Improved indoor location tracking system for mobile nodes

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Abstract: The solutions to the problem of the tracking a wireless node is approached conventionally by: 1) proximity detection; 2) triangulation; 3) scene analysis methods. In these, scene analysis method is simple, accurate and less expensive. Indoor localisation technologies need to address the existing inaccuracy and inadequacy of global positioning-based systems (GPS) in indoor environments (such as urban canyons, inside large buildings, etc.). This paper presents a novel indoor Wi-Fi tracking system with minimal error in the presence of barrier using Bayesian inference method. The system integrates an android app and python scripts (that run on server) to identify the position of the mobile node within an indoor environment. The received signal strength indicator (RSSI) method is used for tracking. Experimental results presented to illustrate the performance of the system comparing with other methods. From the tracked nodes, a theoretical solution is proposed for finding shortest path using Steiner nodes.

Keywords: location tracking; global positioning-based systems; GPS; MANETs; mobile nodes; Wi-Fi access points; wireless local area networks; WLAN; Bayesian inference; received signal strength indicator; RSSI; shortest paths; Steiner nodes.

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1 Introduction

The exponential growth of usage of mobiles as handheld devices demands innovative applications such as location-tracking (Haeberlen et al., 2004). Determination of the position of a mobile device has many useful applications such as navigation, tracking of minors or other individuals, and/or other location-based service (LBS) offered through a wide area mobile communication network.

In addition to the services available from wireless/mobile communication networks, many localities uses wireless internet access via wireless local area networks (WLAN) technologies. A WLAN provides flexible network connectivity, making it possible for mobile data users to stay connected as they move freely within a building, around a campus or in public hot spots (e. g., airports, hotel and other public spaces). In mobile ad hoc networks (MANETs), where the nodes are arbitrarily moving, the tracking mechanism will provide knowledge about location of nodes. This information will support for packet delivery to all nodes in a given geographic region (Ali et al., 2004).

Positioning can be either in indoor or outdoor environments and the tracking or locating a device is based preferably on the strength of wireless signals. In these applications, the main challenge is how accurate is the tracking or locating an individual node particularly when the node is moving (Paul and Wan, 2009). Using global positioning-based systems (GPS) may offer acceptable solutions for outdoor applications but it is not suited for indoor applications (Haeberlen et al., 2004; Ali et al., 2004). This limited performance is due to presence of the barrier (walls in the rooms). An existing signal of strength S_E is attenuated to λS_E in the presence of a nearby metal barrier where $0 < \lambda < 1$ (λ can be even close to zero). In this paper an improved positioning algorithm is proposed to locate the nodes in the presence of barriers.

The LBS is essential and useful in applications such as goggle maps (Bellavista et al., 2008; Gu and Ren, 2015) and where to eat (http://wheretoeatapp. com, accessed July 15, 2015). There are research efforts devoted over the years on improving the performance. For outdoor, the GPS technology offers better positioning of nodes (Moore and Crossley, 1999). But in indoor environments, it remains challenging due to poor performance of GPS, presence of complex environments and irregular propagations (Gu and Ren, 2015; Liu et al., 2007). Hence, many researches are taking place in recent times on indoor positioning. The research in indoor positioning is roughly classified in to two groups: model-based approach and fingerprint-based approach (Wu et al., 2013).

The model-based approach uses geometric models to estimate the location of a device. For example, Lim et al. (2007) designed complex model for WLAN by considering the factors like, variations of temperature and humidity level, opening and closing the doors, furniture movement and human mobility. The RF propagation model is proposed specific to wireless sensor networks considering free space path loss, ground reflection loss and RSS variations (Stoyanova et al., 2009). Bayesian hierarchical model (Madigan et al., 2009; Kleisouris and Martin, 2007), hidden Markov models (Morelli et al., 2007) and ray tracing models (Ghobadi et al., 2007; Yang et al., 2011; Rizk et al., 1997) are some of the approaches for more sophisticated models with the account of better characterisation of physical environments.

Though the model-based approach is low cost approach as it requires less site survey and training, the dynamicity of indoor environment poses heavy burden on computation models leads to unstable performance (Gu and Ren, 2015).

In the finger print-based method, the basic idea is, manually gathering the RF RSSI values at every location of a site (i.e., site survey). The databases of the collected information are stored in server. In order to locate nodes within the site, these set of pre stored information's called as 'fingerprints' are compared with RSSI signal observations by the individuals. The indoor localisation system often uses sensors such as, infrared (IR), ultrasound or radio-frequency (RF) for tracking the nodes (Want et al., 1992; Bahl and Padmanabhan, 2000: Priyantha et al., 2000; http://www.sonitor.com/). Though these systems show potential in locating the systems each has its own limitations.

Active badge system is one of the traditional techniques where, the tracked node has a small tag or active badge which emits an IR code once in every 15 seconds. These IR signals are picked by the group of pre placed sensors (around the building) and forwarded to a central station which process the data and triangulates the individuals. High maintenance overhead is the main drawback of this method (Want et al., 1992). RADAR is the traditional RF method which uses RF signals for locating in indoor environment (Bahl and Padmanabhan, 2000). The cricket system is based on RF and ultrasonic pulses; 'multiple beacons' are placed at different locations within the indoor environment. These beacons concurrently transmit RF and ultrasonic pulses. The tracking is done with a listening device carried by the tracked person. The listening device uses time of flight (TOF) difference between the RF and the ultrasonic pulses in order to determine the distance to the beacons (Priyantha et al., 2000). Though cricket system has improved accuracy; high maintenance and cooperation are the main drawbacks of this system.

Sonitor is the commercially available ultrasonic-based system; where in this, the person wears a small tag which emits identification number via ultrasonic signals. Detectors spread around the environment receive this and triangulates the person. When comparing the performance of this system with RF, it is better in terms of immunity to interference but the main drawback is it is highly barrier dependent (http://www.sonitor.com/; Paul and Wan, 2009).

Recently, researchers have refined positioning aspects either by improving the system or proposing for specific applications. Al Alawi (2011) has carried out RSSI measurements in both indoor and outdoor environments to locate wireless sensor nodes. In his work, he has considered the effect of the working environment on the relationship between RSSI and distance. The experimental result shows that the distance estimation is better in outdoor environment than indoor. Savazzi et al. (2014) have proposed localisation technique for tracking device free passive targets (i.e., target not carrying any electronic devices). According to this method, whenever a target moving causes perturbations of the received signal strength (RSS) and measuring these RSS fluctuations at different points in a given space will allow to locate the moving object. Bayesian approach is used for tracking.

Seyyedi et al. (2014) have used virtual reference tags along with real reference tags to estimate the location of the tracking. In this method, based on the RSSI values of virtual reference tags and real tags, the sensing area is divided in to different sections. The tracking tags location is then calculated by tags which are in the section that the object has the highest probability to be enclosed within. Au et al. (2013) proposed RSSI-based navigation module with integrated tracking system provides users with instructions to guide them to predefined destinations. They have used personal digital assistant (PDA) module (HP iPQA hx2750) for their study and the proposal was aiming to guide visually impaired subjects to their desired destinations.

Gu and Ren (2015) presented motion – assisted device tracking algorithm (MADT) to localise devices. It is based on the basic rules of RSSI and environmental factors like distance and direction to guide a user with a device receiving Bluetooth signal from the target to gradually approach them. As Bluetooth-based positioning systems have limitations of lower gross bit error rate (1 Mbps) and short range communication (typically 10–15 m), MADT is useful in such applications.

In this paper, for tracking a node(s), Bayesian approach is used and after locating the nodes a proposal has been made for finding shortest path among the nodes and these are explained in following chapters.

The remainder of this paper is organised as follows. Section 2 states limitations of the existing systems and proposed solutions. Section 3 is for methodology, results and discussion are appearing in Section 4 and Section 5 concludes the paper.

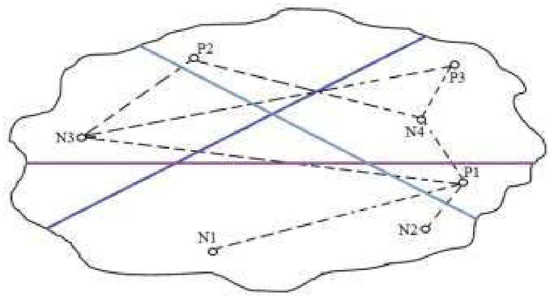
2 Limitations and solutions

In LBS, for better accuracy, line of sight between the user and the access pints is needed. The traditional location determination algorithms are prone to line of sight (LOS) problem (Gosai and Raval, 2014). Apart from this, issues like the presence of barriers and reflections from the uneven surfaces may cause tracking less accurate. Hence in this paper we have proposed the algorithm which will track the mobile nodes with minimum error.

2.1 Barrier problem

Typically the Wi-Fi access points (P_i) and mobile nodes (N_i) are positioned as in Figure 1.

Figure 1 Wi-Fi access points and mobile nodes topology (see online version for colours)



The signal strength at Wi-Fi point P_1 denoted by S_1 is mathematically expressed as,

$$S_1 \propto \sum_{i=1}^{3} d\left(W^{(1)}, N_i\right) \tag{2.1}$$

$$S_1 = k1 \propto \sum_{i=1}^{3} d\left(W^{(1)}, N_i\right) \tag{2.2}$$

Expression (2. 1) varies with position to give a new value S_2 as,

$$S_2 \propto \sum_{i=1}^{3} d\left(W^{(2)}, N_i\right) \tag{2.3}$$

$$S_2 = k2 \propto \sum_{i=1}^{3} d\left(W^{(2)}, N_i\right) \tag{2.4}$$

where

d	distance in metres
$W^{(1)}$ and $W^{(2)}$	Wi-Fi placement at positions 1 and 2, respectively
k_1 and k_2	constant values which are equivalent to sum of signal strengths at positions P_i for $i = 1, 2$ respectively.

In equations (2.2) and (2.4), the values of S1 and S2 depends on so many factors such as terrain, reflections, barriers etc. and are not uniform. The variation in signal strength is represented by the mean square error given by

$$MSE(X) = E\left\{[s_1 - s_2]^2\right\} \neq 0 \tag{2.5}$$

In the conventional sensor-based tracking methods, the presence of $MSE(X)$ (barrier problem) is not included. A modified algorithm to include this variation in signal strength is presented in this work. Algorithm to compensate for Barrier Problem is given below:

1 *Measure* $S1(W, N1)$, $S1(W, N2)$, $S1(W, N3)$, ……, $S1(W, N_j)$.

2 *Measure* $S2(W, N1)$, $S2(W, N2)$, $S2(W, N3)$, ……. , S2(W, Nj).

3 *Infer* $d(S1, N1)$, $d(S1, N2)$, $d(S1, N3)$, … $d(S1, N_j)$.

4 *Measure* $d\,(N1, W)$, $d(N2, W)$ …. $d(N_j, W)$.

5 *Rank* $d(N1, N2 \ldots N_j)$ [*If* $j = 2$, *then this ranking is equal to finding the maximum of the two*];

6 *From step 5, associate* N_j *with* S_i *such that* $S\,(N_j, S_i)$ is maximised.

Apart from barrier, each mobile node may move on other directions (like left and right directions).

From a mathematical point of view, all that matters are the sets of left and right options that a mobile node can be reached from any given position. If the tracking is represented by a rooted tree with vertices representing positions and with oriented edges labelled *L* or *R* according to the wireless signal strength. The root represents the initial position, and the edges from any position lead to another rooted (sub-) tree, the root of which represents the position the mobile node just reached.

Identifying a node with its initial position is completely described by the sets of left and right options. This leads to a recursive Definition 2.1(1). Descending tracking condition (2) simply says that the mobile node will be tracked no matter how it is tracked; the number of moves until the tracking can usually not be bounded uniformly in terms of the tracking only.

Definition 2.1:

1 Let L and R be two directions of tracking problem. Then the ordered pair $T := (L, R)$ is a successful tracking.

2 There is no infinite sequence of tracking $T_i = (L_i, R_i)$ with $T_{i+1} \in L_i \cup R_i$ for all $i \in N$.

In the recursive definition of tracking, the tracking is described with ‘0’= ({}, {}) with $L = R = \{\}$ for the node at its initial position. If it is ‘1’ = ({0}, {}) then it indicates a left move and ‘–1’ = ({}, {0}) is for right move.

The notations are simplified as, let $L = \{T^{L1}, T^{L2}, \ldots\}$ and $R = \{T^{R1}, T^{R2}, \ldots\}$ be two arbitrary sets of tracking; then for $T = (L \cdot R) = (\{T^{L1}, T^{L2}, \ldots\}, \{T^{R1}, T^{R2}, \ldots\})$.

We write $T = \{T^{L1}, T^{L2}, \ldots, \mid T^{R1}, T^{R2}, \ldots \ldots\}$. Hence a tracking is really set with two distinguished kinds of elements: the left respectively right options.

2.2 Proposal for shortest path

Once the mobile nodes are identified /tracked then a network of mobile nodes such as MANET can be constructed among the neighbour nodes. Let, $M(x_m, y_m)$ and $N(x_n, y_n)$ be any two arbitrary nodes in a network and if the Euclidean distance $\sqrt{(x_m^2 - x_n^2) + (y_m^2 - y_n^2)}$ between two nodes are less than or equal to transmission rang of the nodes then they are said to be neighbour nodes. In his paper, we are proposing a methodology on finding out the shortest path between any two nodes. This by forming nodes in to groups and number of groups is equal to number of Wi-Fi access points used in the system.

Set of nodes that have signal strength above a threshold with respect to access point are grouped and in this, there may be some nodes called as overlap nodes where signal strength of such nodes exceeds threshold values of more than one access point are called as overlap nodes. These threshold value (T_{dB}) can be application specific and for example equations (2.6) and (2.7) had given below for a random value:

- Application 1 (AP_1):

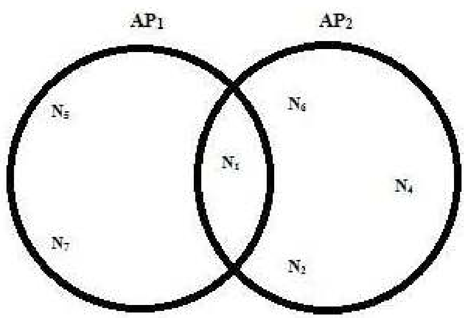
$$\{N_1, N_2, N_3\} > T_{dB} \tag{2.6}$$

- Application 2 (AP_2):

$$\{N_6, N_1, N_4\} > T_{dB} \tag{2.7}$$

Based on the above, clustering of nodes as good signal strength nodes and poor signal strength nodes is possible as shown in Figure 2.

Figure 2 Application specific clustering of nodes



According to Yan et al. (2005), a candidate for Steiner node is N_1 or the set of overlapping nodes for AP_1 and AP_2 and with this node, the shortest path can be calculated as:

1	*Group nodes as* AP_1 and AP_2;
2	*If* $AP_1 \cap AP_2 = \emptyset$;
3	*Steiner node set* (SNS) = Ø;
4	*Else* ($AP_1 \cap AP_2 \neq \emptyset$);
5	*If cardinality(SNS) >1 then*
	$Max_{signal\ strength}$ *(SNS) will guarantee shortest path and minimum energy loss*;
6	*Else cardinality(SNS) = 1 then*;
7	*Only one shortest path will exist*;
8	*Go to step1 and repeat for different cases.*

We can have more than one Steiner node to establish the shortest path. But to establish optimum shortest path, the placement of Steiner node is crucial. So it is recommended to use only one Steiner node in the overlap area.

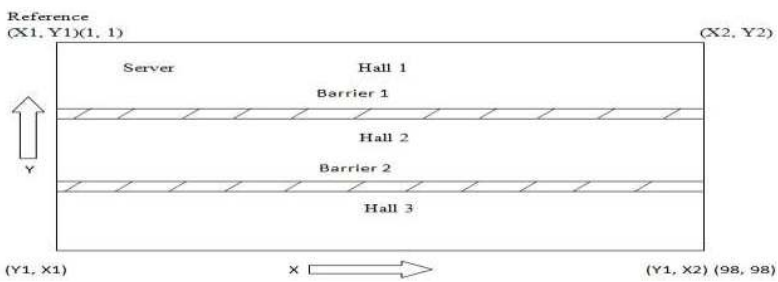
3 Methodology

3.1 Location tracking model

The location tracking model consists of a server, Wi-Fi access points and mobile nodes (MNs). The app is developed using Eclipse and Android SDK. Either windows or Linux platform could be used. The Server is developed and run on Linux platform. As stated in Lee et al. (2015), Android smart phones are known for their computational power, communication capability and sensing power, they are used as mobile nodes.

For testing, we have used three of our class room halls and Wi-Fi nodes are kept in different points as per the tested floor plan shown in Figure 3.

Figure 3 Tested floor plan



The rooms are considered to be of equal size, but unequal sizes can also be considered. The barriers mentioned in Figure 3 are walls of the room and students working tables (30 working tables) and during study the class rooms were students free. There are two modes for the App and the Server, the first is training mode, in which the App sends the RSSI values and current coordinates of the Mobile device. This is received by the Training server that collects enough data and stores the data in a text database for location calculation in the tracking mode. This kind of training is done for different rooms within the considered area and all the training data is stored by the server in training mode.

The other mode is the tracking mode and in which the app just sends the RSSI values to the server. The server using the trained data and by applying Bayesian interface methods the location of the mobile device is predicted with in the considered area and prints out the information both on the app as well as on the tracking server. The time gap between the training and the actual sampling is 15 minutes.

The algorithms for both location builder and tracker are shown below:

- Algorithm for location building server:
  1. *Open UDP port and wait for RSSI data from the app*;
  2. *Receive RSSI data and location info from the app*;
  3. *Write the data to database file*;
  4. *If count of data received from app >maximum data required per grid*;
  5. *send stop to app*;

6 *Else go to step 2.*

- Algorithm for location tracking server:
  1 *Open UDP port and wait for RSSI data from the app*;
  2 *Receive RSSI data from the app*;
  3 *Prepare Bayesian map for most likely probability*;
  4 *Print out the most likely region based on the Bayesian probability*;
  5 *Go to step 2.*

3.2 Bayesian inference

In Bayesian inference, the Bayes theorem is used to compute how the degree of belief in a proposition changes due to available evidence (Madiganl et al., 2005). In Bayesian statistics, all parameters are assumed to be random variables. In Bayesian statistics by forming statistical models from an observed sample and by using prior information, unknown parameters are easily explored.

For the decision process, it would be beneficial to have a measure of the quality of the different possible decisions, the different possible states under the feature vector represented evidence. In Bayesian inference this measure is given by the joint probability between the state '*S*' and the feature vector '*X*' with:

$$P(X, S) \tag{3.1}$$

Equation (3.1) evaluates under the definitions of probability theory to a scalar value in the range [0 … 1]. Furthermore, if '*X*' and '*S*' are conditionally independent, the joint probability can be factored into the two conditional forms that are essential for the Bayes theorem as shown in equation (3.2)

$$P(X, S) = P(X \mid S) P(S) = P(S \mid X) P(X) \tag{3.2}$$

In equation (3.2), $P(S \mid X)$ is called the posterior probability as it represents the belief that the state follows the evidence given by '*X*'. The term $P(S)$ is the prior probability and represents an evidence independent knowledge about the probability how often the state '*S*' will be observed. And finally $P(X \mid S)$, is the state-conditional probability that represents the probability to observe the evidence '*X*' under assumption that the environment is in state '*S*'. The term $P(X)$, the probability to observe specific evidence, has not been given a dedicated name as it will be unimportant for the sought decision rule. The decision rule should obviously lead to a high quality decision. This should therefore be the decision with the maximum joint probability. By this reasoning, the Bayes decision rule *rbayes*: $X \rightarrow S$ is defined as:

$$rbayes(X) = \arg\max SP(X, S) \tag{3.3}$$

by substituting equation (3.2) in the equation (3.3) we get,

$$rbayes(X) = \arg\max S\left[P(S \mid X) P(X)\right] \tag{3.4}$$

Since argmax *S* is independent of $P(X)$, this is an intuitive result. In this, the decision that is based on the posterior probability leads to the same result as using the joint probability.

But it is still unknown how to obtain the posterior $P(S \mid X)$. Therefore, the Bayes theorem will be used again as shown in equation (3.5)

$$P(S \mid X) = P(X \mid S)P(S)P(X) \tag{3.5}$$

Inserting the factored posterior into the decision rule:

$$\begin{aligned} rbayes(X) &= \arg\max S\left[\frac{P(X \mid S)P(S)}{P(X)}\right] \\ &= \arg\max S\left[P(X \mid S)P(S)\right] \end{aligned} \tag{3.6}$$

Since argmax S is independent of $P(X)$.

The prior $P(S)$ is a discrete probability density function (PDF), due to the discrete nature of the states that can be determined by simple counting of the occurrences of 'S'. Modelling the state conditional distribution $P(X \mid S)$ is more complicated. If the prior analysis that has led to $P(X \mid S)$ which is modelled according to the true nature of the environment, the free parameters of the model need to be determined. Similar to learning the structure of the prior $P(S)$, the parameters of $P(X \mid S)$ can be learned from the environment. But due to the coupling 'S' of and 'X', special state-annotated evidence-data is needed. Ignoring the problem of gathering this data, parameter estimation techniques like maximum-likelihood can then be applied to the set of training samples. If $P(X \mid S)$ is modelled as a Gaussian, this results in estimating the mean and the variance. The results are summarised as

The Bayes decision rule [equation (3.6)] conducts a search for the state 'S' with the maximum posterior probability $P(S \mid X)$ for an observed feature vector 'X'. The Bayes decision rule is therefore a function with input given by some measured evidence 'X' leading to the output of the most probable state 'S' of the environment. Instead of directly evaluating the posterior probability $P(S \mid X)$, the prior $P(S)$ and state-conditional $P(X \mid S)$ are employed as they can be learned from the environment. If these concepts are applied to the positioning problem with RSSI measurements, this leads to the following example model:

1. A state 'S' is an enumerable region of space, a location.
2. The feature vector 'X' is the jointly received vector of RSSI values for different access points (APs).
3. $P(S)$ is the probability to be in a specific location. In a geographically restricted mobility-model, $P(S)$ would be zero for unreachable regions.
4. $P(X \mid S)$ is the probability to receive the measurements 'X' at the location 'S'. $P(X \mid S)$ can be modelled as a multi-variate Gaussian, with a mean vector that represents the anticipated AP-specific RSSI values at the location 'S'. Assuming equal noise over all APs, a signal variance of around 5dBm will be chosen.
5. The AP-specific means of $P(X \mid S)$ will be obtained from a radio propagation model.

For a new RSSI vector observation X, the Bayes decision rule is used to decide for the most probable location 'S' that explains the observation. This means, evaluating the posteriors $P(S \mid X)$ for all the locations, and selecting the location 'S' with $\max(P(S \mid X))$. Due to the unavailability of a direct form of $(S \mid X)$, the maximisation is carried out over the known prior $P(S)$ and the state-conditional $P(X \mid S)$.

4 Results and discussion

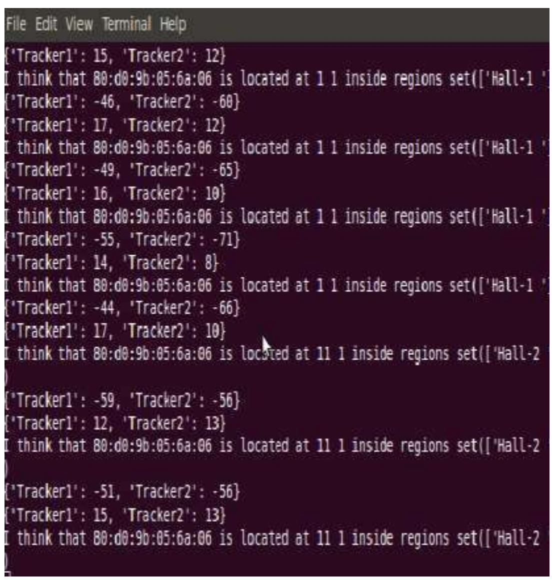
In this work, we have used signal strength information to infer the location of the node. The MN can get the RSSI from AP on WLAN. The behaviour of RSSI with respect to distance from AP is defined by log path loss model as per the equation (4.1)

$$RSSI = -\left(10n \log_{10} d - A\right) \tag{4.1}$$

where n is the attenuation factor (n = 2. 1 *for free space*), d indicates distance from AP and A is offset parameter (A = 27) and it is the measured RSSI at 1m far from AP.

In this study, for server, we have used Hewlet Packcard (HP) laptop with i5 processor works in 1.6 GHz. We have used Linux platform in the server and Python scripts are used at the server to identify the position of the mobile device with in an indoor environment based on the RSSI value sent from the mobile app. The sample tracking information is shown in Figure 4.

Figure 4 Location tracking display (see online version for colours)



We have tested the algorithm with different factors as listed in Table 1, where the defaults are highlighted.

The experiments were carried out by collecting samples for each 1m distance from the reference point as mentioned in Figure 3. For each location the RSSI samples are collected on all directions and test is repeated for 40 times. For comparison purpose, we have used the average values. The RSSI values are decreasing exponentially as the distance from the reference point is increased. This behaviour is compared with traditional log path loss model as shown in Figure 5.

Figure 5 Comparison with log path loss model (see online version for colours)

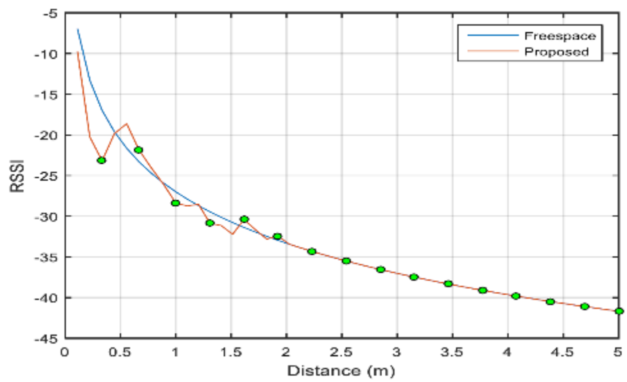
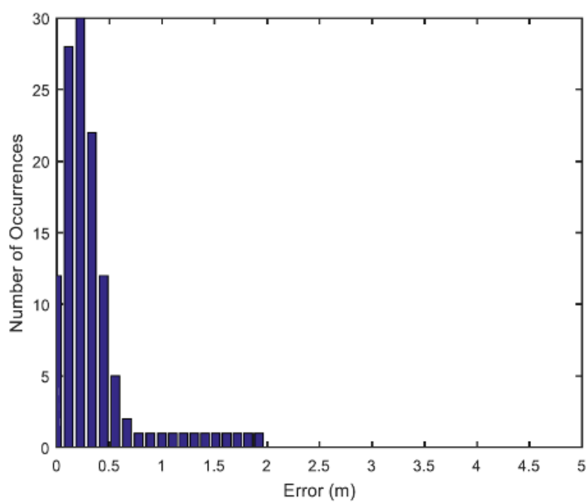


Figure 6 Error distribution (see online version for colours)



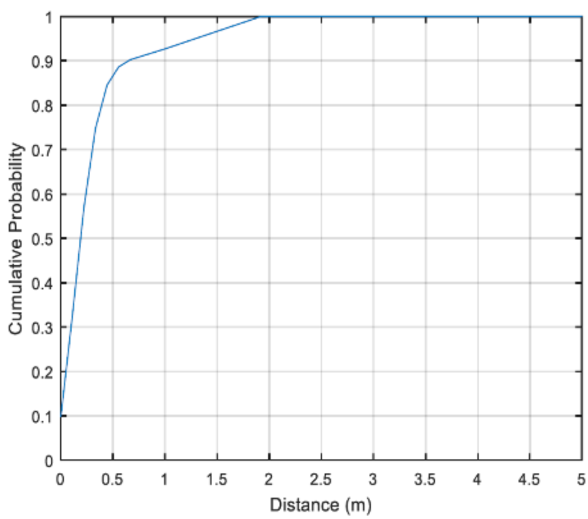
Further to evaluate the accuracy of the algorithm, we have used error distance as the performance metric and it is the difference between the original distances to the measured distances as shown in Figures 6–7.

Figure 6 show that most of the error occurs at distance less than 2 m. From Figure 7, it can be observed that the proposed localisation system can achieve a resolution of 1 m with a probability of 0.92 m this is better performance than RADAR (Bahl and Padmanabhan, 2000), and RF finger-printing (Park and Park, 2011) methods.

Table 1 Factors under study (defaults highlighted)

Factors	*Value*
Wi-Fi units	2
Testing combination	{Hall 1 and Hall 2, Hall 2 and Hall 3, Hall 1 and Hall 3}
Test Site	8 m × 10 m
Sampling rate	1
Number of samples	40
Time of the day	{Morning, afternoon evening}

Figure 7 Cumulative error distribution (see online version for colours)



The summarised accuracy information for 25th, 50th and 75th percentiles are shown in Table 2 for comparison of different methods with the proposed method.

From the above results, it is observed that the performance of the proposed method is comparable with those in literature. It was seen that at 25th percentile, it gives improvement of 1.67 m and 0. 15 m over RADAR (Bahl and Padmanabhan, 2000) and DOA using SMART antenna (Lim et al., 2007) methods respectively. At 50th percentile, the improvement is 0.2 m compared to SDR platform (Tsai et al., 2016). Also in 75th percentile, it gives an improvement of 3.77 m and 0.58 m comparing to RADAR and RF finger printing methods (Park and Park, 2011), respectively.

Table 2 Results summary

Method	*25th percentile*	*50th percentile*	*75th percentile*
RADAR	1.92 m	2.94 m	4.69 m
RF finger printing	0–0.6 m	0.25 m–1 m	1.2 m–1.5 m
DOA using SMART antenna	0.4 m	0.57 m	0.85 m
SDR Platform	0.15 m	0.5 m	0.8 m
Proposed Method	0.25 m	0.3 m	0.92 m

5 Conclusions

This paper introduces a novel indoor tracking system of mobile nodes in the barrier environment using Bayesian inference method. Based on several experiments conducted on different conditions we verified that the proposed algorithm estimates the location with acceptable accuracy even in the presence of barriers. Hence, this modified algorithm is recommended for both LOS and non-line of sight (NLOS) cases. The simulation results show that the resolution accuracy is better than conventional techniques. The algorithm is tested with Android phone with loaded APP. However, testing with the other forms of mobile nodes such as laptops or others will be considered as future scope of this work.

We also proposed a Steiner node-based theoretical approach for finding shortest path between any sources to any destination when group of nodes are located.

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