Interdisciplinary Information Sciences, Vol. 12, No. 2, pp. 133–146 (2006)

A Comparative Performance Evaluation of Indoor Geolocation Technologies

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Received February 16, 2006; final version accepted April 30, 2006

As more location aware services are emerging in the market, the needs for accurate and reliable localization has increased and in response to this need a number of technologies and associated algorithms are introduced in the literature. Severe multipath fading in indoor areas, poses a challenging environment for accurate localization. In this article we provide a comprehensive overview of existing indoor localization techniques. We address the bandwidth requirement, advantages and disadvantages of *received-signal-strength* (RSS) and *time-of-arrival* (TOA) based localization algorithms. We describe a repeatable framework for comparative performance evaluation of localization algorithms. Using this framework we compare the performances of two TOA-based and two RSS-based algorithms. The TOA-based algorithms are the least square TOA (LS-TOA) and closest neighbor with TOA grid (CN-TOAG). The RSS-based algorithms are the maximum likelihood estimator and the recently introduced ray tracing assisted closest neighbor (RT-CN).

KEYWORDS: indoor geolocation, wireless channel model, localization algorithm, location-aware services, user location tracking

1. Introduction

Localization via radio signals has been considered as an application to wireless communication since World War II, where locating soldiers in emergency situation was critical. This problem was addressed by the US Department of Defense many years after, during the war in Vietnam, when they launched a series of satellites under a project called Global Positioning System (GPS). In the early times of GPS, these satellites were designated for military applications only. However, later on around 1990 they became partially available for commercial use. Today, GPS is widely used in commercial and personal applications. Although GPS have attracted numerous popular outdoor applications, since its accuracy in indoor environments is considerably degraded new technologies have emerged for indoor geolocation. In this paper we provide a comprehensive overview of the challenges for indoor geolocation and the emerging technologies to address these challenges.

In late 1990s, at about the same time that E-911 technologies were emerging, another initiative for accurate indoor geolocation began independently, motivated by a variety of applications envisioned for indoor location-sensing in commercial, public safety, and military settings [1–3]. In commercial applications there is an increasing need for indoor location-sensing systems to track people with special needs, the elderly, and children who are away from visual supervision. Other applications include systems to assist the sight-impaired, to locate instrumentation and other equipment in hospitals, to locate surgical equipment in an operating room, and to locate specific items in warehouses. In public safety and military applications, indoor location sensing systems are needed to track inmates in prisons and to guide policemen, fire-fighters, and soldiers in accomplishing their missions inside buildings. Accurate indoor localization is also an important part of various personal robotics applications [4] as well as in context-aware computing [5]. More recently, location sensing has found applications in location-based handoffs in wireless networks [6], location-based *ad-hoc* network routing [7, 8] and location-based authentication and security. These and other applications have stimulated interest in modeling the propagation environment to assess the accuracy of different sensing techniques [9–11], as well as in developing novel technologies to implement the systems [12–14]. We have already seen implementation of the first generation of indoor positioning products using a variety of technologies [15–17] the more accurate second generation of products demand extensive research in understanding of the channel behavior and development of relevant algorithms.

Depending on the application of geolocation, the accuracy of the positioning system differs. In particular desired positioning accuracy for indoor environments is higher. For an outdoor system accuracy in the order of 30–50 m is acceptable [18], while for indoor applications the accuracy must be in the order of 1–10 m [19]. For example, the required accuracy for E-911 standard (also known as E-112 in Europe) is 100 meters at %67 of the time. However, an application such as child-tracking mandates a locating accuracy within the dimension of a room which is only a few

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meters. The existence of various applications and their requirements increases the need for different approaches to the indoor geolocation problem.

The common denominator part of all these widely ranged applications is the behavior of the radio channel in the indoor environment. In Section 2 we describe challenges to precise indoor geolocation that are associated with any indoor environment and we introduce an UWB calibrated ray tracing algorithm to represent the behavior of the channel. Section 3 describes how we can use different metrics, exploit wider bandwidths, and use different algorithms to remedy the challenges posed to accurate indoor localization. Section 4 provides a comprehensive overview of the emerging applied algorithms using different attributes of the received signal in a location sensor. In Section 5, we describe a framework and a scenario for performance evaluation of indoor localization techniques; based on the UWB measurement calibrated ray tracing. We use the introduced scenario for comparative performance evaluation of the algorithms introduced in Section 4. Section 6 provides the summary and conclusions of the paper.

2. Localization Challenges in Indoor Environment

In this section we first introduce an UWB calibrated ray tracing algorithm for analysis of the multipath behavior of the radio channel for indoor geolocation application. Then we describe the effects of multipath in wideband time of arrival (TOA) measurements, effects of undetected direct path conditions on accuracy of TOA range measurements, and lack of reliability of the power based range estimation techniques as challenges to precise indoor geolocation.

Indoor environment is a multipath rich situation, to cope with this phenomenon, multipath channel impulse response is usually modeled as [20, 21]:

$$h(\tau) = \sum_{k=1}^{L_p} \alpha_k \delta(\tau - \tau_k) \tag{1}$$

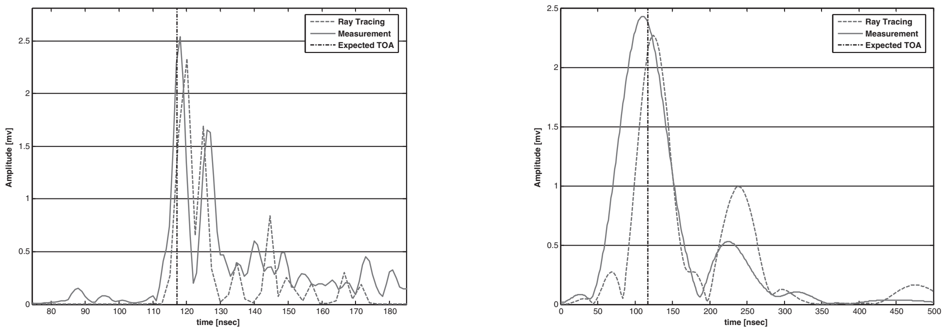
where L_p is the number of multipath components, and $\alpha_k = |\alpha_k| e^{j\phi_k}$ and τ_k represent site specific random complex amplitude and random propagation delay of the k-th path, respectively [22]. We define the direct *line-of-sight* (LOS) path between transmitter and receiver antennas as the *direct-path* (DP) and *time-of-arrival* (TOA) of this path indicates the distance between the transmitter and the receiver.

The goal of channel modeling is to determine the parameters of (1) for any transmitter-receiver location in a building. These models can be developed by extensive on site measurements or by channel modeling simulation tools. *Ray-Tracing* (RT) is a simulation tool encompassing the geometrical information of a floor plan in addition to the reflection and transmission coefficients of building materials that models the radio channel behavior in different areas. The predictions from ray tracing software are particularly accurate for propagation of radio signals at frequencies greater than 900 MHz where electromagnetic waves can be described as traveling along localized ray paths. For a pair of transmitter-receiver at some known locations, RT determines the necessary information of a channel such as $\alpha_k = |\alpha_k| e^{j\phi_k}$ and τ_k as defined in (1), arrival angle, departure angle, phase, number of reflections, and number of transmissions by sending a set of rays from the transmitter and tracing them until they either reach the receiver or largely attenuated that can not be detected by the receiver. The TOA, magnitude, and phase of each path are recorded for each ray. This method is shown to be accurate for indoor environments. RT can be used to produce large databases of channel impulse responses for statistical analysis of the channel. Therefore RT is a viable alternative to physical measurement [22]. As an example of a calibrated RT, two sample channel profiles between known transmitter–receiver locations are shown in Fig. 1(a–b) for both a RT simulation and measurement with bandwidths of 500 and 26 MHz respectively. The expected TOA in both cases are shown by the dotted line.

This figure illustrates that RT predicts the major paths fairly well. However, it should be noted that the RT must be calibrated for different areas and in general one should compare the statistical characteristics of the channels on a particular area with the results of RT [23]. We use RT to illustrate indoor localization challenges in the upcoming sections.

2.1 Multipath in wideband TOA measurements

Figure 2 shows the basic concepts involved in the wideband TOA measurement using arrival time of the DP in a typical indoor multipath environment. In this figure the solid vertical lines represent the ideal channel impulse response generated by RT for two arbitrary locations in an office area. The DP is also the strongest path and location of this path is the expected value of the TOA. Other paths arriving after a number of reflections and transmissions occur after the DP with lower amplitudes. These paths generated by ray tracing algorithms would have been observed at the receiver if the bandwidth of the system was infinite. In practice where the bandwidth is limited by physical or regulatory constraints, each impulse is spread in time and smeared into adjacent pulses. The resulted received signal is the summation of such pulses, which in Fig. 2 we refer to as the channel profile [22]. In TOA based indoor geolocation systems we use the first detected peak of the channel profile above the detection threshold as the estimated TOA of the DP, we call this peak *first-detected-peak* (FDP). In *time-of-arrival* (TOA) based positioning systems, the TOA of the FDP, $\hat{\tau}_w$ is an estimation of the TOA of the DP, τ_{DP}. Therefore the estimated distance between the transmitter and the receiver antennas are obtained from:



(a) (b)

Bandwidths	:	(a) 500MHz,	(b) 26MHz
DME (RT)	:	(a) 10 [cm],	(b) 2.1 [m]
DME (Meas.)	:	(a) 24 [cm],	(b) 2.2 [m]

Fig. 1. Typical channel impulse response.

$$\hat{d}_w = c \times \hat{\tau}_w \tag{2}$$

where c is the speed of light. We use the subscript w to reemphasize that generally $\hat{\tau}_w$ depends on the receiver's bandwidth w.

In a single path environment the actual expected and the estimated DP are the same. However, in multipath conditions, as shown in Fig. 2, the peak of the channel profile gets shifted from the expected TOA resulting in a TOA estimation error caused by the multipath condition. *Distance-measurement-error* (DME) is defined as the ranging error caused by erroneous estimate of the TOA by:

$$\varepsilon_{d,w} = |\hat{d}_w - d| \tag{3}$$

Note the comparable DME values in Fig. 1(a–b) that validates the simulated channel profile as a good approximation of the actual radio channel.

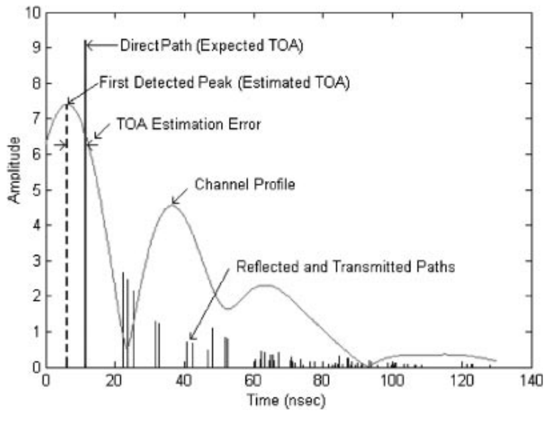


Fig. 2. Parameters involved in wideband TOA measurement using the arrival of DP.

2.2 Undetected direct path conditions

Another very important challenge in the indoor environment that is mostly neglected by the literature is the presence of *obstructed-LOS* (OLOS) multipath conditions. In such cases, DP goes below the detection threshold of the receiver while other paths are still detectable, the receiver assumes the FDP in the profile to be the DP which results in large DME value. We refer to this phenomenon the *undetected-direct-path* (UDP) condition [9, 10]. Figure 3 shows an example of a UDP condition, obtained from the results of RT for a transmitted pulse with a bandwidth of 200 MHz. Since the difference between the strength of the strongest path and the DP is more than the dynamic range (the range of detectable signal level below the strongest path) of the receiver [9], we observe a UDP condition which causes a DME of 5.23 m.

2.3 Lack of reliability for power based ranging

Power based geolocation systems associate the *received-signal-strength* (RSS) to the distance between the transmitter and the receiver. Finding an accurate relationship between RSS and distance is a challenging problem in a multipath and scatter rich indoor environment. In general, the relation between the average power in dB, RSS, and distance is given by:

$$RSS_d = 10\log_{10} P_r = 10\log_{10} P_t - 10\alpha\log_{10} d + X \tag{4}$$

in which α is the distance-power gradient, X is the shadow fading (a normal distributed random variable), and Pt is the transmitted power. Equation (4) does not provide a good distance estimation because the power gradient (α) changes in different buildings and shadow fading is highly unpredictable component in indoor environment. Therefore, the distance estimated from this equation based on the RSS is very unreliable and if we use this metrics we need to compensate the unreliability with more complex localization algorithm. We will describe this in further details in the following section.

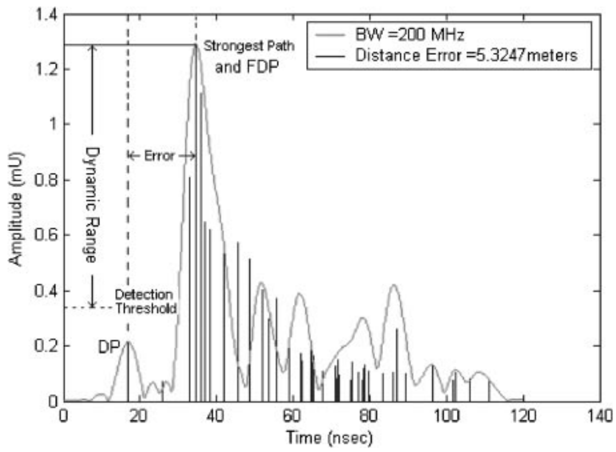


Fig. 3. UDP multipath condition from results of ray-tracing simulation and a channel profile with 200 MHz.

3. Remedies for Indoor Localization Challenges

In the previous section we explained the existing challenges for indoor geolocation systems caused by sever multipath in indoor environment. In this section we describe various approaches to overcome those obstacles in order to deploy a reliable, accurate, and scalable indoor geolocation system.

3.1 Use different metrics

Figure 4 shows the block diagram of an indoor localization system. Wireless sensors measure some signal parameters (metrics) that can be used for localization. Depending on the application of a particular localization system, these metrics can be TOA, RSS, *angle-of-arrival* (AOA), *power-of-arrival* (POA), etc. The positioning algorithm

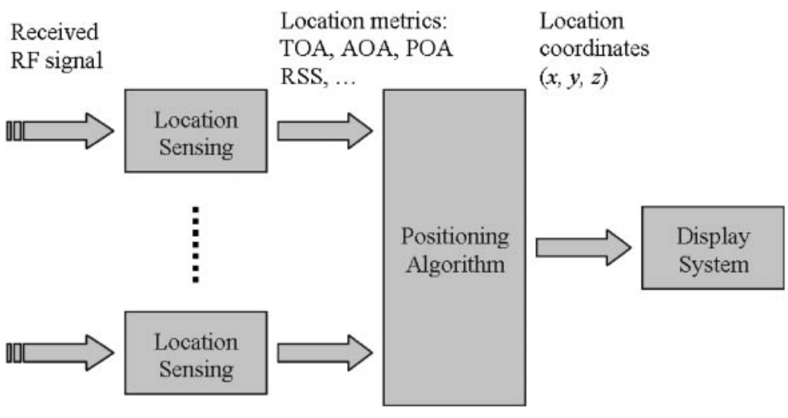


Fig. 4. Block diagram of a localization system.

combines the generated metrics to determine the location of a *mobile-station* (MS) in a process called data fusion. This figure also illustrates all the major adjustable components that can be tailored to meet the challenging requirements of indoor geolocation.

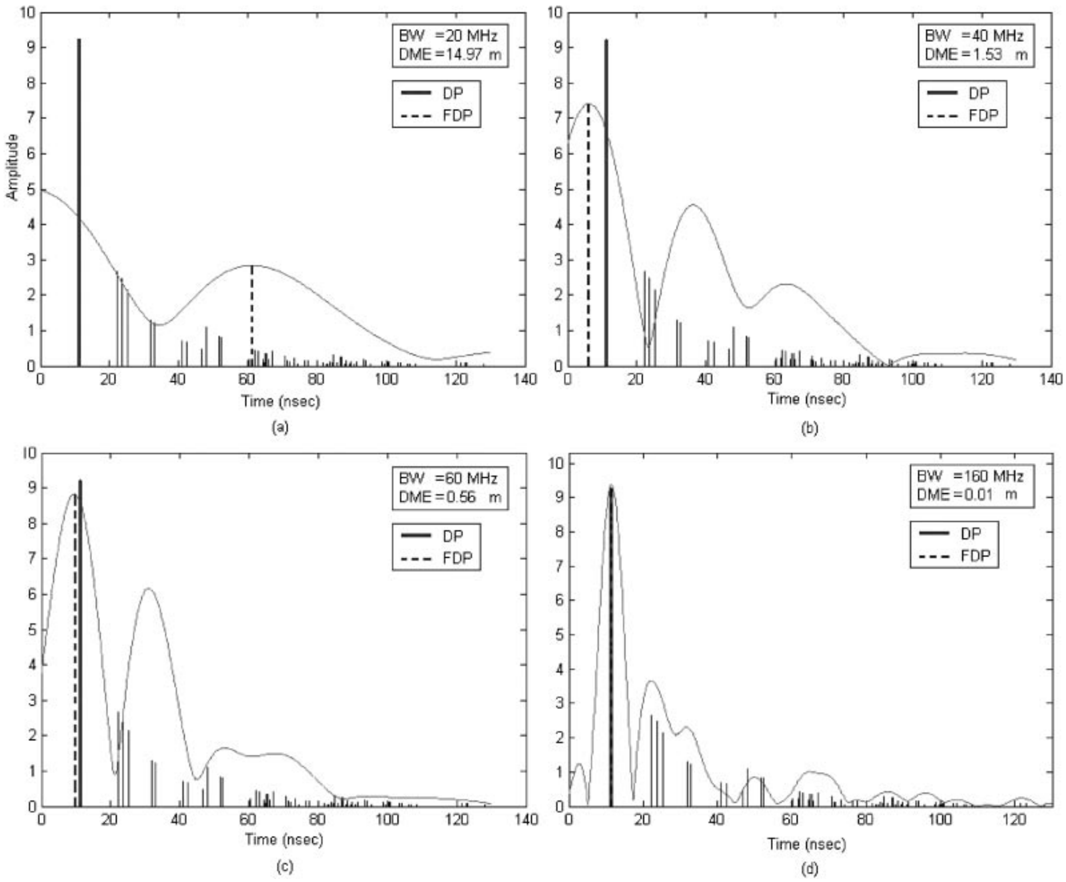
3.2 Use wider bandwidth

Two major metrics that are widely used for indoor localization are TOA and RSS. As mentioned earlier, in a TOA based system DME is a function of system bandwidth [24, 25]. This relationship is best described by a set of channel profiles. Four channel profiles, with four different bandwidths, accompanied with an ideal channel profile generated by RT with an infinite bandwidth, associated to one pair of Tx/Rx located at some fixed locations are shown in Fig. 5. It can be seen that as the bandwidth increases the channel profiles become more and more similar to the ideal channel profile, *i.e.* channel impulse response. At the same time by increasing the bandwidth DME decreases. Channel profiles similar to those in Fig. 5 in which the LOS path is both detectable and also the dominant path, are called *dominant-direct-path* (DDP) channels [9].

The above example demonstrates that in DDP channels DME can be reduced by increasing the system bandwidth. However, in most practical wireless communication systems bandwidth is a fixed system requirement that can not be increased. Moreover, increasing bandwidth can not circumvent UDP conditions. RSS based systems on the other hand are less sensitive to the available bandwidth and more resilient to UDP conditions. However, TOA systems can provide higher accuracy compared to RSS based systems in DDP cases.

3.3 Use different positioning algorithms

There are many positioning algorithms available in the literature. Here, we classify the positioning algorithms into distance based algorithms and pattern recognition based algorithms.



bandwidths: (a) 20MHz, (b) 40MHz, (c) 60MHz, and (d) 160MHz

Fig. 5. Channel profiles generated from RT, using one pair of Tx/Rx, with different bandwidths.

In distance based algorithm, the localization system determines the distances (via the selected metrics) between MS and each transmitter and locates MS through triangulation. Figure 6 shows the triangulation technique in distance based algorithms when MS observes signals from three transmitters. In pattern recognition based algorithms the positioning system gets enough training prior to locate MS to create a reference database of possible locations in an environment with an associated fingerprint at those locations. We refer to this pregenerated reference database as radio map. The radio map can be generated through a training or simulation process. During the localization period system compares the characteristics of the observed signal with the existing ones in the radio map and chooses the location that matches best with the existing data and declares that as the MS's current location. Figure 7 shows a sample scenario of a pattern recognition method. A grid of reference points in a typical floor plan within the range of five transmitters is created. MS can be located by matching its observed signal metric with the training data.

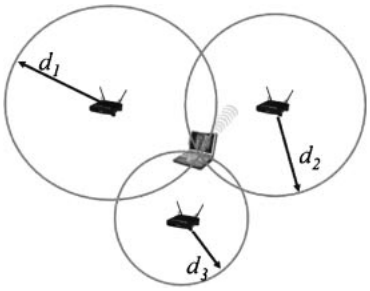


Fig. 6. A sample distance based localization system.

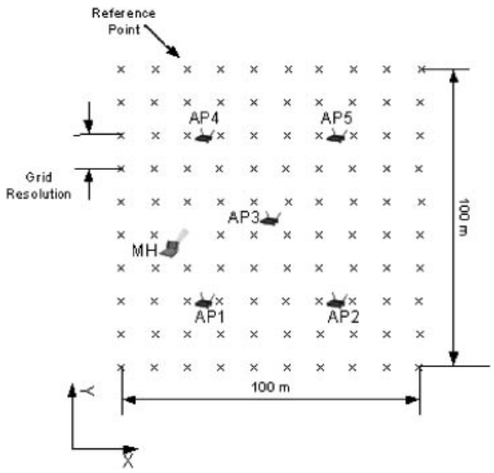


Fig. 7. A sample pattern recognition based localization system.

4. Indoor Localization Algorithms

The goal of an indoor localization system is to estimate the location of MS by combining measurement metrics from a number of *access-points* (AP) distributed in the area in a process called data fusion. We classify indoor geolocation techniques based on the signal attribute being used for localization into RSS and TOA based algorithms. Each class is further sub-classified based on their data fusion algorithm into distance based or pattern matching based subclasses.

In this section we introduce details of two TOA-based and two RSS-based algorithms. The TOA-based algorithms are the distance-based least square TOA (LS-TOA) and the pattern matching closest neighbor with TOA grid (CN-TOAG) [26]. The RSS-based algorithms are the maximum likelihood estimator [16] and the recently introduced ray tracing assisted closest neighbor (RT-CN) [28] which are both pattern matching techniques. In section five we provide the comparative performance evaluation of these algorithms.

4.1 RSS based localization algorithms

RSS is a signal metric that most off the shelf wireless devices can measure. As an example the MAC layer of IEEE 802.11 WLAN provides RSS information from all active AP's in a quasi periodic beacon signal that can be used as a metric for positioning [13, 27]. In open outdoor environments RSS decays linearly with log distance thus a MS can uniquely map an observed RSS value to a distance from a transmitter and consequently identify its location by using distances from three or more AP's. Unfortunately instantaneous RSS inside a building varies over time; even at a fixed location; this is caused largely by channel variations due to shadow fading and multi-path fading. Consequently statistical approaches using pattern matching algorithms to location estimation prevail. In this section we describe three pattern matching algorithms that use RSS metric for indoor localization.

Let (x, y) be the MS location to be determined, $\mathbf{O} = [\mathrm{p}_1\ \mathrm{p}_2\ \ldots\ \mathrm{p}_m]$ is an observed RSS vector from $AP_1, AP_2, \ldots, AP_m$ located at $(x_1, y_1), (x_2, y_2), \ldots (x_m, y_m)$ respectively. Let $\mathbf{Z}(x, y) = [z_1(x, y)\ z_2(x, y) \ldots z_m(x, y)]$ be the vector of expected RSS measurements at (x, y). The MS's location can be estimated as $(\hat{x}, \hat{y})$ where $\mathbf{Z}(\hat{x}, \hat{y})$ provides a good approximation of $\mathbf{O}(x, y) = [\mathrm{p}_1\ \mathrm{p}_2\ \ldots\ \mathrm{p}_m]$. We define the error function as:

$$\varepsilon(x, y) = \|\mathbf{O}(x, y) - \mathbf{Z}(x, y)\|^2 = \sum_{i=1}^{m} (\mathrm{p_i} - \mathrm{z_i}(x, y))^2 \tag{5}$$

The estimated location for $(\hat{x}, \hat{y})$ must minimize (5). In other words:

$$\nabla \varepsilon(x, y) = \mathbf{0} \tag{6}$$

$$(\hat{x}, \hat{y}) = \operatorname{argmin}(\varepsilon(x, y)) \tag{7}$$

Applying (6) to (5) we obtain:

$$\sum_{i=1}^{m} (\mathrm{p_i} - \mathrm{z_i}(x, y)) \frac{\partial \mathrm{z_i}(x, y)}{\partial x} = 0 \tag{8}$$

$$\sum_{i=1}^{m} (\mathrm{p_i} - \mathrm{z_i}(x, y)) \frac{\partial \mathrm{z_i}(x, y)}{\partial y} = 0 \tag{9}$$

or in a matrix form:

$$\begin{bmatrix} p_1 - \mathrm{z}_1(x, y) \\ p_2 - \mathrm{z}_2(x, y) \\ \vdots \\ p_m - \mathrm{z}_m(x, y) \end{bmatrix}^T \begin{bmatrix} \frac{\partial \mathrm{z}_1(x, y)}{\partial x} & \frac{\partial \mathrm{z}_1(x, y)}{\partial y} \\ \frac{\partial \mathrm{z}_2(x, y)}{\partial x} & \frac{\partial \mathrm{z}_2(x, y)}{\partial y} \\ \vdots & \vdots \\ \frac{\partial \mathrm{z}_m(x, y)}{\partial x} & \frac{\partial \mathrm{z}_m(x, y)}{\partial y} \end{bmatrix} = \mathbf{0} \tag{10}$$

Path loss models are often represented by a constant and a logarithmic component [22]:

$$z_{\mathrm{i}}(x, y) = \beta_0 - \beta_1 \ln[(x - x_i)^2 + (y - y_i)^2] \tag{11}$$

where β_0, β_1 are some site specific constant values. Thus:

$$\begin{aligned} \frac{\partial z_{\mathrm{i}}(x, y)}{\partial x} &= \frac{-2\beta_1 (x - x_i)}{(x - x_i)^2 + (y - y_i)^2} \\ \frac{\partial z_{\mathrm{i}}(x, y)}{\partial y} &= \frac{-2\beta_1 (y - y_i)}{(x - x_i)^2 + (y - y_i)^2} \end{aligned} \tag{12}$$

Substituting (11) and (12) in (10) results in a set of nonlinear over-determined equations.

To find a numerical solution for the set of nonlinear equations most RSS based positioning systems create a priori conditional probability distribution of RSS in an environment (radio map) during an offline training phase called fingerprinting [13, 16, 29]. A high resolution grid of reference points at known locations will be selected. At each k-th reference point on the grid a reference fingerprint vector $Z(x_k, y_k) = [z_{k1}\ z_{k2} \ldots z_{km}]$ is collected. During the localization period the MS uses a matching algorithm to map an observed RSS fingerprint vector to a physical location. In this algorithm the MS can determine its location without knowing the exact location of the access points. The basic algorithm in this class is called nearest-neighbor (NN) [13]. In this algorithm MS compares an observed RSS vector with all available fingerprints in the reference radio map and finds a reference point with the smallest Euclidean distance in signal space and reports that as the current location of the device. Suppose that MS observes $\mathbf{O} = [\mathrm{p}_1\ \mathrm{p}_2\ \ldots\ \mathrm{p}_m]$. The Euclidean distance between this vector and the k-th reference point entry in the radio map $Z(x_k, y_k) = [z_{k1}\ z_{k2} \ldots z_{km}]$ is given by:

$$D_k = \left(\sum_{i=1}^{m} (p_i - z_{ki})^2 \right)^{1/2} \tag{13}$$

This technique maps the location of MS to an entry on the radio map. Another variation of this algorithm finds the M closest reference points and estimate the location based on the average of the coordinates of these M points [29].

Since the total RSS value is the sum of signal strengths of each individual path in a multipath environment, RSS based systems take advantage of the existing multipath diversity in the channel. Furthermore, the timing requirement in

RSS based systems is less rigorous and the system is more tolerant in UDP cases. Two more algorithms from the patten matching RSS based localization algorithms described in the following sections.

4.1.1 Maximum likelihood RSS based location estimation

The performance of the NN method depends on the number of reference points on the radio map and their resolution. Using more reference points on the map provides a higher localization accuracy. In order to achieve a fine resolution from a coarse location estimation based on a given radio map, [16] applies a machine learning technique to interpolate between several reference points on the map. The advantage of this approach compared NN is that, in this method the estimated location is not restricted to existing reference points, thus we can reduce the number of reference points. This gives us a trade off mechanism between the number of reference points and estimation accuracy.

We want to estimate the location of the MS, given that $\hat{\mathbf{o}} = (\hat{p}_1, \hat{p}_2, \ldots, \hat{p}_m)$ is the RSS values received from m access points (AP_1–AP_m). The following section we describe the training process in which we create a likelihood function at each reference point on the radio map through either a measurement campaign or simulation.

Given a set of n distinct reference locations $L = \{l_1, l_2, \ldots l_n\}$; $l_i = (x_i, y_i); i \in \{1, 2, \ldots n\}$; in area $\mathbf{A}$ and k observations at each location where:

$$\mathbf{O} = \{\mathbf{O}_1, \mathbf{O}_2, \ldots, \mathbf{O}_n\} \tag{14}$$

$$\mathbf{O}_i = \{\mathbf{o}_{i1}, \mathbf{o}_{i2}, \ldots, \mathbf{o}_{ik}\}; i \in \{1, 2, \ldots, n\} \tag{15}$$

$$\mathbf{o}_{ij} = (p_{ij1}, p_{ij2}, \ldots, p_{ijm}) \tag{16}$$

$\mathbf{O}_i$: A set of k observation at reference location $l_i = (x_i, y_i)$
$\mathbf{o}_{ij}$: RSS values from m access points (AP_1–AP_m)
p_{ijt}: j-th RSS observation from AP_t at reference location $l_i = (x_i, y_i)$
m: Number of access points

We denote the probability of observing $\mathbf{o} = (p_1, p_2, \ldots, p_m)$; as $\mathrm{p}(\mathbf{o})$ and the prior probability of being at location $l = (x, y)$, $\mathrm{p}(l)$ respectively. We obtain the posterior distribution of the location by applying Bayes rule:

$$\mathrm{f}_l(l|\mathbf{o}) = \frac{\mathrm{f}_o(\mathbf{o}|l) \cdot \mathrm{p}(l)}{\mathrm{p}(\mathbf{o})} = \frac{\mathrm{f}_o(\mathbf{o}|l) \cdot \mathrm{p}(l)}{\sum_{l' \in L} \mathrm{p}(\mathbf{o}|l')\mathrm{p}(l')} \tag{17}$$

where $\mathrm{f}_l(l|\mathbf{o})$ and $\mathrm{f}_\mathbf{o}(\mathbf{o}|l)$ are conditional probability distribution functions of being at location $l = (x, y)$ given the observation $\mathbf{o} = (p_1, p_2, \ldots, p_m)$, and the probability distribution function of observing $\mathbf{o}$ given location $l = (x, y)$, respectively. Generally, the prior probability density function of $\mathrm{p}(l)$ is a mechanism to incorporate previous tracking information to this system. Here for simplicity we assume that $l = (x, y)$ follows a uniform distribution, and $\mathrm{p}(\mathbf{o})$ does not depend on location l so it can be considered as a normalization factor. Application of these assumptions reduces (17) to (18), where η is a constant normalization factor.

$$\mathrm{f}_l(l|\mathbf{o}) = \frac{\mathrm{f}_o(\mathbf{o}|l) \cdot \mathrm{p}(l)}{\mathrm{p}(\mathbf{o})} = \eta \cdot \mathrm{f}_o(\mathbf{o}|l) \tag{18}$$

The term $\mathrm{f}_\mathbf{o}(\mathbf{o}|l)$ is called the likelihood function, which in discrete domain gives the probability of observing a profile $\mathbf{o} = (p_1, p_2, \ldots, p_m)$ at a given location $l = (x, y)$. Equation (18) shows that estimation of the likelihood function $\mathrm{f}_\mathbf{o}(\mathbf{o}|l)$ leads to finding $\mathrm{f}_l(l|\mathbf{o})$. The posterior distribution function $\mathrm{f}_l(l|\mathbf{o})$ can be used to find the optimum location estimator based on any desired loss function. In particular, using expected value of the location minimizes the mean squared error and (19) shows this estimation:

$$\mathrm{E}[l|\mathbf{o}] = \eta \cdot \sum_{l' \in L} l' \cdot \mathrm{f}_o(\mathbf{o}|l') \tag{19}$$

Here we use a Gaussian kernel function to model the likelihood function $\mathrm{f}_\mathbf{o}(\mathbf{o}|l)$. Suppose we have k observations at point $l = (x, y)$. Equation (20) defines one prospective likelihood function:

$$\mathrm{f}_\mathbf{o}(\mathbf{o}|l) = \frac{1}{k} \sum_{i=1}^{k} \mathrm{K}(\mathbf{o}, \mathbf{o}_i) \tag{20}$$

$$\mathbf{o} = (p_1, p_2, \ldots, p_m) \text{ and } \mathbf{o}_i = (p_{i1}, p_{i2}, \ldots, p_{im})$$

where $\mathrm{K}(\mathbf{o}, \mathbf{o}_i)$ denotes the kernel function. We assume that RSS p_t from access point t is a Gaussian random variable $\mathrm{N}(\mu = p_t, \sigma^2)$; where σ^2 is an adjustable parameter. If we assume that the consecutive values of p_t are independent, we can use a Gaussian kernel function and obtain:

$$\mathrm{K}_{\mathrm{Gauss}}(p_1, \ldots p_m, p_{i1}, \ldots, p_{im}) = \frac{e^{-\frac{1}{2\sigma^2}\sum_{r=1}^{m}(p_r - p_{ri})^2}}{(\sqrt{2\pi}\sigma)^m} \tag{21}$$

Combining (20), and (21) we conclude:

$$\mathrm{f}_{\mathrm{p}_1 \cdots \mathrm{p}_m}(p_1, \ldots, p_m|l) = \frac{1}{k(\sqrt{2\pi}\sigma)^m} \sum_{i=1}^{k} e^{-\frac{1}{2\sigma^2}\sum_{r=1}^{m}(p_r - p_{ri})^2} \tag{22}$$

This is the likelihood function of observing $\mathbf{o} = (p_1, p_2, \ldots, p_m)$ at location $l = (x, y)$. We generate these likelihood functions at each reference point on the radio map during the offline training phase. In order to find the location of the MS when it observes the RSS vector $\hat{\mathbf{o}} = (\hat{p}_1, \hat{p}_2, \ldots, \hat{p}_m)$, we apply this observation to (18) and (19) at each reference point on the map to find the expected value of the location.

4.1.2 Ray tracing assisted closest neighbor (RT-CN)

Generally an RSS radio map is generated using on-site measurement in a process called training or fingerprinting. On site measurement is a time and labor consuming process in a large and dynamic indoor environment. In [30] we have introduced two alternative methods to generate a radio map without on site measurements. The RT-CN algorithm uses a two-dimensional RT to generate the reference radio map. During localization MS applies the NN algorithm to the simulated radio map. In this way we can generate a very high resolution radio map and obtain higher localization accuracy. In order to generate an accurate radio map in this technique the localization system requires to know the location of access points within the coverage area.

4.2 TOA based localization algorithms

There are two shortcomings with current RSS based localization techniques. The first limitation is caused by the fact that RSS based systems do not use the physical characteristics of the signal directly and rely on an environment dependent radio map which needs to be generated and calibrated for each and every building, thus RSS based algorithms are restricted to a campus or inside a building area, and do not scale well for large service areas. The second shortcoming of RSS based algorithms is low accuracy. In mission critical applications such as public safety, patient tracking, *etc*. the positioning system must be able to find the location with an estimation error of less than 1–5 meters in urban/indoor areas. In order to achieve such a high accuracy the localization algorithm must rely on other signal metrics such as TOA of a signal. In this section we describe two TOA based data fusion techniques that can be used for urban/indoor positioning applications.

4.2.1 Least square TOA (LS-TOA)

TOA based positioning systems estimate the distance between the MS and all the AP's in an area by measuring TOA of a transmitted signal. Let r_i be the TOA based estimated distance between the MS and $\mathrm{AP_i}$, as defined in. Any inaccuracy in clock or measurement errors creates an error in distance estimation. In an ideal scenario, MS can identify its location by using three distance estimates from three AP's (AP_1–AP_3) in a process called triangulation.

Let (X_M, Y_M) be the location of MS to be determined, $r_1, r_2, \ldots, r_m$ are estimated distances between MS and AP_1–AP_m which are located at $(x_1, y_1) \ldots (x_m, y_m)$ respectively. It can be shown that the location of MS is the solution to the set of linear over-determined equations defined by [19]:

$$X = [X_M Y_M]^T \ ; \ HX = b \tag{23}$$

where H and b are *(m-1)* $\times$ *(m-1)* and *(m-1)* $\times$ *1* constant matrices. The least square solution for this set of equations can be derived as [31]:

$$\hat{X} = (H^T H)^{-1} H^T b \tag{24}$$

Another way to look at the LS-TOA location estimation algorithm is to view it as a minimization problem, with an objective function:

$$f(\mathbf{x}) = f(x, y) = \sum_{i=1}^{m} \left(\sqrt{(x - x_i)^2 + (y - y_i)^2} - d_i \right)^2 \tag{25}$$

where m is the number of access points, and d_i's $(i = 1, 2, \ldots m)$ are the observed range measurements from each AP. The square-root term is readily recognized as the range between a point (x, y) in the Cartesian coordinate system, and an AP located at (x_i, y_i). The difference in the parentheses is commonly called the *residual* of the estimate. Iterative variations of LS-TOA algorithm try to find the point (x, y), where $f(x, y)$ is minimized [32–34].

4.2.2 Closest-Neighbor with TOA grid (CN-TOAG)

The performance of LS-TOA algorithm is very sensitive to UDP conditions. Moreover, implementation of LS-TOA using (24) requires a complex matrix operation. Reference [35] introduces a TOA based pattern matching localization technique, Closest-Neighbor with TOA Grid (CN-TOAG) Algorithm, where the observed distance measurement vector is compared to vectors of expected distances in the radio map that characterize a given indoor area. Associated with each point in radio map is a vector of distances from each AP. This vector is known as the *range signature*. The CN-

TOAG algorithm compares the vector of observed distance measurements to the range signature at each point, and selects the point with the minimum Euclidean distance as the location estimate. It must be noted that the range signature associated with each point is exact, since it is based on straightforward geometrical calculations. In this way the localization system does a database search rather than a complex matrix operation as defined by (24). The second advantage of this technique is that it makes the estimation error a bounded value. Application of Eq. (24) for an indoor environment with UDP conditions can generate very large errors but CN-TOAG estimated location must be a reference point within the radio map. It must be noted that the estimation accuracy of the CN-TOAG algorithm; like most pattern matching based localization algorithms; depends on the granularity of the radio map, which is determined by the spacing between the reference points.

5. Comparative Performance Evaluation

In this section, based on UWB measurement calibrated ray tracing analysis of the behavior of the indoor radio channel, we describe a framework and a scenario for comparative performance evaluation of the algorithms introduced in Section 4. We first describe the frame work and the experimental scenario for performance evaluation. Then we discuss the simulation results for maximum likelihood RSS based location estimation, RT-CN, LS-TOA, and CN-TOAG algorithms.

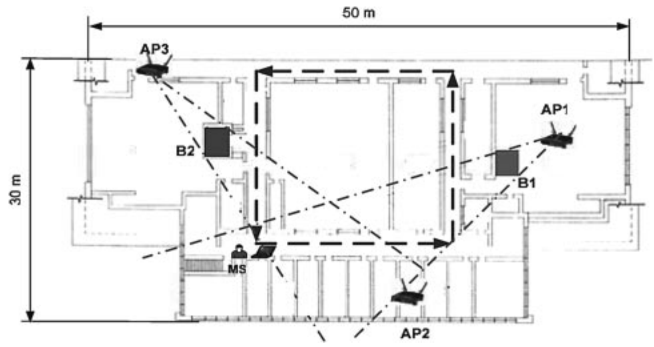


Fig. 8. Experimental scenario.

5.1 Experimental scenario and framework

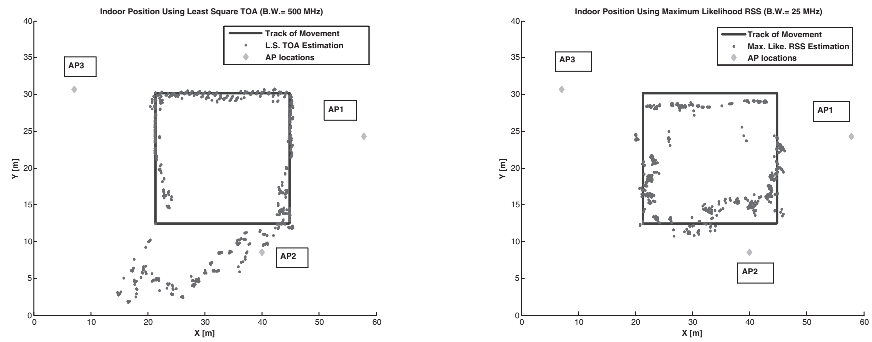
To assess and compare the performance of RSS and TOA based localization algorithms, we have implemented a simulation environment as shown in Fig. 8. This testbed simulates the third floor of the Atwater Kent building located in Worcester Polytechnic Institute, which is a typical multi floor office building. Three access points (AP_1–AP_3) are located in this floor at known locations. MS moves along existing hallways on this floor which consists of 578 points. B1 and B2 are a metallic chamber and a service elevator located in this floor, respectively. Both B1 and B2 obstruct the DP component of the transmitted signal from AP_1 and AP_3 in some locations on the movement track, causing ranging estimation errors by generating UDP channel profiles. Our objective is to determine the X–Y location of the MS by applying various RSS and TOA based localization algorithms, and compare their performance and bandwidth requirements.

For comparative performance evaluation of RSS and TOA based algorithms we need to define a wideband channel model between AP_1–AP_3 and MS at different locations of the test area where we examine the performances. We use a two-dimensional RT; which encompasses the geometrical information of the floor plan in addition to the reflection and transmission coefficients of building materials for this building; as our wide band channel modeling tool.

In this paper we present a comparison among two RSS based (RT-CN and Maximum likelihood RSS based location estimation) and two TOA based (LS-TOA and CN-TOAG) algorithms for applications with bandwidths of 25 and 500 MHz, representing typical WLAN and *wireless-personal-area-networks* (WPAN) geolocation applications. The required radio map for pattern matching based algorithms contains a grid of 1040 reference points covering the entire floor plan and is generated by RT. This radio map is used in both RT-CN and CN-TOAG localization techniques. This approach gives us a repeatable framework for performance evaluation of any TOA or RSS based localization algorithm.

5.2 Simulation results

The overall track of movement of MS along with the estimated track by LS-TOA algorithm in a 500 MHz system and the estimated track by a maximum likelihood RSS based estimator with only 25 MHz of bandwidth are depicted in Fig. 9(a–b) respectively. The starting point index on the track is the lower left corner of the path. We observe that LS-TOA algorithm experiences large errors ($10 < \text{DME} < 40$ m) on the lower horizontal part of this track while it provides very accurate estimation ($0 < \text{DME} < 1\,\text{m}$) for the other parts of the track. This observation motivates us to classify the points on the path into two distinct classes. The first class is the set of points that observe DDP channel profiles from all three access points (DDP points). The second class includes all the points that observe one or more UDP channel profiles from access points (UDP points).

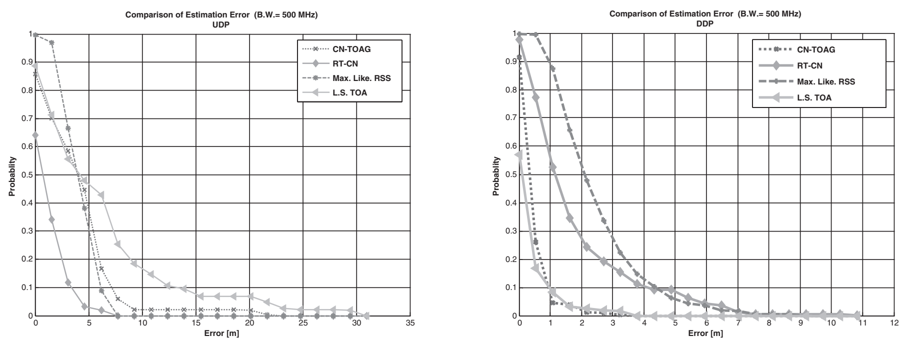


(a) LS-TOA (BW:500 MHz)   (b) Max. like. RSS (BW:25 MHz)

Fig. 9. Estimated track.

Visual comparison of Fig. 9(a–b) reveals that the performance of a 25 MHz RSS based localization algorithm is superior to a 500 MHz TOA based system at UDP points. However, if we limit our experiment to all DDP points on this track and use a wide band receiver ($\text{BW} > 200\,\text{MHz}$), we see that TOA based algorithms perform better than RSS based techniques. Statistical comparison between the RSS based and TOA based techniques in a system with 500 MHz of bandwidth through their *complementary-cumulative-distribution-function* (CCDF) of localization error at both UDP and DDP points are depicted on Fig. 10(a–b) respectively. These CCDF graphs validate our previous observation.

The effect of bandwidth on localization error at all points on the path, are illustrated in Fig. 11(a–b). It is obvious that RSS based algorithms outperform TOA based algorithms in a 25 MHz system. This shows that TOA based localization is not a suitable solution for a wireless communication system with limited bandwidth such as WLAN.

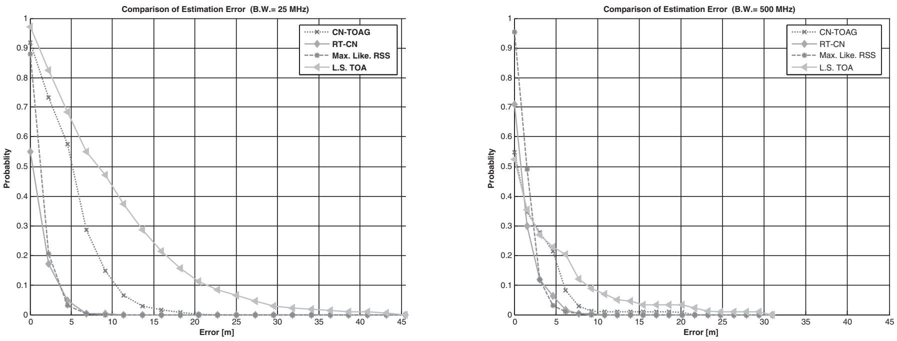


(a) UDP Points   (b) DDP Points

Fig. 10. Complementary CDF of localization error.

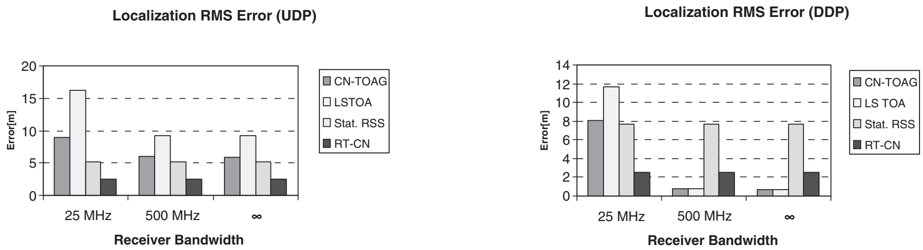
Comparison between Figs. 10(a–b) and 11(b) shows that in our scenario RSS based algorithms show a better performance compared to the TOA based algorithms due to the number of UDP points on this track.

We have included *root-mean-square* (RMS) of localization error at various bandwidths for both RSS and TOA based techniques at UDP and DDP points in Figure 12. The performance of TOA based systems in DDP points can be improved by increasing system bandwidth [Fig. 12(a)]. Although increasing system bandwidth reduces localization error in TOA based algorithms, but TOA based techniques can not outperform RSS based algorithms at UDP points [Fig. 12(b)]. Another important observation is that increasing the bandwidth beyond 500 MHz does not have a major impact on localization performance.



(a) BW: 25 MHz (b) BW: 500 MHz

Fig. 11. Effect of bandwidth in localization error at all points (UDP+DDP).



(a) UDP Points (b) DDP Points

Fig. 12. RMS of localization error.

6. Summary and Conclusions

With recent proliferation of wireless devices and networks, support for localization services using radio signals has attracted tremendous attention in research community. This article has described how RSS and TOA of a signal can be used for indoor geolocation application. A comparative performance evaluation among different RSS and TOA based localization algorithms and their bandwidth requirements is provided. The performance of RT-CN and statistical maximum likelihood RSS based positioning algorithms are compared with CN-TOAG and least square TOA based localization algorithms. The accuracy of TOA localization in DDP points depends on the system bandwidth. Increasing bandwidth of the system does not necessarily improve the accuracy of TOA based localization in UDP points. These observations suggest that by identification of UDP profiles we can improve the performance of a geolocation system using RSS based algorithms.

Acknowledgments

The authors would like to thank Dr. Allen Levesque for his constructive review and comments.

Appendix

Continued on next page.

Table 1. List of acronyms.

Acronym	Description
AOA	Angle of Arrival
AP	Access Point
BW	Bandwidth
CCDF	Complementary Cumulative probability Distribution Function
CDF	Cumulative probability Distribution Function
CN-TOAG	Closest-Neighbor with TOA Grid localization algorithm
DDP	Dominent Direct Path
DME	Distance Measurement Error
DP	Direct Path
FDP	First Detected Peak
GPS	Global Positioning System
LOS	Line of Site
LS	Least Square algorithm
LS-TOA	Least Square - TOA based localization algorithm
MAC	Medium Access Control
MS	Mobile Station
NLOS	Non Line of Site
NN	Nearest Neighbor localization algorithm
OLOS	Obstructed Line of Site
PDF	Probability Distribution Function
POA	Power of Arrival
RMS	Root Mean Square
RSS	Received Signal Strength
RT	Ray Tracing
RT-CN	Ray Tracing - Closest Neighbor localization algorithm
Rx	Receiver
TOA	Time of Arrival
Tx	Transmitter
UDP	Undetected Direct Path
WLAN	Wireless Local Area Network
WPAN	Wireless Personal Area Network

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