

# A Simple Localization System for Ad-hoc Indoor Meetings Through Wireless Connection Points

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## ABSTRACT

Wireless sensor technologies have become popular in recent years as the cost of electronics decreases. In addition, various sensors were incorporated into a smartphone, which caused the integration of many applications into one device. Navigation is a typical application of a smartphone. A common assumption in navigation is that a person's position has to be known exactly so most papers have focused on the localization process itself rather than customizing it for a specific application. In this paper we will show that complex systems or algorithms are not necessary for the purpose of getting two parties to meet in indoor situations. A robust localization system was implemented using popular sensors in a smartphone and simple localization techniques. We show that this system can localize a person with room-level accuracy to help two people to meet each other in a building.

## Categories and Subject Descriptors

H.2.8 [Database Management]: Database Applications—*Spatial databases and GIS*

## General Terms

Design, Algorithms

## Keywords

Indoor localization, Spatial information, Location-based services

## 1. BACKGROUND

Various indoor localization algorithms have been studied in recent years. Some of these algorithms are based on the characteristics of radio or acoustic signals received by a device [2, 3, 6, 8, 9, 10] and others use additional context information such as social encounters or ambient light to

improve the localization result [1, 5, 7]. These algorithms can be broadly classified into three categories depending on the localization technique [4]. Triangulation determines coordinates based on the physical characteristics of a radio or acoustic signal [6, 8, 9], scene analysis maps position-dependent features to a location [1, 2, 10] and proximity exploits spatial closeness for localization [5].

However, these techniques focused less on applications. Their main focus was to compute more accurate positions or to automate the localization process with little human intervention. However, such heavyweight and complex algorithms might not be necessary for a range of applications. In our opinion, it is more beneficial to optimize a localization algorithm for an application-specific purpose.

In this paper we suggest an easy-to-deploy indoor localization system for ad-hoc meetings. To be more specific, our proposed system can guide two people when they spontaneously want to see each other in a building. The observations for this situation are as follows:

- High centimeter-level accuracy indoor localization is not necessary but room-level localization is sufficient.
- The localization should be fast to be accepted by the human user in real world applications.
- Hardware or infrastructure used in the system should use off-the-shelf technologies.
- The software should be easily usable and deployable by non-technical people.

To satisfy these requirements, we have designed a client-server system using a smartphone as a client device. In our system, a web server is used as a common resource shared among the client devices and each client device runs a mobile application with a simple interface.

Our approach combines two localization techniques: triangulation and scene analysis in [4]. To make the system easily deployable, only off-the-shelf technologies are used. Thus, instead of an antenna array, which is not incorporated into a smartphone, the human body is used to obtain angular information with a smartphone's omni-directional antenna.

The system maps each position to a tuple of Received Signal Strength Indicator (RSSI) and a wireless router's signal direction at a position. Thus, a person having a smartphone can be localized based on the tuple obtained by the smartphone's sensors. Because this architecture only requires a

web server, wireless routers and clients' smartphones, the system has advantages in that it can be easily applied to the real world situations and can be used by non-technical people. The proposed algorithm aims to compute the position of a person at room-level accuracy, which is sufficient for ad-hoc meetings and does not require many wireless routers.

## 2. SYSTEM OVERVIEW

Our system works at a cell-based granularity on a floor-by-floor basis so one floor is divided into multiple cells, each of which is the localization unit in the system and corresponds to a room. The system is based on a radio-map and uses physical characteristics of the signal to extract signal's direction which is useful for making the position in the radio-map more recognizable. The mapping of each position to a tuple of a RSSI-average and a Wi-Fi signal direction at a person's position, called a fingerprint, has an advantage. Compared with other additional information such as color, light or sound used in [1], the direction information can give a more distinguishable fingerprint and does not require additional sensors. For two adjacent positions, RSSI and direction act as a radial coordinate in a two dimensional plane because they are orthogonal to each other.

### 2.1 Environment

Indoor localization algorithm's performance depends on the accuracy of sensor values. However sensor readings are not accurate due to many causes such as poor sensors and environmental effects. Therefore reducing errors is one of the first challenges of indoor localization algorithms. To minimize errors for our system, multiple RSSI samples are averaged and an error range for the orientation of a smartphone is used to filter the fingerprints in our system.

Signals can traverse multiple routes to reach one position. Due to this multi-path effect, it is possible that RSSI can fluctuate even with a small change of the environment, which can be a problem if high accuracy is needed. However, because our system is designed to work at a room-level granularity, the small changes of RSSI do not affect the localization results of the system.

### 2.2 System architecture

The overall system follows a client-server architecture. The server is used as a common resource for all clients and the client is used to interact with a user.

**Server.** The server acts in two different ways at each step of the radio-map based localization. In the pre-processing step, the server is used for data storage. It stores a floor-map image and a radio-map uploaded by a client. After the radio-map is uploaded, the server can process clients' localization requests. When it receives a fingerprint from a client, it can find where it was made from the radio-map and can send the corresponding cell position back to the client.

**Client.** A simple GUI-based application is used at the client side to download a floor-map image and create a fingerprint. When a radio-map is being made, the client software collects signal samples, computes fingerprints at multiple cells in a floor by using the samples and uploads them to the server. Then the server stores a group of these fingerprints as a radio-map in its database. If the client device comes into the floor where a radio-map is already made, it can do the same process to generate a fingerprint at its position. However, in this case, instead of uploading it to the

server, it can send a query message with its fingerprint to the server to learn its current cell position.

### 2.3 Phases of the system

The system operates in three phases. Firstly, a staff member divides the whole floor into multiple cells. In this phase, the division usually ensures that one cell corresponds to one room but if higher accuracy is required the number of cells can increase. Secondly, at the representative position of each cell, mostly the center of each room, the staff creates a fingerprint with signal samples collected from multiple wireless routers. This is repeated for all cells while the staff goes around a floor. As a result, a cell-based radio-map on the area where each fingerprint acts as an index to a specific cell, is made. These two phases form the pre-processing of the system to make a localization algorithm work. After the pre-processing is finished, other users can localize themselves at a cell-based granularity by making a fingerprint and using it as a key in the server's radio-map database.

### 2.4 Radio-map and fingerprint format

In our system, one fingerprint is composed of RSSI-averages and arrival angles of signal samples from multiple wireless routers, so it has the format as:

$$FP = \{(SSID_i, s_i, \theta_i) | i = 1, \dots, N\} \quad (1)$$

where  $N$  is the number of wireless routers installed in a floor,  $SSID_i$  is the identifier,  $s_i$  is the average of RSSI and  $\theta_i$  is the arrival angle of a signal from the wireless router  $AP_i$ . SSID, RSSI and an arrival angle together compose the  $i$ th component of one position's fingerprint. The radio-map maps a fingerprint to each cell, a division unit of the area, so that it can convert data collected from wireless routers to spatial information. This radio-map can be represented as follows:

$$RadioMap = \{(C_j, FP_j) | j = 1, \dots, M\} \quad (2)$$

where  $M$  is the number of cell divisions in the floor,  $C_j$  is the  $j$ th cell and  $FP_j$  is the fingerprint computed at the representative position  $p_j$  of  $C_j$ .

## 3. IMPLEMENTATION

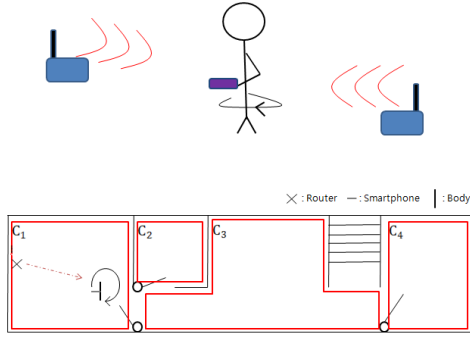
### 3.1 Radio-map generation

#### *Floor's cell division*

For the purpose of helping two people to meet each other and guiding them, knowing the room in which a person could be located is sufficient. Therefore to make the system work at a room-level granularity, a floor is divided along the walls so that each cell corresponds to one room. Figure 1b shows this room-level division of a floor. The advantage of this division is that it can give good localization results with a small number of routers because the algorithm does not have to differentiate a large number of cells and each cell can be distinguished better by a large RSSI difference caused by the attenuation of the walls between adjacent cells.

#### *Calculation of the smartphone's orientation*

A magnetic sensor and an accelerometer are used to get the orientation of the smartphone. The mechanism is as follows:



**Figure 1: A person who collects signal samples to create a fingerprint (top), top-view of the person in a floor (bottom)**

1. The accelerometer computes a plane orthogonal to the gravity direction.
2. The magnetic sensor measures how much angle the smartphone is rotated from North Pole in the plane given by the accelerometer.

#### *Computation of signal's arrival angle*

In our system, each component of a fingerprint is composed of a RSSI-average and a received signal's arrival angle. Unlike RSSI, which can be measured directly by the smartphone, getting the direction of Wi-Fi signal requires a specific mechanism because the smartphone does not have a directional wireless antenna. Thus, we have used a person's body to stand in the signal path from the router to make the antenna act like a directional one with the help of smartphone's orientation measurement.

As can be seen in Figure 1, while a person turns around with her smartphone, Wi-Fi signal samples are collected with an angle measurement. When the person directs her back toward the router during her rotation, her body acts as an obstacle to reduce the signal strength before it reaches her smartphone. If this attenuation makes RSSI values small enough to be differentiated, the arrival angle of received signal can be obtained.

To extract reliable direction information, we have used K-means clustering with low 10 percent RSSI samples and Sum of Squared Error as an cluster evaluation metric under the assumption that the samples with low RSSI values are likely to occur near the arrival angle of the signal. Then the biggest cluster is formed near the right direction and anomaly samples are excluded from this cluster. As a result, the center of the biggest cluster, a direction-average of samples, can give an approximate value of the arrival angle.

#### *Computation of RSSI average*

Another component of the fingerprint is the average of RSSI. However computing the average of all samples directly can give the biased result because the samples are affected by noise and they include the low RSSI samples which are collected when a person's body shields the signal. To remove the bias, the samples having angles within the smartphone's orientation error-range from the signal's arrival angle are removed first. After that, the samples having high and low

10 percent RSSI values are deleted to exclude the anomaly samples. After this pruning, the average of the remaining ones gives an average RSSI value.

## 3.2 Localization

When the server has a radio-map database, it can compare a fingerprint sent by a person with its database to find the most similar fingerprint. When the server receives a fingerprint, it firstly uses direction information to filter the fingerprints in the database to extract candidates, one of which was made at the person's current cell position. Thus, fingerprints having a direction within the smartphone's orientation error range from the person's fingerprint direction are selected as candidates. After candidates are chosen, the differences of the person's fingerprint RSSI and candidates' RSSI from all wireless routers are summed together and compared to find the fingerprint closest to the person's one. Then the closest fingerprint is used to show the person's current cell position in her smartphone.

## 3.3 Deployment and Use

Our system does not require any special hardware or software. A staff member who wants to use our localization system for a building, can use any web server for the system. To make localization algorithm work, he can store a map of the building on the server by just downloading or taking a photo of the existing floor-plan, and then create a radio-map simply by collecting samples and uploading the result fingerprints to the server.

If the building's radio-map and floor-map are stored on the server, and the server is easily accessible in the building, for example by means of a default gateway, a non-technical person can locate herself by getting a mobile application from the mobile app market. After localization, if she wants to meet another person, she can send her cell position to the other and can wait until the other party comes to her cell. Because a cell corresponds to a room, they can see each other if they are in the same cell.

## 4. EXPERIMENT RESULTS

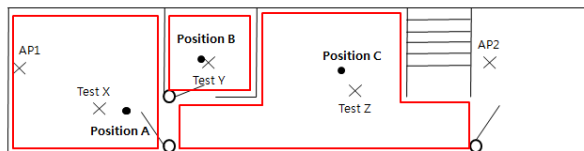
### 4.1 Experiment setup

The client side was implemented as an Android mobile application on Sony Xperia-ray and a virtual node with Ubuntu 12.04.4 in the University of Melbourne's Nectar Cloud was used as a server. The server stored fingerprints in CouchDB. D-Link DSL-2642B and Netgear BigPond were used as wireless routers and installed in a flat of a building in real settings.

### 4.2 Differentiation of three adjacent cells

To examine if the application can find a correct cell given a fingerprint, a floor was divided into three cells and the application was tested in these cells. To create a radio-map, 200 samples from two routers are collected at multiple angles at position A to C to make a fingerprint. Figure 2b is the resultant radio-map which is composed of three fingerprints, each of which is a group of RSSI averages and Wi-Fi signal's arrival angles from two routers.

After the radio-map is created, a fingerprint was generated again and sent as a query to a server to test the localization result. This was repeated 10 times for each cell. As can



(a)

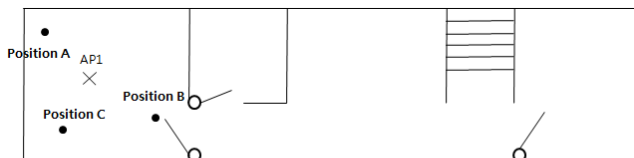
	Wi-Fi AP1		Wi-Fi AP2	
	RSSI (dBm)	Direction (degree)	RSSI (dBm)	Direction (degree)
Position A	-56.663	124.9	-72.636	-98.02
Position B	-63.336	93.99	-64.37	-82.14
Position C	-74.877	64.9	-57.007	-61.89

(b)

	Position A	Position B	Position C
Test X	80%	20%	0%
Test Y	10%	90%	0%
Test Z	0%	10%	90%

(c)

Figure 2: Experiment settings (a), radio-map database (b), localization result (c)



	Wi-Fi AP1	
	RSSI (dBm)	Direction (degree)
Position A	-60.248	-72.61
Position B	-60.626	109.93
Position C	-59.72	-160.11

Figure 3: Experiment settings (top), radio-map database (bottom)

be seen in Figure 2c, our system could achieve 80 percent accuracy for test X and 90 percent for Y and Z.

### 4.3 Differentiation of positions in the same cell

Our algorithm has the additional advantage in that it can distinguish three different locations in the same room with only one router because the fingerprint has a direction as its component. As the table in Figure 3 shows, three positions cannot be differentiated if only the RSSI value is used, because those three positions have the same distance from the router. Therefore the use of direction in a fingerprint can help the system to get higher localization accuracy or can minimize the number of used wireless routers.

## 5. CONCLUSION

We present a simple radio-map based localization system for ad-hoc meetings. Because the application does not require high accuracy, the cell-based division of the floor is suf-

ficient for the system to provide high precision. The system has the advantage of adaptability and accessibility because it does not use special hardware or infrastructure but only uses smartphones which are easily available. Another merit of the system is the use of angular information. It enables the system to differentiate spatially close positions so can be used to improve localization accuracy or reduce the number of wireless routers used in the system.

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