (Section 4) with commercial tablet devices in an indoor space spanning 175,000 square feet across multiple floors, show that our system can determine the floor with 99.97% accuracy and the location with an average location error of 7m, and with very low computational requirements. Though our system has a higher location error as compared to fingerprinting techniques, we believe it still serves as a competitive alternative particularly in scenarios where extensive fingerprinting is not feasible or affordable or it is preferable to trade a little precision for saved human effort. To the best of our knowledge, our system is the first calibration-free system for floor as well as location determination in multi-story buildings. Active Campus [4] has options for user adjustments to correct the computed floor while in [5], the testbed is assumed to be on a single floor. Skyloc [8] uses GSM based fingerprinting for floor determination only and determines it correctly in 73 % of the cases while FTrack [9] uses an accelerometer to capture user motion data to determine floor but requires user input for initial floor.

2 Data and Experimental Setup

2.1 Signal Strength Data Gathering

The testbed for Locus is a four story academic office environment at the University of Maryland - the A.V. Williams Building. Figure 1 shows the floor maps with the location of the APs and test points where the RSSI values were recorded. The APs deployed in the building and used for Locus are of the Cisco AIR-LAP1142N-A-K9 model that can run multiple virtual APs. They are mounted on the ceiling and have an omnidirectional radiation pattern in the azimuth plane. Most of the APs are located in corridors rather than within offices, but are not at the same location on every floor. The indoor dimensions as of the four floors are shown in Table 1, covering a total of 175,000 square feet of deployment area. The number of APs for each floor are also shown.

The RSSI samples were taken in the corridors of each floor and a few accessible rooms. Two sets of samples were taken, the first set contained 500 samples



(a) Floor Map of the first floor

(b) Floor Map of the second floor

(c) Floor Map of the third floor

(d) Floor Map of the fourth floor

Fig. 1. Floor Maps

Table 1. Building Parameters

Floor	Dimensions (ft.)	Area (ft.^{2})	Number of APs
1	354 x 62, 2 x 182 x 80	51068	15
2	354 x 62, 2 x 182 x 80	51068	19
3	354 x 62, 2 x 182 x 80	51068	20
4	354 x 62	21948	10

from 120 test points and the second set contained 300 samples from 90 test points. Each sample contained the network name (SSID), MAC address, signal strength and frequency for each AP heard and was recorded with the (x, y, floor) coordinates for the test point.

2.2 Access Points Data

We have obtained a database of the 64 APs deployed in the A.V. Williams building, that includes their MAC addresses, AP IDs (the room number of the nearest room), and the floors and wings where they are installed. We have also added the (x,y) coordinates for each AP to the database.

3 Locus Floor and Location Determination System

3.1 Client Side Processing

The client application is an Android mobile application running on a tablet. The application scans the environment for Wi-Fi access points using the standard Android scan functionality. This data is then sent by the client to the Locus Location Server in XML format. On the server, we then lookup the database for every AP's (x,y) coordinates and floor.

In our experimental environment, each AP runs several virtual APs. The last hexadecimal digit for the base MAC address (for one physical AP) is 0, for instance 00:25:84:86:96:20 while for each virtual AP, it is varied as [1,9], for example 00:25:84:86:96:22, 00:25:84:86:96:24, etc. Some MAC addresses of virtual APs were seen to repeat for 802.11a and 802.11b/g/n networks.

3.2 Locus Floor and Location Determination Algorithm

The Locus system determines the location in two phases: the floor determination phase and the location determination phase for that floor.

Floor Determination. Locus uses four *properties*, of every sample of signal strength data that it receives from the client, to determine the floor. The values of the properties are basically floor number(s). The properties are :

1. *maxNumFloors*: Floors with maximum count of signals [1]
2. *maxSSFloor*: Floor with maximum signal strength
3. *maxAvgFloor*: Floor with maximum average signal strength
4. *maxVarFloor*: Floor with maximum signal strength variance

These properties were selected based on the fact that AP signals are attenuated when passing through ceilings and floors. As a result, a client is more likely to hear signals from its current floor than other floors, and those signals are likely to be stronger. Because of the same fact, both the average signal strength and variance of signal strengths of APs from the same floor will be higher on average. Signal strengths from a different floor will be weaker and hence their average signal strength will be less. In addition, since a large number of APs from a different floor are not heard, the signal strength variance is lower as well. There are exceptions to these heuristic, particularly for the floors below and above the true floor, but the combined use of the four properties yields the correct floor with very high probability ($> 99.9\%$), as we observed empirically.

A dataset of 500 samples was collected and pruned to remove all detected signals weaker than a threshold value of -90dBm.[2] This data was then used as a

[1] We saw several cases where two floors had the same count of signals and have handled this in our implementation.

[2] We selected a threshold value of -90 dBm because we observed the sensitivity of the android devices to be in the range of -20dBm to -95 dBm but all the signals less than -90dBm were very weak and inconsistent.

Table 2. Accuracy for individual properties and combination of properties

Combination/Property	Precision	Recall	F-Score/Accuracy
maxNumFloors = maxSSFloor= maxAvgFloor = maxVarFloor	1.0	0.67	0.802
maxNumFloors = maxSSFloor= maxAvgFloor	0.97	0.79	0.87
maxNumFloors= maxAvgFloor = maxVarFloor	1.0	0.725	0.84
maxNumFloors = maxSSFloor= maxVarFloor	0.975	0.727	0.833
maxSSFloor= maxAvgFloor = maxVarFloor	1.0	0.672	0.80
maxNumFloors = maxSSFloor, maxVarFloor = maxAvgFloor	1.0	0.7	0.824
maxNumFloors = maxAvgFloor, maxVarFloor = maxSSFloor	0.997	0.690	0.816
maxNumFloors = maxVarFloor, maxSSFloor = maxAvgFloor	0.997	0.678	0.807
maxNumFloors = maxSSFloor	0.97	0.866	0.915
maxAvgFloor = maxVarFloor	0.92	0.889	0.905
maxSSFloor = maxAvgFloor	0.948	0.812	0.874
maxNumFloors = maxAvgFloor	1.0	0.76	0.86
maxNumFloors = maxVarFloor	0.925	0.81	0.86
maxSSFloor= maxVarFloor	0.945	0.737	0.828
maxNumFloors	-	-	0.907
maxAvgFloor	-	-	0.848
maxSSFloor	-	-	0.857
maxVarFloor	-	-	0.816

training input to a classification algorithm which produced a label floor, based on heuristics derived from the four properties and their combinations, along with an accuracy measure for each heuristic. The combinations included taking two, three and all four properties together. The heuristics were:

1. If all four properties are equal, then the floor which matches all the four properties is the label floor.
2. If three properties are equal, then the floor which matches the three equal properties is the label floor.
3. If two properties are equal and the other two are not equal, then the floor which matches the two equal properties is the label floor.
4. If pairs of properties are equal, then the pair with the higher F-Score (explained next) is the label floor.

The accuracy measure for a heuristic is its F-Score which is the harmonic mean of precision and recall. Precision and recall are defined here as:

$$\text{Precision p} = \frac{\begin{array}{c}\text{Number of test cases for a heuristic}\\ \text{where the label floor matched with the ground truth floor}\end{array}}{\begin{array}{c}\text{Number of test cases that were valid for}\\ \text{a heuristic}\end{array}}$$

$$\text{Recall r} = \frac{\begin{array}{c}\text{Number of test cases that were valid for}\\ \text{a heuristic}\end{array}}{\text{Total number of test cases in the test dataset}}$$

$$\text{F-Score f} = \frac{2 * p * r}{p + r}$$

Algorithm 1. Locus Floor and Location Determination Algorithm

```
Data: network name, mac address, and RSSI value for each AP heard
Result: client's estimated location
remove all APs with signal strength less than threshold;
while not at end of data do
  | map mac to floor, x,y;
end
foreach floor do
  | compute num of signals, average SS, max SS, variance of SS
end
Check the combinations and individual properties in the order they are
mentioned in Table 2 to determine label floor;
compute weights for every AP on label floor based on signal strength;
location ⟵ weighted average of locations of n APs heard from labelFloor;
```

The accuracy measure for every individual property is

$$\text{Accuracy a} = \frac{\text{Number of test cases where ground truth floor was equal to the individual property}}{\text{Total number of test cases in the test dataset}}$$

Based on these accuracy measures (shown in Table 2), we established an order for these heuristics in Locus Floor and Location Determination Algorithm (Algorithm 1) to determine the label floor. Since the first heuristic involving a combination of all four properties being equal encompasses all other combinations, it is tested first. Similarly, the heuristics of three properties being equal are tested next as they include the combinations of two of the properties being equal within them, and so on.

Location Determination. Once the algorithm determines the label floor of the client, it uses a simplified radio propagation model and determines the client's approximate location by normalizing the signal strength of each AP and taking a weighted average of the location of the n strongest APs on the label floor, where n is varied from 1 to the maximum number of APs heard from the label floor.[3] The signal strength for each AP is essentially the average of the signal strength of all the virtual APs running from it. The weights are calculated by converting this averaged signal strength to power (mW) and normalizing it. This nullifies the effect of location of APs that are far away and have weaker signal strengths, as they will have a much lower weight as compared to APs that are closer and have stronger signal strengths. Thus,

$$\text{Power } P_i = 10^{\frac{\text{signal strength of AP}_i \text{ in dBm}}{10}}$$

$$\text{Weight } w_i = \frac{P_i}{\sum_{i=1}^{n} P_i}$$

[3] When n =1, the location of the strongest AP is picked as the client's location.

Table 3. Average Location Error for n ∈ [1,7] (n = Number of strongest APs)

n	Average Location Error (in feet)	(in m)
1	30.86	9.4
2	24.15	7.36
3	23.66	7.21
4	23.66	7.21
5	23.83	7.26
6	23.92	7.29
7	23.90	7.28

4 Evaluation

4.1 Test Dataset

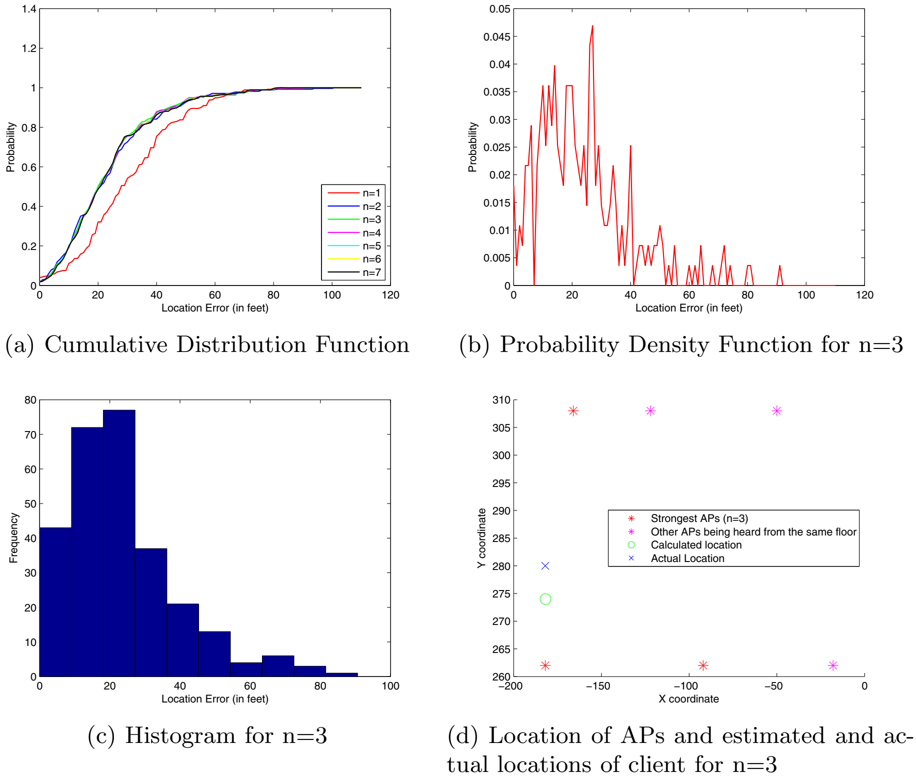
A test dataset containing 300 samples readings generated by Locus was collected using the methodology explained in Section 2.1.

4.2 Results

We evaluated our approach with respect to six performance measures: Floor Accuracy, Location Error, Complexity, Scalability, Robustness and Cost.

1. Floor Accuracy: Since our test site is a multi-story building, we have considered floor accuracy to be a measure of the percentage of correct floor estimations by Locus. We believe that it is an important performance measure especially for practical environments such as multi-story buildings, offices, hotels, or malls that have multiple APs on each floor. The floor accuracy of our system is 99.97 %.
2. Location Error: Once the floor is determined, we determine the client's location by calculating a weighted average of the locations of the n strongest APs being heard on that floor. Table 3 shows the average location error for $n \in [1, 7]$. [4] As seen in the table, the average location error settles around 24 feet (7.3 m) with $n \geq 3$. This implies that localization can be done by Locus by using a minimum of 3 APs. The best average and median location errors are 23.71 feet (7.2 m) and 20.43 feet (6.2 m) for n=3. Figure 2(a) shows the CDF plots of location errors for $n \in [1, 7]$ and Figures 2(b) and 2(c) show the PDF and histogram of the location errors for n= 3. 25 % of the errors lie within 12 feet, 50 % within 20 feet and 75% within 30 feet. Figure 2(d) shows a visualization of the locations of APs and the calculation of the client's location by Locus.
3. Complexity: Complexity can be measured in terms of software or hardware. Since our approach requires no proprietary hardware and is based solely on

[4] For $n \geq 7$, the average location error did not change significantly.



(a) Cumulative Distribution Function

(b) Probability Density Function for n=3

(c) Histogram for n=3

(d) Location of APs and estimated and actual locations of client for n=3

Fig. 2. Location Error

existing infrastructure, the hardware complexity is minimal. Also, the Locus system runs on a central server that has ample processing capability and power supply. The client side application is very lightweight and is restricted only to scanning and detecting the APs being heard, and then sending this information to the server.

4. Scalability: Scalability of a location system can be assessed in terms of Geographic scalability which means that the system will work even when area or volume covered is increased and Density scalability which means that as the number of units located per unit geographic area/space per time period, wireless signal channels may become congested, and hence more calculations or communication infrastructure may be required to perform localization. Another measure of scalability is the dimensional space of the system. Locus can be used in multi-story and 3D spaces as shown by the experimental studies. Since the density of APs is part of the infrastructure, we have tested Locus on different floors of the same building where the density varies. Also, the localization process in Locus is independent of the number of floors in the building and hence, it can be used for any multi-story building.

5. Robustness: Since Locus avoids any dependency on radio maps, it is robust to changes in the environment such as the time of the day, number of people in the closed space etc. Even if the positions of APs are changed, only the AP database will have to be updated. The deployed system and its underlying algorithm will remain unchanged unlike fingerprinting, where the radio map has to be calculated afresh.
6. Cost: One of the biggest advantages of Locus is that it has zero cost for deployment and maintenance as it relies solely on the existing infrastructure. The time cost of setting up is also minimal as it only requires setting up access to a database with the AP information.

5 Location-Aware Applications

5.1 Navigation

We present *Mye-Nav*, an indoor navigation tool that provides navigation instructions between rooms in a building. The application is being developed with the core modules functional. Based on the floor and location information obtained from Locus, the application displays the user's current location on the appropriate floor map of the building, tiled over an ArcGIS ESRI map. He/she can then select a particular point on the map to set the destination by a simple tap gesture. It could be a room or a point in hallway. The application immediately calculates a shortest path to the destination and reflects it on the map, as in Figure 3(a) and figure 3(b).

For accomplishing this, we maintain floor plan of every floor of the building divided into two segments - *room segment* and *walkable segment*. The room segments are defined bounded areas that have some information associated with them, such as room number, classroom/conference room/office room, occupant(s), phone number etc. The walkable segment area is where the user can move in order to reach the destination point. Our algorithm starts with the nearest point to the source in the walkable segment and tries to calculate successive points in the walkable segments towards the nearest walkable point to the destination point. We maintain a graph data structure associated with each floor, with vertices defined with respect to corners, rooms and other prominent landmarks in the hallways. The path is calculated in two phases - *Long hops* - wherein a shortest path between the source and destination is calculated in the graph. This path would be between two nodes, in the graph, that are at proximate distance from the source and destination points respectively; and *Short hops* - where the path is completed between the nearest graph nodes to the actual source/destination points at the location coordinates level.

We have tested Mye-Nav on the fourth floor of our test site (A.V Williams Building) successfully and intend to test it on the other floors and buildings. The main challenge we face is unavailability of readily usable building floor plans which makes the whole process tedious. We intend to discuss Mye-Nav and the experiments associated with it in detail in a follow-up paper.

(a) Mye-Nav application screenshot (b) Mye-Nav application screenshot (c) Caller location displayed on the dispatcher console

Fig. 3. Screen shots of applications using Locus for indoor localization

5.2 Tracking

M-Urgency [7] is a public safety system that redefines how emergency calls are made to a Public Safety Answering Point (PSAP) like the 911 system and is designed to be context-aware of the situation in which it is used. M-Urgency enables mobile users to stream live audio and video from their devices to local PSAP along with the real time location. A precise information about the callers location will be extremely helpful for the responders to get to the location of emergency, avoiding confusions and delay. During a normal 911 call, the emergency personnel are able to locate the building where the call originates from, but often find it difficult to zero in on the actual floor and the location of the caller on that floor. A system like Locus is essential here.

As an M-Urgency call is made to the police department, the caller application makes a *location request* to the Locus. From the Wi-Fi information provided by the caller application, Locus resolves the floor and the approximate location of the caller with an error of few metres and makes it available to the dispatcher as shown in figure 3(c). We intend to incorporate this feature in the next release of the already deployed M-Urgency system at the UMD Police Department.

6 Conclusion and Future Directions

In this paper, we presented the Locus system and its underlying algorithm, for floor and location determination in multi-story buildings, that are solely based on heuristics derived from signal strengths. The system requires no calibration, fingerprinting or proprietary hardware. It is a low-cost solution suitable for location determination with minimum setup, deployment or maintenance. It is readily deployable and robust to environmental change. Initial experimental results in an indoor space spanning 175,000 square feet show that it can determine the floor with 99.97% accuracy and the location with an average location error of 7m. These results give us confidence that a calibration-free system can achieve a better precision if a more sophisticated radio propagation model is employed for calculating location. We also believe that the precision of the system can be greatly enhanced by taking into account, the building structure, floor plans as well as the AP locations and using this information to pinpoint the exact location of the client, and are working in this direction. Other factors that will come into play as part of this analysis is the number of APs not being heard and the substance through which signals pass. Though this may make the system less generic, we are in the process of analyzing this additional data in such a way that the system still retains its generality and flexibility. Meanwhile, we are also in the process of testing the system in other locations on our campus, by the means of crowdsourcing, to ensure its usability across test sites.

References

1. Bahl, P., Padmanabhan, V.N.: Radar: An in-building rf-based user location and tracking system. In: Proceedings of the IEEE Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies, INFOCOM 2000, vol. 2, pp. 775–784. IEEE (2000)
2. Bahl, P., Padmanabhan, V.N., Balachandran, A.: Enhancements to the radar user location and tracking system. Technical report, Microsoft Research (2000)
3. Ekahau, `http://www.ekahau.com/`
4. Griswold, W.G., Boyer, R., Brown, S.W., Truong, T.M., Bhasker, E., Jay, G.R., Shapiro, R.B.: Activecampus-sustaining educational communities through mobile technology. University of California, San Diego, Department of Computer Science and Engineering. Technical Report (2002)
5. Li, X.: Ratio-based zero-profiling indoor localization. In: IEEE 6th International Conference on Mobile Adhoc and Sensor Systems, MASS 2009., pp. 40–49. IEEE (2009)
6. Lim, H., Kung, L.C., Hou, J.C., Luo, H.: Zero-configuration indoor localization over ieee 802.11 wireless infrastructure. Wireless Networks 16(2), 405–420 (2010)
7. M-Urgency, `http://m-urgency.umd.edu/`
8. Varshavsky, A., LaMarca, A., Hightower, J., de Lara, E.: The skyloc floor localization system. In: Fifth Annual IEEE International Conference on Pervasive Computing and Communications, PerCom 2007, pp. 125–134. IEEE (2007)
9. Ye, H., Gu, T., Zhu, X., Xu, J., Tao, X., Lu, J., Jin, N.: Ftrack: Infrastructure-free floor localization via mobile phone sensing. In: 2012 Tenth Annual IEEE International Conference on Pervasive Computing and Communications. IEEE (2012)
10. Youssef, M.A., Agrawala, A., Udaya Shankar, A.: Wlan location determination via clustering and probability distributions. In: Proceedings of the First IEEE International Conference on Pervasive Computing and Communications (PerCom 2003), pp. 143–150. IEEE (2003)