Chapter 8

One Stage Indoor Location Determination Systems

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Additional information is available at the end of the chapter

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1. Introduction

Recent advances in communication technologies have great impact on location determination systems. Location determination systems are deployed in almost every building, from hospitals where the location of patients and doctors or any medical equipment can be determined, or sending information to customers based on their location and capability, to organize the traffic and reducing congestion in the highways.

Global Positioning System (GPS) is a standard location determination system that enables the users to locate themselves in outdoor environments. Unfortunately, GPS does not work well in indoor locations because it requires a line-of-sight between the mobile station and the satellites. Hence, an alternative approach is to use a specialized positioning infrastructure that was built exclusively for positioning purposes.

Although these systems generally provide high accuracy rate, but in many situations, they suffer from high cost, and they require an extensive work to build and for maintenance. On the other hand, recent researchers have taken advantages of the available wireless LANs infrastructure, which was built solely for the communication purposes in the first place, and try to develop their positioning systems on the top of the wireless LANs [4]. The main advantages of this approach are low cost, easy to maintain and the availability of WLAN in almost every building.

These systems are commonly called *Off-the-shelf* positioning systems. The basic idea of this approach is to collect radio *fingerprints* at random or predetermined *reference points* to build a *radio map*. These fingerprints are usually a collection of received signal strengths (RSS) combined with their (x, y) coordinates. In the next phase, the system reads the current RSS with unknown location and search for the nearest value in the radio map. The search for the nearest value may include a single or a set of values.

Various positioning systems have been developed using different positioning techniques such as Proximity Sensing, Lateration and Angulation techniques. But due to the complex nature of the indoor environments, it represents an obstacle for such techniques to be applied for indoor positioning systems. This obstacle is known as the multipath phenomenon that includes reflection, diffraction and scattering.

The improvements of the fingerprinting approach are the way of representing the reference points in the radio map. These reference points could be represented either by a single value or by a collection of RSSs values. Another way to improve this approach is to collect a large number of fingerprints or to use other properties of the radio signals such as the Bit Error Rate (BER), Signal-to-Noise Ratio (SNR), Time of Arrival (ToA), Time Difference of Arrival (TDoA), Angle of Arrival (AoA) or Phase of Arrival (PoA). Some research have suggested that by combining two or more radio signal properties, this resulted in a better performance but an increased in system complexity.

Figure 1 shows the structure of the conventional location determination systems and the single-phase systems. In the conventional systems, an off-line training phase is required in order to build a radio map, the radio map is constructed either by empirically collecting a single or multiple RSS fingerprints at predetermined or random anchor points, or by using a model based indoor propagation model [15]. In the on- line phase, the location is estimated by matching the RSS fingerprint stored in the radio map with the RSS measured in the real time. Examples of such systems can be found in [2, 4].

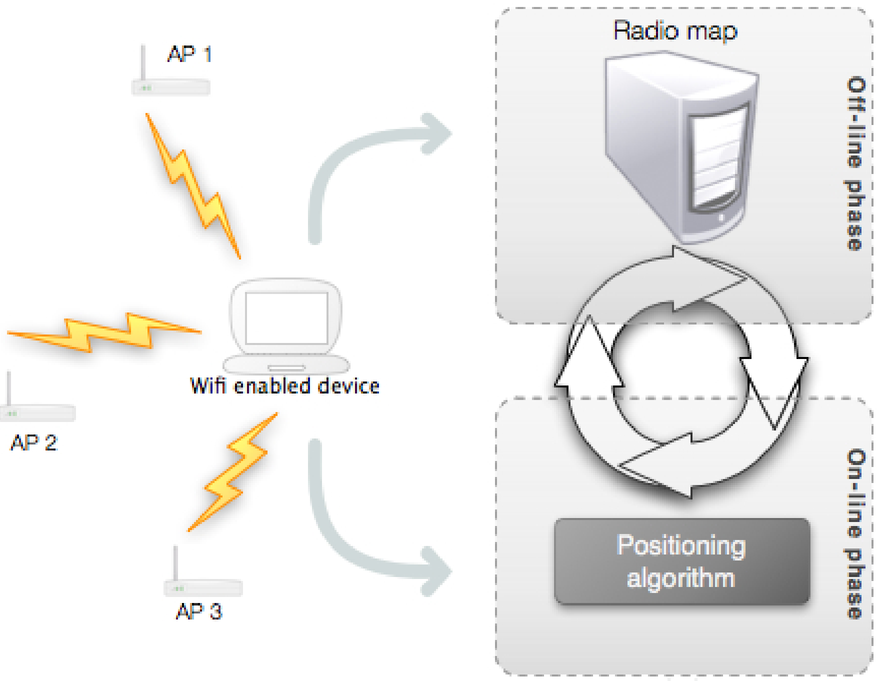


Figure 1. Structure of location determination systems showing conventional system

Single-phase systems do not require an offline phase; instead, they use the online RSS fingerprints to estimate the target's location. Usually such systems compromise the offline stage for the system's accuracy. A zero configuration system proposed in [21] uses the online RSS readings between WLAN Access Points (APs) and between mobile terminals and their AP neighbors. The system suggests a singular value decommission (SVD) technique to implement a mapping between RSS fingerprints and the true location. Table 1 shows a comparison between conventional and single-phase location determination systems [35].

System	Type	Observable	Accuracy
RADAR[4]	Conventional	RSS	2 - 3 m
Ekahau	Conventional	RSS	3.1 m
Nibble[6]	Conventional	SNR	10 m
Lim H. et al.[21]	Single-phase	RSS	2.57 m
Mazeulas et al. [25]	Single-phase	RSS	~ 4 m.

Table 1. Comparison between conventional and single-phase location determination systems

Mazeulas et al. [25] presented a single phase indoor location determination system that first searches for the best propagation model that is proper for the current environment, and then estimates the target's location from the online RSSs obtained by the mobile target from the available APs using lateration techniques. The system estimates the distance d from each AP by calculating the maximum likelihood as follows:

$$\hat{d} = 10^{\left(\alpha - P_{R_i}\right)/10n_i} \tag{1}$$

where α is a constant depends on various indoor phenomenon's such as multipath and shadowing, P_{R_i} is the RSS from the i^{th} AP and defined as follows:

$$P_R = \alpha - 10 \cdot n \cdot \log_{10}(d) + X \tag{2}$$

where n is the multipath exponent. The system achieved an average location error lower than 4 m. Off-the shelf location determination systems use the existing wireless LAN infrastructure deployed in almost every building. The main advantage of these kinds of indoor location determination systems is the ease of installation and deployment. A popular location determination system of this category is the Horus system proposed in [37], it is a probabilistic positioning system that uses a location clustering technique to reduce the computational cost by grouping the locations in the radio map based on the APs covering them. During the on-line stage, the system uses discrete space estimator which estimates the target's location x by finding value that maximizes the probability of obtaining location x given a signal strength vector s, $P(x|s)$. Correlation between RSS fingerprints from each AP was introduced to improve the system performance.

Specialized location determination systems do not use the building WLAN infrastructure, instead they developed a sophisticated devices such as Active Badges [36], Bats [10] and Crickets [30]. The Cricket location system is an example of specialized indoor positioning systems, it consists of a number of crickets, which serve as listeners that scan for data coming from anchor points called beacons deployed through the building. The system uses a combination of ultrasound and radio signals emitted from these beacons to locate the target. Since the RF signals are faster the ultrasound impulse, it is used as indication for the arrival of this ultrasound impulse, which can be used to calculate the distance between listeners and beacons [20]. A sensor fusion technique was proposed in [26] in order to improve the accuracy of the Cricket system by using multi-sensor of four listeners covering a horizontal plane angled at 90° from each other, a 0.3 m accuracy was achieved using the sensor fusion technique compared to 10.8 m location error in the original Cricket system. Although the small location errors achieved by specialized systems, the high cost of such systems represents an

System	Type	Accuracy	Cost
Cricket [30]	Specialized	Low	High
Mitilineos et al. [26]	Specialized	High	High
Bats [10]	Specialized	Medium	High
Horus [37]	off-the-shelf	Medium	Low

Table 2. A comparison between specialized and off-the-shelf location determination systems

obstacle for such systems to be used. Table 2 shows a comparison between specialized and off-the- shelf location determination systems.

Our main objective in this research is to design and evaluate an indoor location determination system that is capable to locate a mobile terminal in a multi-floored building using probabilistic Bayesian graphical models, the proposed system will be compared with similar positioning systems.

2. Positioning systems overview

Pahlavan et al [28] presented a general block diagram for the common components of a positioning system as shown in Figure 2. Firstly, the different positioning systems use different types of received signals ranging from radio signals, ultrasound to infrared. Location sensors such as mobile terminals collect these signals in order to produce an informative data. These informative data can be in form of Received Signal Strength (RSS), Angle of Arrival (AOA) or Time of Arrival (TOA). The produced data will be used to compute the location of the mobile terminal using positioning algorithms, which can be either a Deterministic or Probabilistic method. The estimated location can be symbolized by an (x, y) coordinates or a descriptive location. Finally, the display system displays the estimated mobile terminal's location in a textual of graphical form.

3. Received signal technologies

There are different sensing technologies used in indoor positioning systems. These technologies are affected by the indoor multipath phenomenon, which includes diffraction, reflection and scattering. The most common used sensing technologies are [34]:

3.1. Radio Frequency (RF)

The ability of RF signals to penetrate the walls and floors attract researchers to develop their positioning systems based on RF technology. RF Signals have also a good coverage area of 10 to 30 m compared to other technologies, which means fewer numbers number of sensors are required to cover a certain area. RF signals also have a high speed of 3×10^8 m/s. Since most buildings are equipped with wireless LAN technology, such systems can then be developed on top of these networks without extra equipment. This indicates the ability to develop a low cost positioning systems. Another advantage to using WLAN based positioning systems is that most of these networks operate in 2.4 GHz unlicensed frequency, which can reduce the interference with other devices [34].

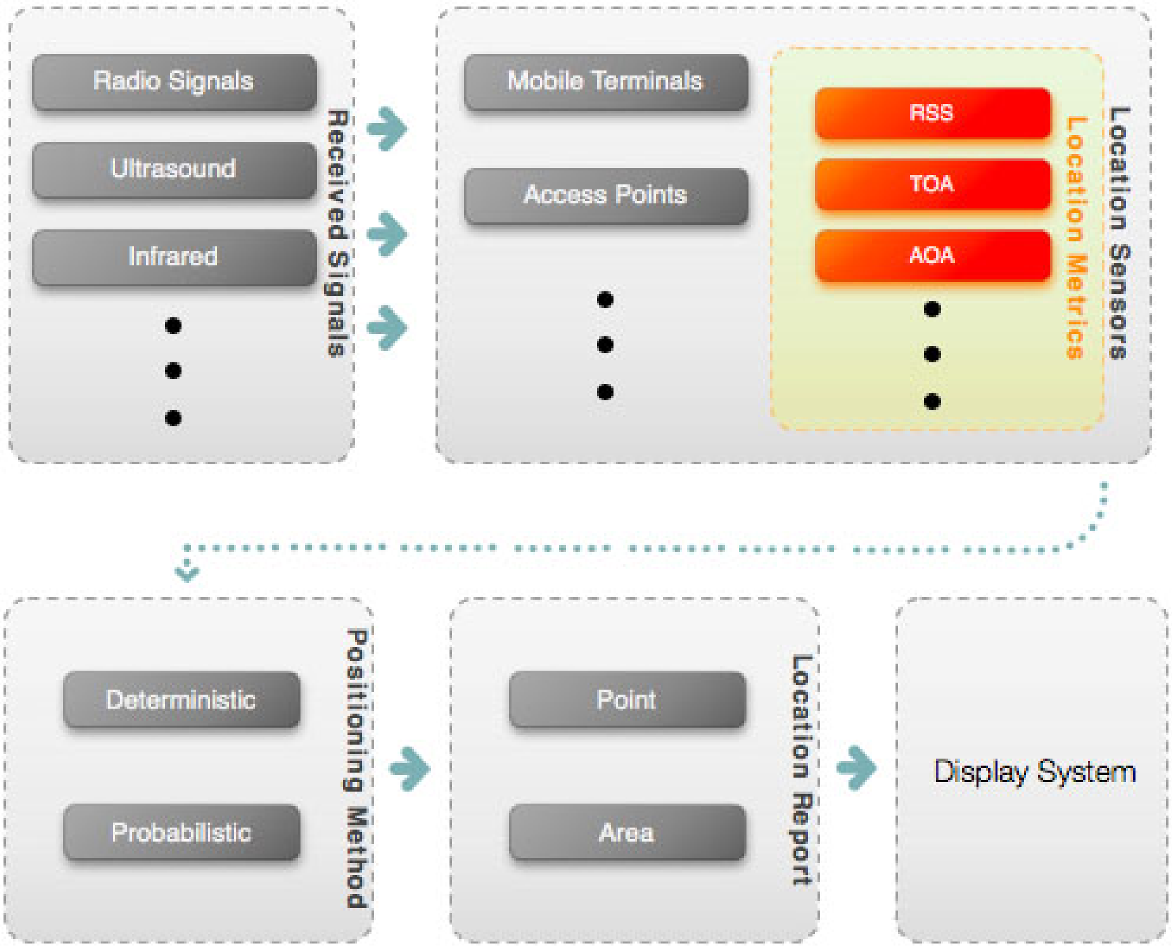


Figure 2. The basic structure for positioning systems [28].

3.2. Infrared

Although infrared signals have the same high speed as the RF signals of 3×10^8 m/s, Infrared signals are interfered with the ambient light. The properties of Infrared signals which are inability to penetrate walls and a limited range of 5 m may be considered as an advantage in some systems where it can provide coarse grained area accuracy by implementing special devices in each room. These devices are called beacons, they transmit signals every 10 seconds, which makes these devices consume low power.

The disadvantages of developing an Infrared based positioning system lies in maintenance time required to keep these beacons work properly and the high installation cost.

3.3. Ultrasound

Since ultrasound wave travels at a low speed of about 345 m/s, it is used in positioning systems by measuring the travel time between the transmitter and the receiver. These signals usually operate between 40 and 180 kHz. The same as Infrared signals, Ultrasound waves have a short coverage range of about 3 to 10 m and could be reflected by the walls. In addition, Ultrasound waves also affected by the environment temperature.

4. WLAN indoor positioning techniques

Indoor positioning techniques can be summarized into four main positioning methods [3]:

(a) Proximity sensing.

(b) Triangulation

  (i) Lateration

  (ii) Angulation

(c) Fingerprinting

(d) Hybrid techniques

4.1. Proximity sensing

Proximity sensing is considered to be the simplest positioning technique because it does not require any modification to the existing network infrastructure, it can be either used in the cellular networks or WLAN. It depends on the small coverage range of the radio, the idea behind proximity sensing is that it obtains the location of the target from the position of the base station that has the highest RSS.

The disadvantage of this positioning method is that it provides accuracy depending on the AP density in indoor environments as shown in Figure 3 where the real location of the mobile terminal (blue circle) is estimated to be the same (x, y) coordinates of AP4.

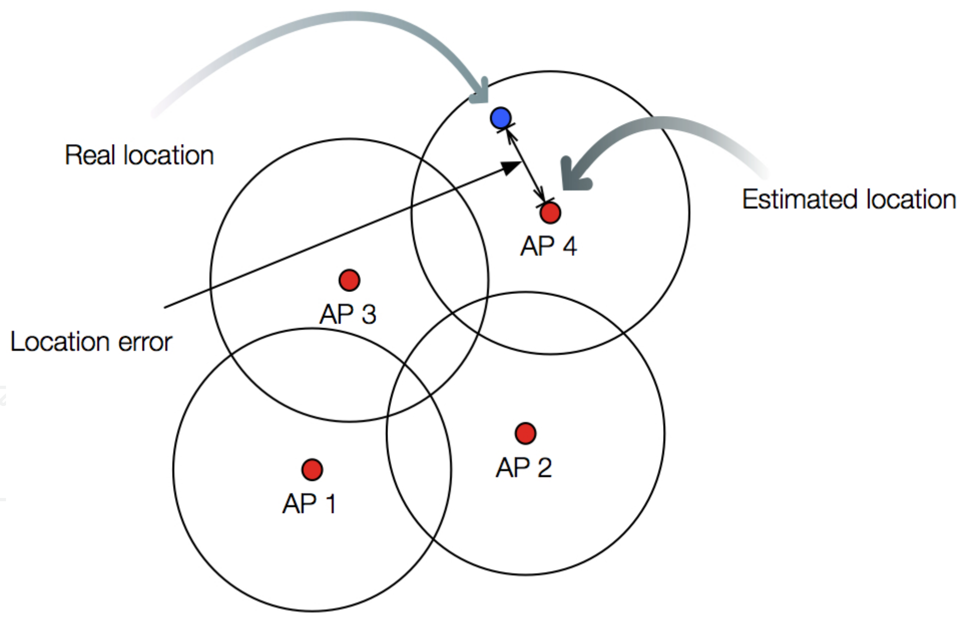


Figure 3. Proximity sensing technique showing the real location in blue and the estimated Bayesiand location in red [3].

4.2. Triangulation

The triangulation methods calculate the location of the mobile terminal either by a set of radial distances (Lateration) or a set of angles (Angulation).

4.2.1. Lateration

Lateration positioning method measures the distance between the mobile terminal and a set of at least three reference points (RP) as shown in Figure 4. Different signal metrics are used to estimate the location such as Time of Arrival (TOA), Time Difference of Arrival (TDOA) and others.

Lateration technique assumes that the distance d_i between the mobile terminal and a number $i = 1, 2, \ldots, n$ of RPs is known. In Figure 4(a) where there is only one RP, then the estimated location is considered to be any location point on the circle's perimeter. In Figure 4(b), the intersect between the two circles representing RP_1 and RP_2 reduces the mobile terminal's location uncertainty to only two possible locations. By adding another RP as shown in Figure 4(c) it can produce a single location estimation in which can be calculated by using the Euclidian distance equation:

$$d_i = \sqrt{(X_i - x)^2 + (Y_i - y)^2} \tag{3}$$

where (X_i, Y_i) is the coordinates of the i^{th} RP and (x, y) is the coordinates of the mobile terminal.

4.2.2. Angulation

Angulation technique calculates the angle θ_i between the target the the i^{th} RP. θ is called Angle of Arrival (AOA) or Direction of Arrival (DOA). Unlike the lateration technique, this method requires at least two RPs to locate a mobile terminal as shown in Figure 5.

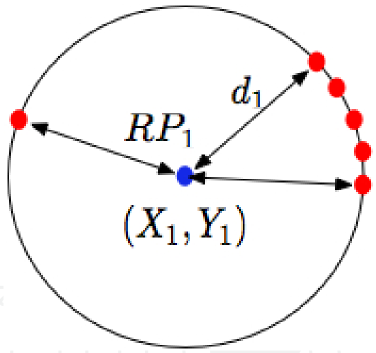
In Figure 5(a), θ_1 is the angle of the transmitted signal calculated at the RP. Although it is known the direction from which this signal has been sent, but the distance is unknown and considered to be at any point along the line between the mobile terminal and the RP. By adding another RP as in Figure 5(b), then the estimated location is the intersection between the two lines.

Triangulation techniques usually require a line -of-sight between the transmitter and the receiver, which is unavailable in indoor environments most of the times. Therefore, they cause the multipath phenomenon where the signals are received from multiple sources. This disadvantage of triangulation techniques prevent the researchers from developing indoor positioning systems based on this techniques.

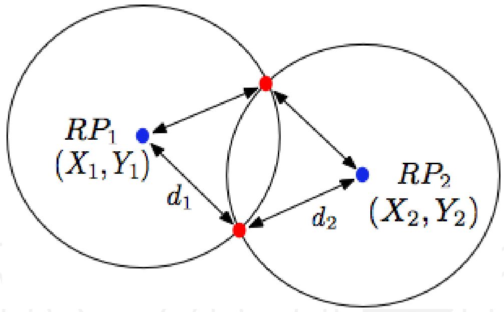
4.3. Fingerprinting

Fingerprinting techniques is also called pattern recognition techniques. In general, every fingerprinting techniques woks in two stages, *Offline* and *Online* stages.

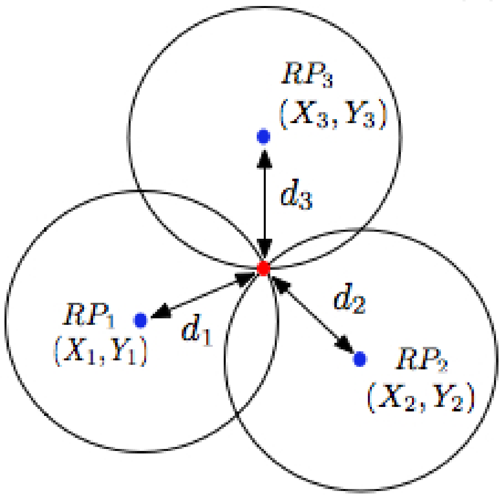
In the offline stage, the test bed is covered by a set of predetermined or random points called *reference points*. At each reference point, the user must collect a set of readings, each set contains the coordinates of that point and *signal to noise ratio* (SNR) or in the most popular systems the *received signal strength* (RSS) values from multiple APs and then store these readings in a server - in case of network based systems - or in the target device. In the online



(a)



(b)



(c)

Figure 4. Lateration positioning method where the blue circles represent the reference points and the red circles symbolize the mobile terminal in (a) single reference point (b) two reference points and (c) three reference points[3].

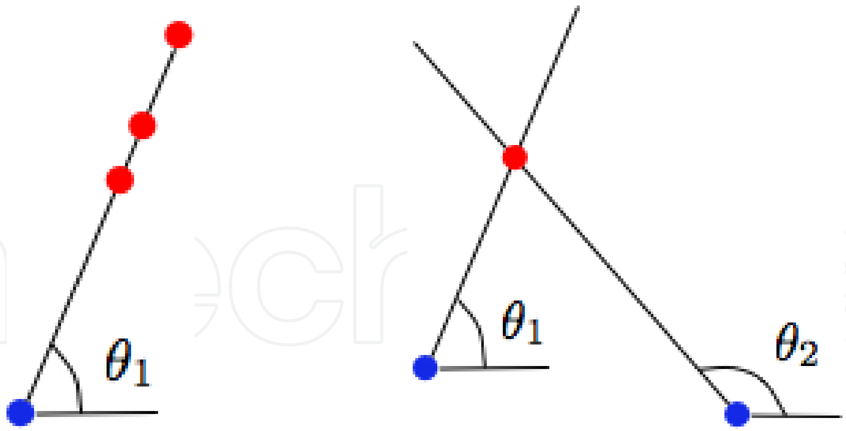
stage and when the target's location is needed, the target collects a set of RSS readings and try to match them with the stored fingerprints from the offline stage.

5. Category of indoor positioning systems

Indoor positioning systems can be divided into two main categories. Either by the infrastructure they implemented in or by the positioning algorithms. Each of these categories are subdivided into many sections.

5.1. Based on infrastructure

Figure 6 shows the categories of indoor positioning systems based on the their infrastructure. They are divided into infrastructure based and infrastructure-less or decentralized. In the Infrastructure based positioning systems, the target's location is determined using the installed network infrastructure in the testbed whereas the decentralized indoor positioning systems locate the target's location in an ad-hoc network setup.



(a) (b)

Figure 5. Angulation technique where the blue circles represent the reference points and the red circles symbolize the mobile terminal in (a) one reference point and (b) two reference points [3].

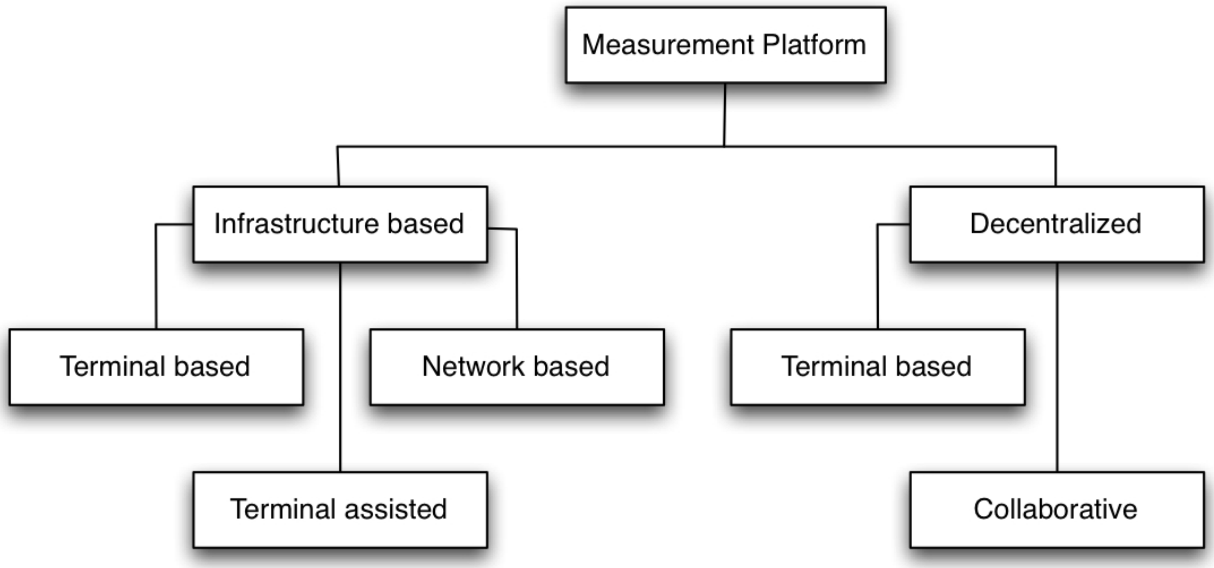


Figure 6. Category of Positioning systems based on their measurement platform [16].

5.1.1. Infrastructure based positioning systems

This category can be divided into three subcategories as shown in Figure 6. The main differences between these three categories are based on the device used to transmits the signal, the devices used for measurements and estimation [16].

In terminal based systems [29]. The signals are sent by base stations, the mobile terminals are then collect the signals, store them and estimate their location. The advantage of these systems is the privacy they provide where the location of the mobile terminal is exclusive to the users only. In terminal assisted systems [6], the signals are also sent by the base stations but the mobile terminals only collect the signals and send them to a network server where the estimation process occur. Finally, in network based systems [19], the signals are sent and collected by both base stations and mobile terminals. The data are then sent to a network server where the data will be stored and location will be estimated. This property can be beneficial in reducing the computation cost and power consumption on the mobile terminals.

5.1.2. Decentralized positioning systems

In decentralized systems, a special devices act as base stations spread all over the targeted areas in a grid like [30] or randomly distributed [22] in an ad-hoc setups. The purpose of developing such systems is to enable localizing without a prior knowledge about the building layout. This is important in situations where the WLAN infrastructure of a building get damaged because of fire. This category is divided into two categories, *terminal based* where the beacons send signals to a server terminal to calculate the target's location and *collaborative* systems in which the beacons send the signals in order to perform the estimation process.

5.2. Based on positioning algorithm

This category is divided into two subcategories [17], *deterministic* and *probabilistic* algorithms. The main difference between these two subcategories is the way they model the signal properties.

5.2.1. Deterministic systems

In deterministic methods, the estimated locations are represented by a single value such as the average RSS.

Nearest Neighbor in Signal Space (NNSS) is one example of deterministic methods, the target's location is estimated by applying the Euclidian distance algorithm between the nearest value of the signal property stored in the radio map and the current one. The drawback of this method lies in some conditions where the replication of the same stored values for different locations due to multipath phenomenon.

k-Nearest Neighbor (k-NN) was introduced to overcome the limitation of NNSS algorithm where *k* is set of number of signal properties. k-NN works by first searching for the k-values in the radio map having the smallest error mean with the current signal property [17].

5.2.2. Probabilistic systems

T. Roos *et al* [31] have introduced a probabilistic approach for the location estimation problem. The approach is based on calculating the conditional probability distribution of getting a location l given a signal value SV using the Bayes' theorem:

$$P(l \mid SV) = \frac{P(SV \mid l)\, P(l)}{P(SV)} \tag{4}$$

The Bayes' theorem consist of three probability distributions:

(a) Posterior distribution $P(l \mid SV)$: is the knowledge about unknown parameters. It is the product of the prior distribution and the likelihood function [8].

(b) Prior distribution $P(l)$: represents the previous knowledge about the random variable l before obtaining any new information.

(c) Likelihood Function $P(SV \mid l)$: the probability value for random variable SV after obtaining additional information about the location variable l.

The Bayes' theorem will search for the location l which will maximize the posterior distribution $P(l \mid SV)$ and consider this value as the estimated location:

$$argmax_l [P(l \mid SV)] = argmax_l \left[\frac{P(SV \mid l)\, P(l)}{P(Sv)} \right] \tag{5}$$

6. Characteristics of RSS in indoor environments

Signal strength in indoor environments is difficult to predict due to some multipath phenomenon such as reflection, diffraction and scattering. The indoor multipath phenomenon occurs when the signals are sent from the transmitter arrive at the receiver from multiple directions. Generally, there are three main phenomenon as shown in Figure 7

1. Reflection: it occurs when the signal waves collide on a smooth surface object that has dimensions larger than the signal's wavelength.
2. Diffraction: when the signal waves hit an objects with sharp edges, it causes them to diffract off these objects to various directions.
3. Scattering: when the signals impinge on an object that has a rough surface causing them to scatter.

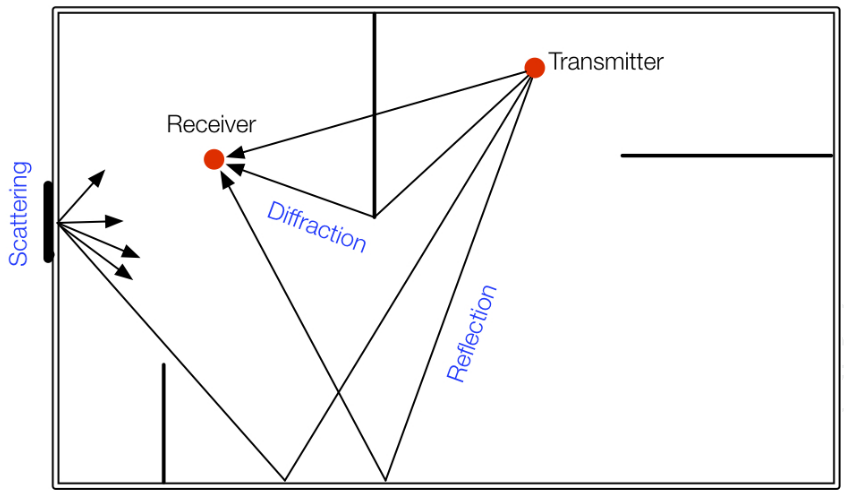


Figure 7. Indoor Multipath Radio Propagation

The RSS distribution in indoor environments are believed to follow a lognormal distribution [32] due to the similar values for the mean, median and mode. Figures [8, 9] and Table 3 , show the RSS histograms at the same location and the statistics from two APs in the first floor of WCC building, respectively.

There are three factors that have an impact on the RSS propagation in multi-floored buildings [33]:

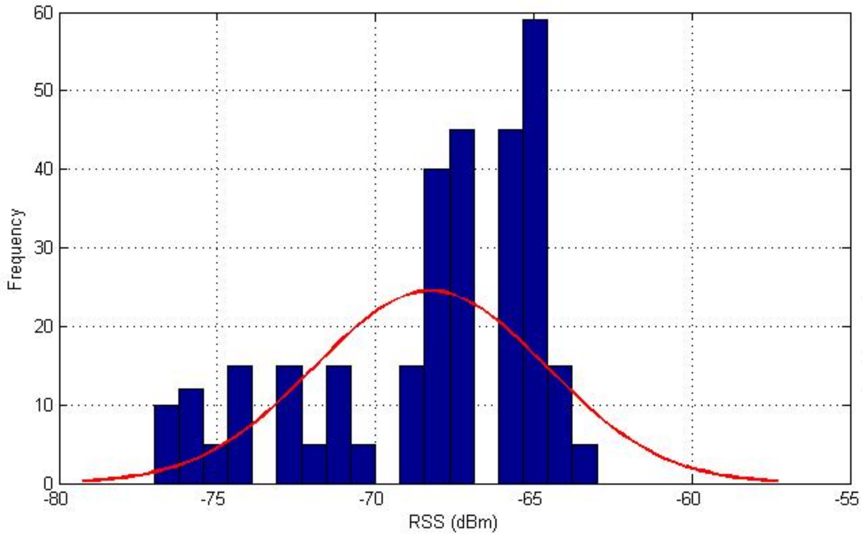


Figure 8. RSS histogram at fixed location for five minutes from AP1

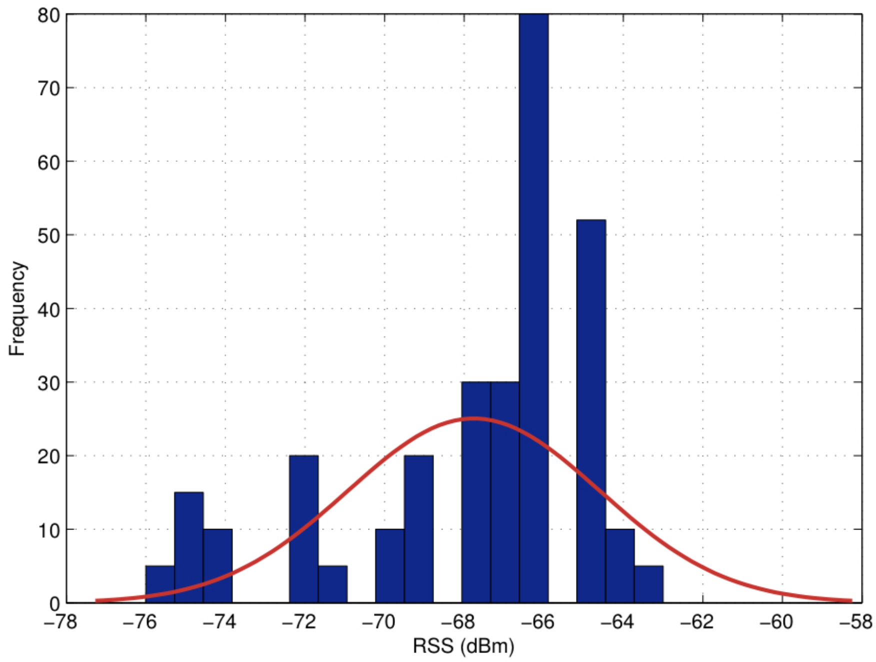


Figure 9. RSS histogram at fixed location for five minutes from AP2

- **Floor Attenuation Factor**: the radio signal that arrives at the receiver after passing through floors.
- **Multiple diffraction at window frames**: the diffracted signals at window frames from different floors.
- **Reflected signals from nearby buildings**: the reflected signals from adjacent buildings.

A concrete floor can reduce the RSS approximately 15 dBm to 35 dBm [18], to investigate this, we conduct a measurement at two vertically location in two different floors from the same AP, the AP5 is placed in the center of the building as shown in Figure **??**, Table 5 shows the

	AP1	AP2
Minimum (dBm)	-77	-76
Maximum (dBm)	-63	-63
Mean (dBm)	-68.25	-67.75
Median (dBm)	-67	-66
Mode (dBm)	-65	-66

Table 3. Statistical values for two APs in the first floor showing the similarity between the mean, median and mode.

	Centre 1^{st} floor	Centre 2^{nd} floor
Mean (dBm)	-72.18	-47.21
Median (dBm)	-72	-47
Std. Deviation	3.592	1.467

Table 4. The floor attenuation factor effect in the centre of the building from AP5

statistics of FAF effect at the centre of the building from AP5, the attenuation on the RSS in the first floor was about 25 dB as shown in Figure 13. The APs installed are DWL-2000 APs operate at frequency between 2.4 GHz and 2.4835 GHz.

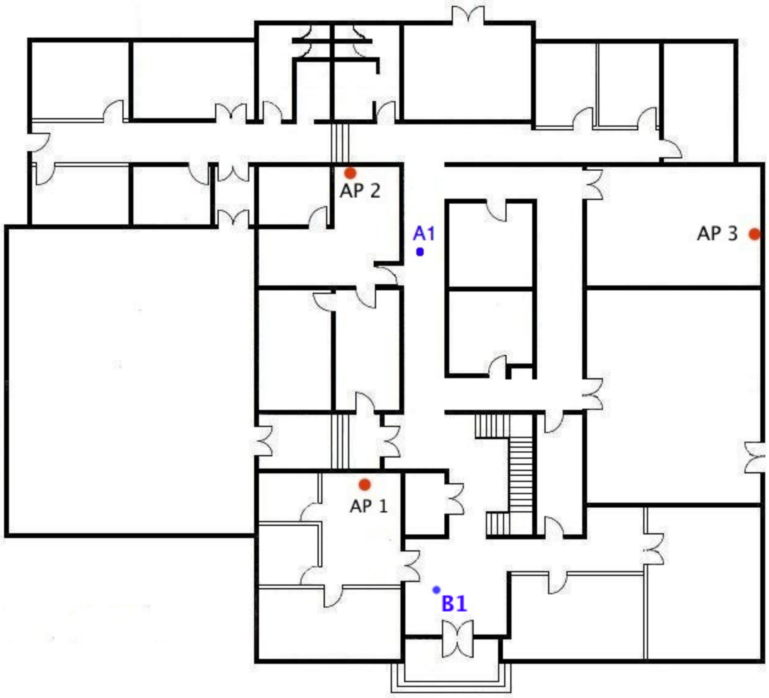


Figure 10. First floor layout with 3 APs

Figure 13 shows the effect of FAF in addition to the diffracted signals arriving from AP4 which is placed near a window in second floor, the receiver was in a vertical place from AP4 in first floor. From Table 5, the attenuation on the RSS near windows was similar to the attenuation achieved in the centre.

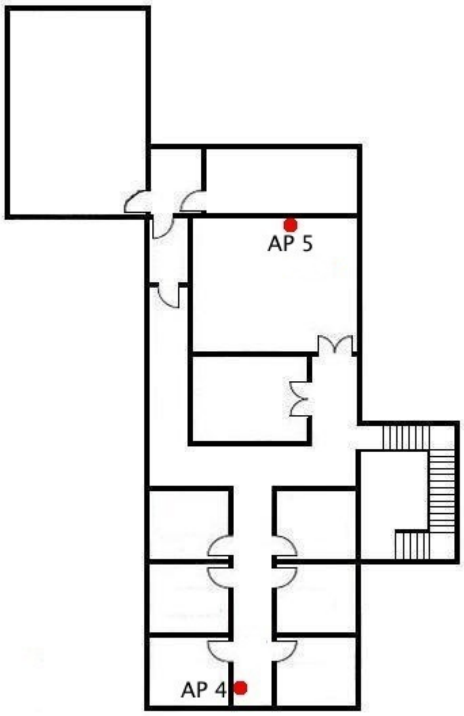


Figure 11. Second floor layout with 2 APs

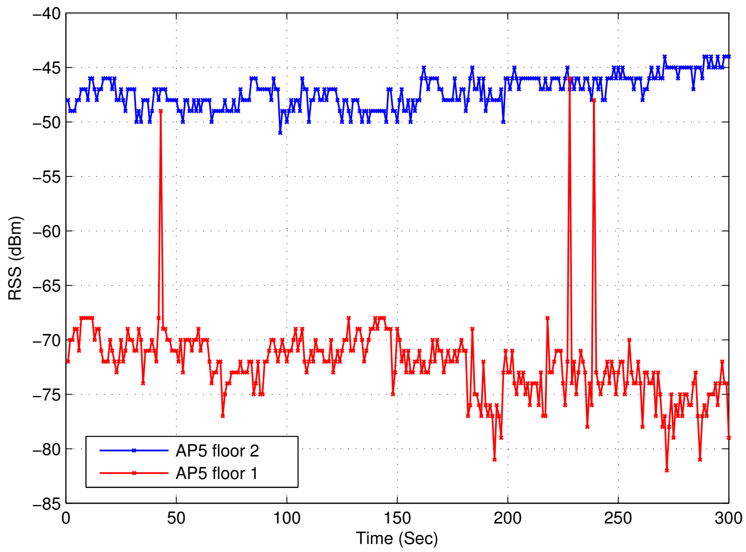


Figure 12. Floor attenuation factor at two vertically location in two different floors from AP5

7. Probabilistic Bayesian graphical models

7.1. Bayes' theorem

Bayes' theorem describes the relationship between the conditional probability and the joint probability of random variables [27]. Let α and β be two random variables in which $P(\beta) > 0$,

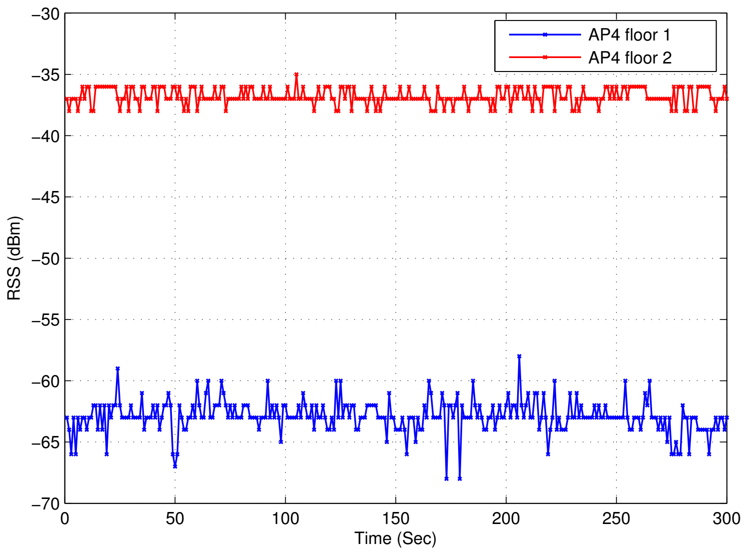


Figure 13. Floor attenuation factor at two vertically location in two different floors from AP4.

	Window 1^{st} floor	Window 2^{nd} floor
Mean (dBm)	-62.89	-36.79
Median (dBm)	-63	-37
Std. Deviation	1.315	0.6753

Table 5. The floor attenuation factor effect in the centre of the building from AP5

then the conditional probability of an event α given event β is :

$$P(\alpha \mid \beta) = \frac{P(\beta \mid \alpha) P(\alpha)}{P(\beta)} \tag{6}$$

$P(\alpha \mid \beta)$ is called a posterior distribution which is a result of the prior distribution $P(\alpha)$ multiplied by the likelihood $P(\beta \mid \alpha)$, the prior distribution represents the previous knowledge about a random variable before obtaining any new information, where the likelihood is the probability value for a certain random variable after obtaining additional information.

7.2. Bayesian networks

A Bayesian Network [13] represents a set of probability distributions, Figure 14 shows a simple graphical model, the nodes symbolize random variables α, β and γ, where the arrows represent the relationships between these random variables. The joint density for random variables in Figure 14 is:

$$P(\alpha, \beta, \gamma) = P(\beta \mid \alpha, \gamma) P(\gamma \mid \alpha) P(\alpha) \tag{7}$$

From Equation 7, the random variable α is considered to the a parent for node γ, and γ is a child for node α. A parent variable is the direct influence on its children, the joint density between parent nodes and their children could be expressed as follows:

$$P(\Delta) = \prod_{\delta \in \Delta} P(\delta \mid parent(\delta)) \tag{8}$$

In some graphical models, we use a plate to handle the replication of random variables. In

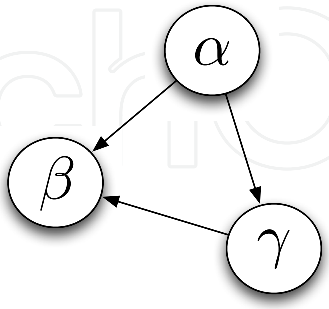


Figure 14. A simple graphical model showing three random variables represented by circles and relationships symbolized by arrows

Figure 15, we show the same graphical model where the replication of random variable μ in 15(a) was handled in 15(b) by a plate notation to some index l.

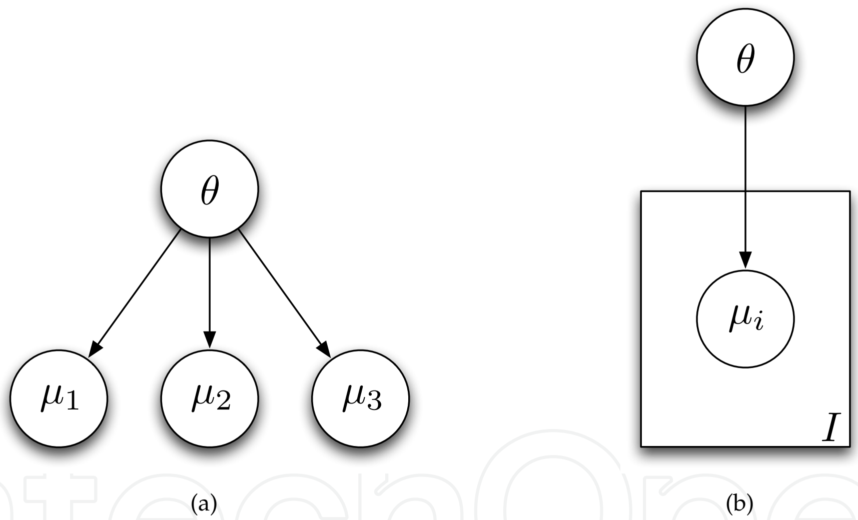


Figure 15. Bayesian graphical models with (a) replication on the children nodes ($\mu 1, \mu 2, \mu 3$) and in (b) with the plate notation to some index I.

7.3. Markov Chain Monte Carlo sampling techniques

Figure 16 shows an example of a Markov Chain (MC) sampling technique, the rejection sampler, here we want to draw samples from a target distribution $P(z)$ which is not a standard distribution, therefore, we draw samples from a proposal distribution $Q(z)$, which we are able to evaluate from, up to some normalizing constant c where:

$$cQ(z) \geq P(z) \tag{9}$$

then, a candidate sample (z, b) is randomly generated in the area below $cQ(z)$, if this sample lied under $P(z)$ then it will be accepted [23].

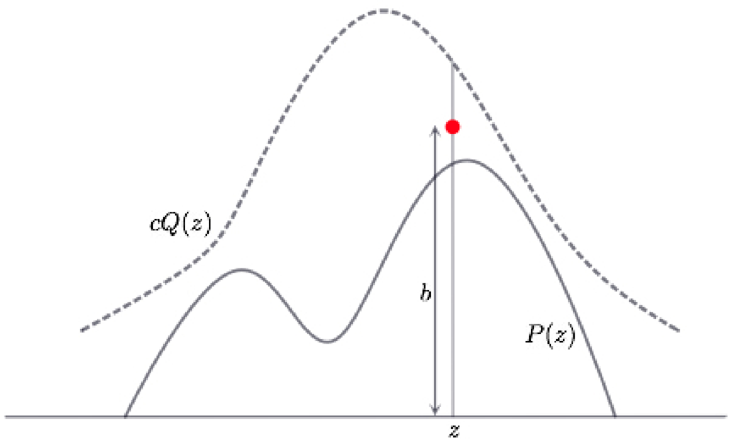


Figure 16. An example of the rejection sampler were point z will be accepted if it lies under $P(z)$ and rejected otherwise [23]

Although the rejection sampler technique is considered to be simple to implement, it suffers from some limitation in cases where a bad choice of Q, or a proper Q with a poor constant c. This will lead to a high rejection rate. To solve this problem, we will use Markov Chain Monte Carlo (MCMC) techniques where the target distribution will eventually converge to the proposal distribution.

7.3.1. The Gibbs sampling technique

Geman and Geman [9] introduced the Gibbs sampler where the samples are drawn sequentially from the full conditional distribution. Suppose we want to draw samples from:

$$P(\Gamma) = P(\gamma_1, \gamma_2, \ldots, \gamma_z) \tag{10}$$

then, the Gibbs sampler replaces the value of γ_i from a sample value drawn from the conditional distribution $P(\gamma_i \mid \Gamma)$ as follows [5, 12]:

$$\begin{aligned} \gamma^{(\pi+1)} &\sim P\left(\gamma_1 \mid \gamma_2^{(\pi)}, \gamma_3^{(\pi)}, \ldots, \gamma_Z^{(\pi)}\right) \\ &\vdots \\ \gamma_\tau^{(\pi+1)} &\sim P\left(\gamma_\tau \mid \gamma_1^{(\pi+1)}, \ldots, \gamma_{\tau-1}^{(\pi+1)}, \ldots, \gamma_Z^{(\pi)}\right) \\ &\vdots \\ \gamma_Z^{(\pi+1)} &\sim P\left(\gamma_Z \mid \gamma_1^{(\pi+1)}, \gamma_2^{(\pi+1)}, \ldots, \gamma_{Z-1}^{(\pi+1)}\right) \end{aligned} \tag{11}$$

7.3.2. The Metropolis-Hasting sampling technique

The Metropolis-Hasting sampling techniques was introduced in [11], it solves the limitation of the rejection sampler where the rejected samples will not be discarded but they are weighted according to an acceptance rate α [23].

Parameter	Specification
Environment	Single/Multi-floor
Estimation technique	Fingerprinting techniques
Fingerprint type	RSS
Sensing device	Mobile terminal
Calculation device	Mobile terminal
Packet scanning	Passive
Estimation algorithm	Bayesian graphical model
Location report	Physical

Table 6. Proposed system specifications

Figure 17 shows an illustration of the Metropolis-Hasting sampler. Suppose we want to draw samples from target distribution $P(z)$, then a candidate sample z^* is drawn from the proposal distribution $Q(z, z^t)$. Later α will determine whether this candidate sample z^* is accepted or weighted as follows:

$$\alpha = \min\left(1, \frac{P(z^*)}{P(z^t)} \frac{Q(z^t; z^*)}{Q(z^*; z^t)}\right) \tag{12}$$

if the candidate sample was accepted then z^{t+1} is set to z^* otherwise it will be set to the same state z^t.

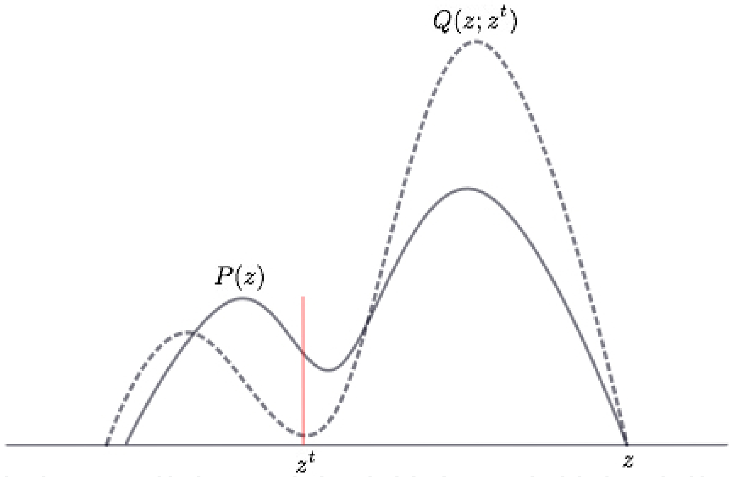


Figure 17. The Metropolis-Hasting sampling technique

8. Model design and measurement setup

8.1. System specification

The proposed system is capable to locate a target in a single or multi- floor buildings using RSS fingerprinting technique, both sensing and calculating processes are done by a mobile terminal equipped with a WLAN card. The system collects RSS fingerprints form the APs and feed them to a BGM which in turn tries to infer the target's location. Table 6 shows the specifications of the proposed system.

Hardware	Specification	
Notebook	Brand	Apple MacBook
	Model	Late 2008
	WLAN card	AirPort Extreme card
	IEEE standards	IEEE 802.11 a/b/g/n
	Operating system	Windows XP SP3
Access Point	Brand	D-Link
	Model	DWL-2000AP
	Operating frequency	2.4 GHz - 2.4835 GHz
	Transmit power	15 dBm

Table 7. Experimental hardware specifications.

8.2. Experimental hardware

A notebook is used as our mobile terminal, the notebook is a MacBook with an AirPort Extreme card that supports IEEE 802 11 a/b/g/n standards running Windows XP SP3. The mobile terminal collects RSS fingerprints from five D-link DWL-2000 APs operate from 2.4 GHz to 2.4835 GHz, each AP has 15 dBm transmission power. Table 7 shows the experimental hardware specifications.

8.3. Experimental test bed

Figure 10 shows the first floor layouts for WCC building at UTM and the second floor layout in Figure 11, the building has 2 floors, the first floor is about 36 m by 30 m and the second floor is 21 m by 28 m. The building is equipped with five APs ($AP1, AP2, ..., AP5$), three in the first floor and two in the second floor, the building's walls are made of concrete and some plaster board walls, the walls thickness is 15 cm and the floor thickness is 80 cm.

8.4. Experimental software

For the Feed and Infer algorithm, we have to use two software applications for each part of the algorithm. For feeding part, the system requires RSS fingerprints at random locations to be collected in order to feed the BGM, therefore we developed *UTM WiFi Scanner*, a network sniffer written in c sharp based on *InSSIDer* by *MetaGeek*.

In the inferring part, *WinBUGS* [7] (Bayesian inference Using Gibbs Sampling) is used to estimate the target's location using Bayesian graphical models, WinBUGS uses Markov Chain Monte Carlo (MCMC) sampling techniques to estimate the posterior distribution, the current RSS fingerprint will be used in WinBUGS as a likelihood for the graphical model.

8.5. Model design

A single unshaded circle represents a continuous random variable and a shaded circle symbolizes a discrete random variable, double circle refers to a logical variable while a square represents a constant, we will provide the prior distributions for each random variable in our model. Figure 18 shows the proposed model which we introduced in [2], Nodes X_i and Y_i

represent the user's location at the ith point and they are assigned to a continuous uniform distribution as follows:

$$X_i \sim dunif\,(0, L) \tag{13}$$

$$Y_i \sim dunif\,(0, W) \tag{14}$$

where L and W represent the length and the width of the test bed respectively. Node Z_i is the floor number and it is assigned to a discrete uniform distribution since we are not interested in the height of the APs instead the floor number of which the ith AP is located in:

$$Z_i \sim DiscreteUinf\,(1, N) \tag{15}$$

but since WinBugs does not support discrete uniform distributions, we had to construct Z_i as a categorical distribution as follows:

$$\begin{aligned} p\,[i] &\leftarrow 1/N \\ Z_i &\sim dcat\,(p\,[\,]) \end{aligned} \tag{16}$$

Categorical distribution is a generalization of the Bernoulli distribution with sample space $\{1, 2, \ldots, n\}$.

$$D_{ij} = \log\left(1 + \sqrt{\left(X_i - \bar{x}_j\right)^2 + \left(Y_i - \bar{y}_j\right)^2}\right) \tag{17}$$

D_{ij} is the Euclidean distance between the jth AP and the ith RSS fingerprint, we exploited the fact that the RSS distribution in indoor environments follows a log-normal distribution [14], we also added 1 to the equation because we do not want to have zero as an argument of the log function.

$$S_{ij} \sim dnorm\left(m_{ij}, \tau_j\right) \tag{18}$$

where

$$m_{ij} = b_{0j} + b_{1j}D_{ij} + b_{2j}Z_i + b_{3j}w\,FAF \tag{19}$$

and

$$\tau_j \sim dgamma\,(0.1, 0.1) \tag{20}$$

The random variable m_{ij} is the mean for the normal distribution assigned to S_{ij} which symbolizes the RSS obtained at the ith location point from the j^{th} AP. m_{ij} is a regression model with four parameters $(b0, b1, b2, b3)$ and four independent variables D_{ij},Z_i,w_i and, FAF (Floor Attenuation Factor). w is a binary variable that takes two values, 0 if the collected RSS is in the same floor with the AP which will cancel the effect of FAF and 1 otherwise.

8.6. Feed and infer algorithm

In Figure 19, we show the flow chart of the proposed feed and infer algorithm, it starts by defining a Bayesian model shown in Figure 18 using WinBUGS, defining a model requires the specification of the location variables X_i, Y_i and Z_i, the floor attenuation factor, the signal strength and the parameters of the regression model.

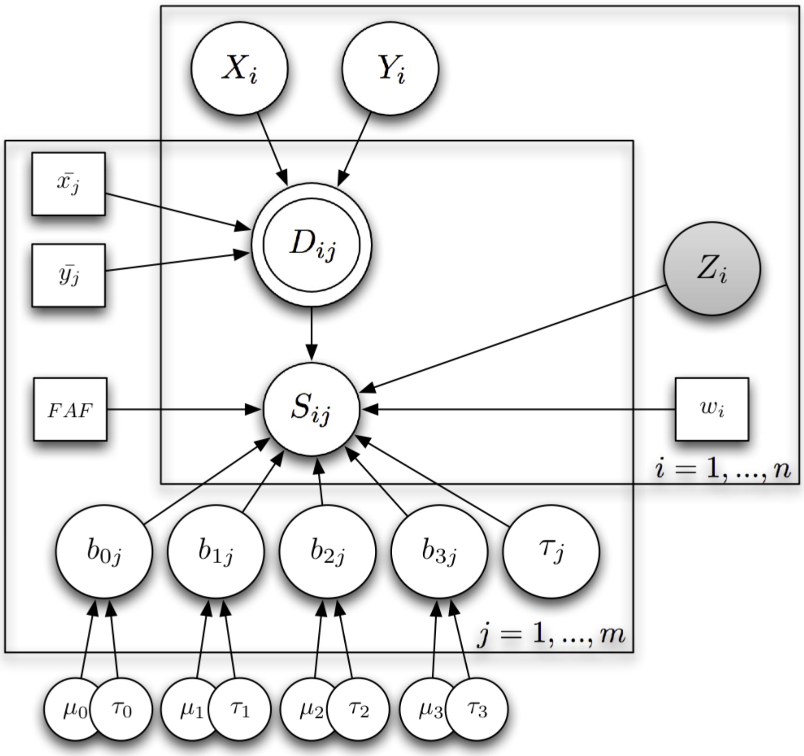


Figure 18. The proposed Bayesian model using WinBUGS plate notation.

In the next step, setting a value for the plate index i which represent the size of the RSS fingerprints collected, $i = 1$ will be set as initial value and will be increasing depending on the RSS sampling time. Next, checking the model error is done by the specification tool in WinBUGS, the specification tool also allows us to specify the initial values for random variables b,τ and μ. After compiling the model, we then specify the size of the burn-in samples which are the samples that will be initially generated and then ignored to allow the Markov chain to reach the stabilization state.

Next, using the inference samples tool in WinBUGS, we choose the random variables that will be later evaluated. Then, we draw samples for the random variables specified in the previous step using update model tool, also in this step we may choose the over-relax which means generating multiple random values and selecting the sample that is negatively correlated with the current sample [27]. Using save state tool, we feed the values again to the model and update the index $i = i + 1$. After collecting sufficient number of RSSs, we check the posterior summary using check state tool and produce the visual kernel estimate of the posterior distribution using the density tool.

8.7. Data analysis

8.7.1. Moving target

Figures 20 and 21 show the location error and the accuracy cumulative distribution function for the three windows $(c1, c2, c3)$ for a moving target inside WCC building, the target was moving throughout the corridors in two different floors. The proposed model started

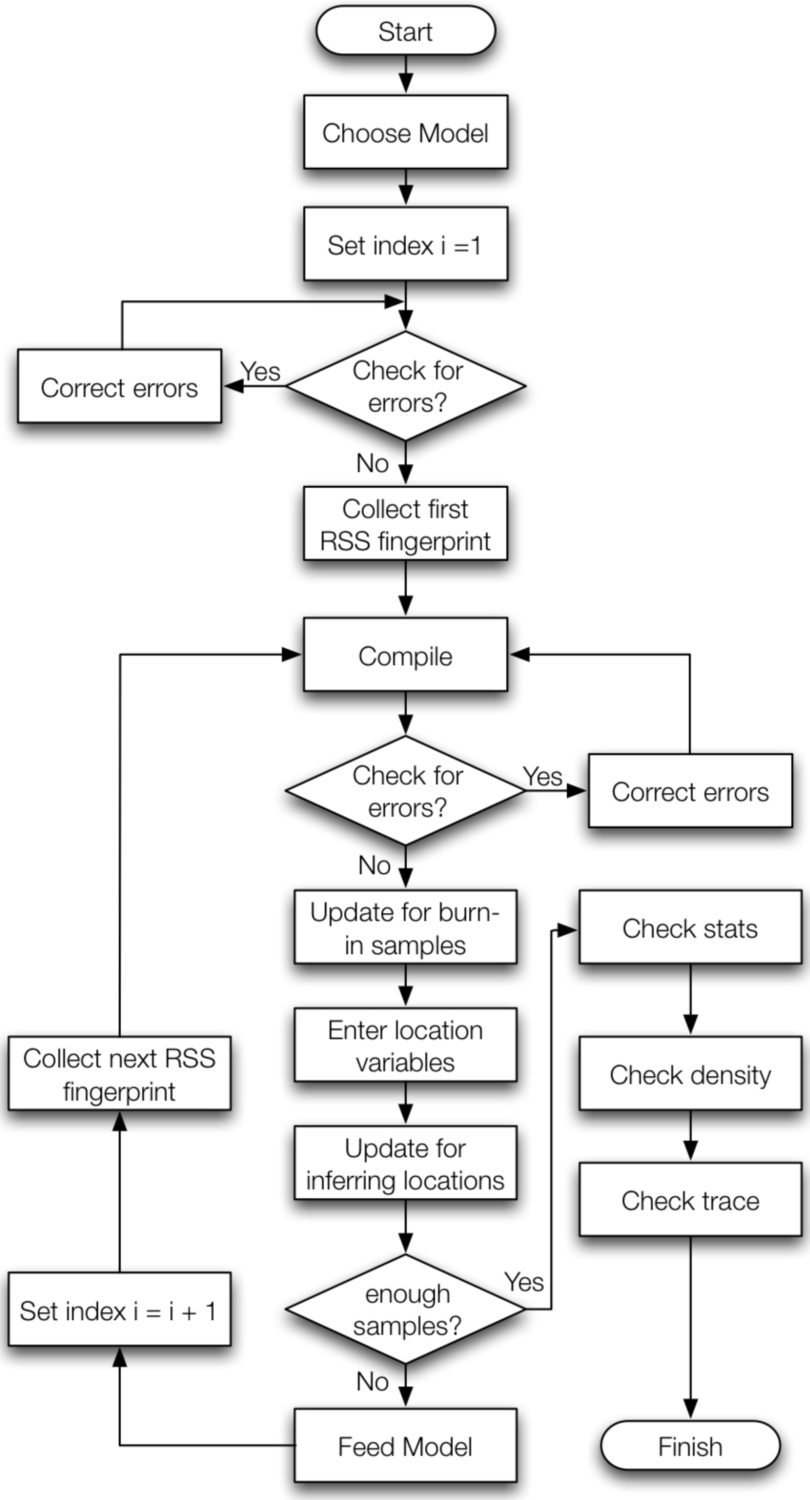


Figure 19. The feed and infer algorithm flowchart.

performing poorly with the first collected RSS, then the accuracy improved while the number of RSS increased, hence we divided the system performance into three windows $(c1, c2, c3)$, each window contains different portions of RSS samples. Window $c1$ contains all the 90 RSS fingerprints that were collected while testing the system, the mean accuracy obtained is about

Window	Number of values	75% percentile	Std. Deviation	Mean
$c1$	90	8.482	4.470	6.385
$c2$	50	5.946	2.689	4.214
$c3$	21	2.601	0.7292	2.272

Table 8. Location error statistics for the three windows

6.38 m. A better accuracy of 4.2 m was obtained from the second window $c2$ which starts from the 50^{th} fingerprint and discarding the previously collected RSSs. In window $c3$, only last 21 RSS samples were included, the location error was much improved with mean error of 2.27 m. Table 9 shows the location error statistics for the three windows.

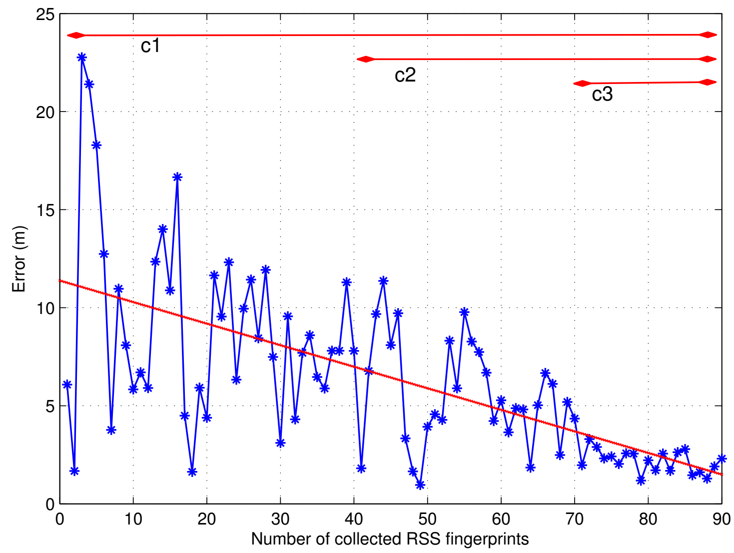


Figure 20. Location error results with all RSS fingerprints included.

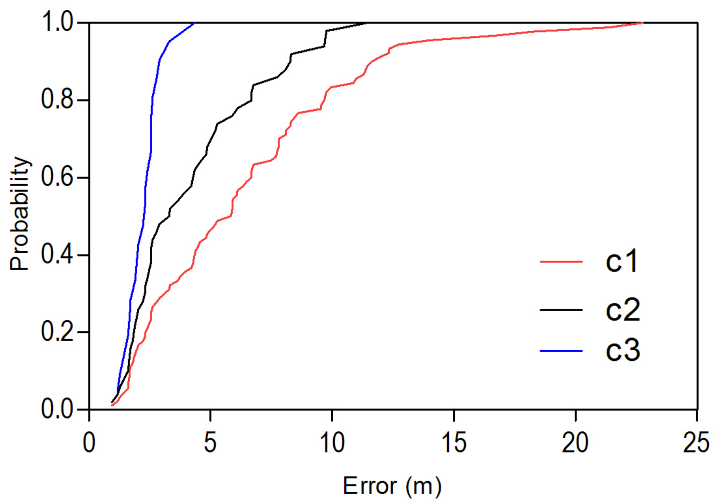


Figure 21. Cumulative distribution function of location error for the three windows.

	Location 1	Location 2	Location 3
Minimum	1.23	1.034	1.822
75% Percentile	2.613	2.809	2.195
Std. Deviation	0.4605	0.8748	0.3154
Mean	2.205	1.989	2.139

Table 9. Location error statistics at three fixed locations

8.7.2. Fixed target

Now we shall consider the system performance when the target is not moving, the system was tested at three random fixed locations, Figures [22-24] show the estimated location of 20 RSS fingerprints at the same location. The system performed slightly different at each location, the mean accuracy acquired was 2.2 m, 1.9 m, and 2.1 m at locations 1, 2 and 3 respectively. Table 9 shows the accuracy statistics at the three fixed locations.

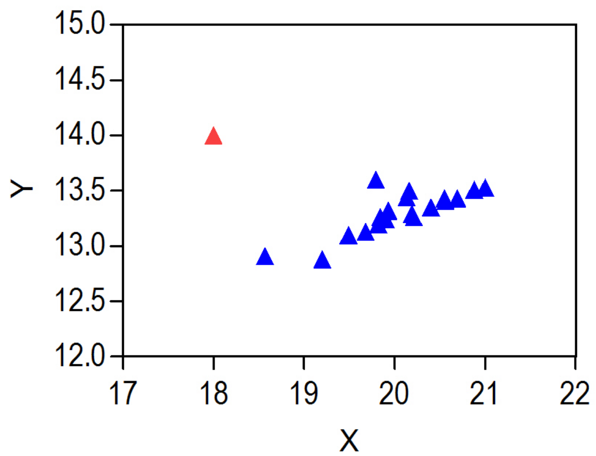


Figure 22. Location error at random location 1

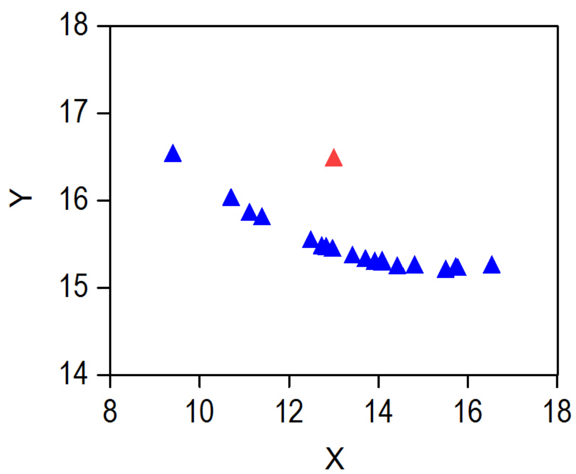


Figure 23. Location error at random location 2

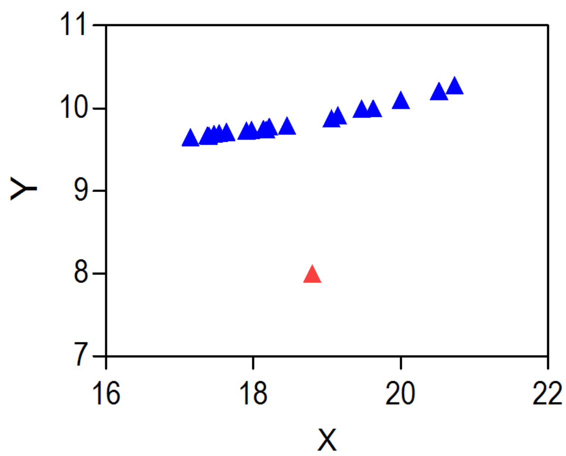


Figure 24. Location error at random location 3

	Madigan	Hyuk L.	Proposed system
Single-Phase	Partially	Yes	Yes
Accuracy	20 feet	2.57 m	2.27 m
Multi-Floor	No	No	Yes

Table 10. Comparison with other indoor location determination systems

In Table 10 we compare the proposed system with other well known single-phase systems, a Bayesian model proposed by [24] and a zero configuration model by [21].

9. Conclusion

This chapter presented a single-phase location determination system using Bayesian graphical models. The proposed system [1] does not require an offline phase to build the radio map. Instead, it uses the online RSS gathered in real time to estimate the user's location in multi-floor environments.

The results showed that the system was capable to locate a mobile target in a multi-floor environment without the need for a time consuming offline training stage to build the radio map. Instead of using Monte Carlo sampling techniques such as rejection sampling which suffer from low performance in complex Bayesian networks, MCMC sampling techniques were used to sample from the posterior distribution for the location random variables X, Y and Z.

Rather than using a single sampling technique, the system uses a collection of MCMC sampling techniques to draw samples from the posterior distribution. The Bayesian graphical model presented a visual approach to visualize the relationships between the random variables.

The Feed and Infer Algorithm presented a way to directly sample from the posterior distribution each time the Bayesian network was fed with a new inferred value from the previous step in order to facilitate the elimination of the training stage. Although the performance of this algorithm was not good enough in the first two windows $(c1, c2)$, the final systems performance was based only on the third window $c3$ that showed an excellent mean accuracy of about 2.27 m.

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