A Bayesian Sampling Approach to In-door Localization of Wireless Devices Using Received Signal Strength Indication

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Abstract

This paper describes a probabilistic approach to global localization within an in-door environment with minimum infrastructure requirements. Global localization is a flavor of localization in which the device is unaware of its initial position and has to determine the same from scratch. Localization is performed based on the Received Signal Strength Indication (RSSI) as the only sensor reading, which is provided by most off-the-shelf wireless network interface cards,. Location and orientation estimates are computed using Bayesian filtering on a sample set derived using Monte-Carlo sampling. Research leading to the proposed method is outlined along with results and conclusions from simulations and real life experiments.

1. Introduction

The boom in wireless networks over the past few years has given rise to a large number of available mobile tools, and their applications are becoming more and more sophisticated by the year. Wireless networks have become a critical part of the networking infrastructure and are available in most corporate environments, airports, shopping malls, hotspots. There is even talk of WiFi enabled cities, with Paris, France, being one of the first targets (see [8]). The fact that wireless networking enables mobility is a key in building "intelligent" mobile devices to perform many routine tasks. Smart devices and homes that are capable of adjusting themselves to provide maximum comfort to a user are slowly becoming reality. With growing demand for the deployment of such systems, network researchers have to address a fundamental and well-known problem in the field of robotics: determining the physical position of a mobile node using uncertain sensors (localization). Location awareness also plays an important role in the development of ubiquitous computing environments with tremendous potential in personal navigation and security, health-care, disability aids, etc.

Many commercial and residential establishments are already equipped with off the shelf wireless access-points (WiFi: IEEE 802.11b, for example) and most off-the-shelf mobile devices today are wireless enabled. Most of these devices are capable of measuring signal strength of received data as part of their standard operation. This paper outlines our research towards using this signal strength, the Receive Signal Strength Indication (RSSI), to reliably determine the location and orientation of a device. One of the significant contributions of this paper is to show that reasonable estimates may be achieved using RSSI readings from a small number of access points, and potentially even a single access point, depending on the structural symmetry and location of the access point in the environment.

2. Localization Techniques

Many popular location estimation techniques like RADAR (RAdio Detection And Ranging) and GPS (Global Positioning Systems) [12] have been in service for several years or decades now. Both these techniques rely on measuring the time taken by radio waves to propagate, and a fairly precise location estimate (relative to the location of the tracking device) may easily be determined by calculating differences in this propagation times. Other methods to determine the location of mobile bodies include LASER (Light Amplification by Simulated Emission of Radiation) and SONAR (Sound NAvigation and Ranging) [13] based techniques. These methods are also widely used in commercial and industrial equipment to estimate the location of mobile bodies indoors, underwater, or in other places.

Many of these approaches rely on proprietary techniques and either require the use of additional

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equipment for deployment or rely on some distinguishing characteristics specific to the environment in which the system is deployed. Furthermore, they require that the targets to be detected are more or less within the receivers' line of sight. This factor prevents, or at least restricts, the use of such systems in populated areas where such a line of sight may not be available. This limitation severely reduces the feasibility of successful deployment in a ubiquitous computing environment where mobile devices (targets) may be wearable or implanted and cannot remain within the receivers' line of sight. RSSI readings from a Radio Frequency (RF) device, on the other hand, are available from the device without the need for a line of sight. While RF waves are capable of penetrating many physical boundaries or structures, these do affect the RSSI reading, albeit in a somewhat predictable fashion. This predictability makes it possible to map RSSI readings from a fixed access point to a region, and thus makes localization using RSSI readings feasible. In addition, these techniques can be easily combined with outdoor-specific techniques to achieve the best possible estimates. For example, cellular phones may use GPS systems integrated into the mobile terminals or use signal strength measurements to trilaterate or triangulate their position relative to fixed base stations [9,10].

2.1. RSSI Based Localization Approaches

Due to the boom in wireless networking and high demand for wireless networking infrastructure, several products that enable wireless networking using IEEE 802.11x, Bluetooth, and other technologies are available and can be fitted to almost any mobile device available today. Furthermore, we can expect wireless networks to play a significant role in the future of ubiquitous computing. As a consequence, techniques to derive location estimates from Received Signal Strength Indication (RSSI) of wireless signals are rapidly gaining popularity.

RSSI based localization techniques generally consist of two phases: A training phase and an estimation phase. In the training phase, a mapping between wireless signal strength and various predefined positions in the environment is established. This is typically achieved by collecting RSSI samples at the predefined locations. In most cases, the environment is divided into cells in order to define these locations. In the estimation phase, an estimate of the target's location is computed using the signal strength mapping (a.k.a. wireless map) via probabilistic or deterministic techniques.

RSSI based location estimation techniques are broadly divided into deterministic and probabilistic techniques. For the use of a deterministic technique, the physical area making up the environment is first divided into cells. Next, the training is performed in which readings are taken from several fixed, known access points. Finally, localization is performed by executing a determination phase in which the most likely cell is selected by determining which cell the new measurement fits best [2,14,17].

Probabilistic methods, on the other hand, construct a probability distribution over the target's location for the physical area making up the environment. In order to estimate the location of the target, different statistics like the mode of the distribution or the area with highest probability density may be used. While probabilistic techniques provide more precision, a trade-off between computational overhead and precision is introduced.

An extended Kalman filter [1] based approach is presented in [9], in which an attempt is made to estimate the intra cell position of a cellular device using RSSI readings from base stations. This estimate, in combination with movement pattern data and velocity vectors, is used to estimate the next cell crossing.

A Bayesian filter based approach is proposed in [16], in which the authors utilize a Bayesian belief network to derive a posterior probability distribution over the target's location. The state-space over all possible locations of the target node is discretized and then used to develop a Bayesian belief network, given: 1) the conditional probabilities of an RSSI reading being measured at each possible location and, 2) an a-priori probability distribution of the node being at a different location. The posterior distribution is then derived by inverting this Bayesian network. The computational overhead involved in this technique is very high. Another similar proposition ([15]) consists of developing the Bayesian estimate based only on the strongest subset of access points rather than all of them.

3. Particle Filters

The technique described in this paper is a probabilistic approach using recursive Bayesian filters based on Sequential Monte Carlo Sampling (a.k.a. particle filtering). The proposed technique computes a posterior distribution of the target's location using Sequential Monte-Carlo Sampling, which is capable of using an arbitrary a-priori distribution to compute a posterior distribution. This method is less computationally intensive and is suited to an indoor wireless enabled environment where standardized distributions of RSSI readings may not be available.

3.1. Recursive Bayesian Filters

We model the localization problem as a stochastic process in which estimates of location and orientation are represented as probability distributions. I.e. if s_n and d_n

denote the state of the system and the RSSI measurement at time $t = n\Delta t$, respectively, where Δt is the sampling interval, we are trying to estimate the *evolving* state s_n given (d_1, d_2, …, d_n). A Bayesian filter is an algorithm that produces such an estimate, $p(s_n|d_1, \ldots, d_n)$, given a model of the measurements, $p(d_n|s_n)$, and the previous estimate, $p(s_{n-1}|d_1, \ldots, d_{n-1})$. This posterior distribution can then be used to compute any statistic of s_n.

A *recursive Bayesian filter* algorithm imposes the constraint that the estimate of $p(s_n| d_1, \ldots, d_n)$ should be generated using only the previous posterior density $p(s_{n-1}| d_1, \ldots, d_{n-1})$ and the most recent measurement d_n. This conveniently avoids storing the entire measurement sequence and reduces the amount of computation performed. Recursive Bayesian filtering requires that the following constraints are imposed on the system:

Markov System: The motion of the mobile node is dependent only on its current state and not on any of it's prior states: $p(s_n|s_0, \ldots, s_{n-1}) = p(s_n|s_{n-1})$

Memory-less channel: An RSSI value obtained in a given state is independent of those obtained in any other state: $p(d_1, \ldots, d_n| s_1, \ldots, s_n) = \Pi\, p(d_i|s_i)$

After applying these constraints, filtering is performed by *iterating* the following steps:

Prediction (Model update): Here, an attempt is made to predict all possible locations to which the node may have moved from its previous location:

$$p(s_n|d_1,\cdots,d_{n-1}) = \int_{s_{n-1}} p(s_n|s_{n-1})\cdot p(s_n|d_1,\ldots,d_{n-1})ds_{n-1}$$

Measurement update: Using the new RSSI measurement, we are now attempting to predict the exact location into which the node has moved:

$$p(s_n|d_1,\ldots,d_n) = \frac{p(d_n|s_n)\cdot p(s_n|d_1,\ldots,d_{n-1})}{p(d_n|d_1,\ldots,d_{n-1})}$$

The prediction model above is of the form $I(f) = \int f(s)\cdot p(s|d)ds$. The solution to this is easily rendered computationally infeasible for non-standard distributions $p(s|d)$. Therefore, instead of seeking an analytic solution, we propose the use of Monte-Carlo integration techniques ([3]), which sample the state space at random, independent of the number of dimensions ([4]). In these techniques, samples are drawn from a Proposal distribution $g(s|d)$ rather than the original $p(s|d)$, where $g(s|d) \propto p(s|d)$ ([6]). The integration technique used in this paper is Sequential Importance Sampling, a.k.a. particle filtering, a brief discussion of which follows.

3.2. Sequential Importance Sampling

Importance sampling permits the derivation of $I(f)$ by sampling from an arbitrary proposal distribution, $g(s|d)$, given that $g(s|d) > 0$ whenever $p(s|d) > 0$ (to guarantee that samples can be drawn for all states for which $p(s|d)$ is non-zero). The discussion in this section draws upon work presented in [5].

We can rewrite $I(f) = \int f(s)\cdot p(s|d)ds$ as

$$I(f) = \int f(s)\cdot w(s)\cdot g(s|d)\cdot ds \qquad (1)$$

where: $w(s) = \dfrac{p(s|d)}{g(s|d)}$

Now, N_p independent samples $\{s^{(i)}\}$ can be drawn according to $g(s|d)$ to approximate $I(f)$ using Monte Carlo integration as $I_{N_p}(f) \stackrel{\Delta}{=} \dfrac{1}{N_p}\sum_{i=1}^{N_p} f(s^{(i)})\cdot w^{(i)}$, where: $w^{(i)} \equiv w(s^{(i)})$

This set $w^{(i)} = \{w^{(1)}, w^{(2)}, \ldots, w^{(Np)}\}$ is referred to as the *importance weights*. This equation may be rewritten as $I_{N_p}(f) = \int f(s)\sum_{i=1}^{N_p}\left(w^{(i)}\cdot\delta_{s^{(i)}}(s)\right)ds$, where: $\delta_{s^{(i)}}(s) = \delta(s - s^{(i)})$ is the *Dirac Delta function.*

If the empirical (random) measure generated by samples $s^{(i)}$ drawn from $g(s|d)$ is denoted by $p_{N_p}(s|d)$ then:

$$p_{N_p}(s|d) \stackrel{\Delta}{=} \sum_{i=1}^{N_p} w^{(i)}\cdot\delta_{s^{(i)}}(s) \qquad (2)$$

Using this, Equations 1 and 2 may be related as $I_{N_p}(f) = \int f(s)\cdot p_{N_p}(s|d)\cdot ds \approx \int f(s)\cdot p(s|d)\cdot ds$ where the approximation improves as $N_p \to \infty$, i.e. as the number of samples chosen increase. The generated random measure represented by Equation 2, $p_{N_p}(s|d)$, not only contains a set of (random) values, a.k.a. *support points*, but also the *importance* (*weight*) of each support point. The complete specification of the distribution $p_{N_p}(s|d)$ can therefore be represented by the set $\{s^{(i)}, w^{(i)}\}_{i=1}^{N_p}$ and each such support point, denoted by $s^{(i)}_{1\cdots n}$, is a randomly generated *sequence of states* for our Bayesian filtering context. Given the previous state of the system, $\{s^{(i)}_{0\cdots n-1}, w^{(i)}_{n-1}\}_{i=1}^{N_p}$, we need to derive the current state of the system, $\{s^{(i)}_{0\cdots n}, w^{(i)}_{n}\}_{i=1}^{N_p}$ where the weights $w^{(i)}$ are computed as:

$$w_n^{(i)} = \frac{p(d_n|s_n^{(i)})\cdot p(s_n^{(i)}|s_{n-1}^{(i)})}{g(s_n^{(i)}|s_{n-1}^{(i)}\cdot d_n)} * w_{n-1}^{(i)} \qquad (3)$$

3.3. Generic Particle Filters

A common problem with Sequential Importance Sampling filters is *Degeneracy*, where, after a few iterations, all but one support point will have negligible weights. Consequently, a significant amount of computation is spent on updating particles that contribute insignificantly to the approximation of $p(s_n|d_{n-1})$ and the quality of the approximation decreases over time. To reduce the effects of degeneracy, it is necessary to remove particles with insignificant weights and concentrate on those with significant weights. This is accomplished, through a technique known as r*esampling*, by drawing N_p independent samples from $p_{N_p}\left(s_n \middle| d_{1\cdots n}\right)$ (Equation 2) whenever degeneracy falls below some threshold N_τ. Because resampling draws from a true posterior (in an approximate sense), the resampled weights remain uniform throughout. Algorithms that incorporate Importance Sampling have gained significance over the past decade. The term *particle filter* is prevalent for such algorithms and we will adopt this term. The support point set $\{s_n^{(i)}\}_{i=1}^{N_p}$ will be referred to as "*particles*". A pseudo code description for such an algorithm (adopted from [7]) is provided below:

$$\left[\left\{s_n^{(i)}, w_n^{(i)}\right\}_{i=1}^{N_p}\right] = PF\left[\left\{s_{n-1}^{(i)}, w_{n-1}^{(i)}\right\}_{i=1}^{N_p}, d_n\right]$$

FOR i = 1 TO N_s

  Draw $s_n^{(i)} \approx g\left(s_n \middle| s_{n-1}^{(i)}, d_n\right)$

  Assign the particle a weight, $w_n^{(i)}$**, according to eqn. 3**

END FOR

Calculate total weight $t = \sum\left[\{w_n^{(i)}\}_{i=1}^{N_p}\right]$

FOR i = 1 TO N_p

  Normalize $w_n^{(i)} = t^{-1} \cdot w_n^{(i)}$

END FOR

Calculate N_{eff} using $N_{eff} = \dfrac{1}{\sum_{i=1}^{N_p}\left(w_n^{(i)}\right)^2}$

IF $N_{eff} < N_\tau$

  Resample according to $w_n^{(i)}$

END IF

Figure 1. Generic Particle Filter [7]

4. The Particle Filter Approach to RSSI Localization

As shown in the previous section, a particle filter allows for a high degree of flexibility as far as the state model is concerned. The filter is capable of handling substantially complex state models including those that are non-linear and non-Gaussian. This allows the use of arbitrary process models, which is of particular interest since a model of wireless signal strength distributions should be neither linear nor Gaussian.

We are primarily interested in tracking the location of a wireless enabled mobile node or device in an indoor environment and thus need to develop valid measurement and movement models for it. Here, we define the location of the mobile node in terms of its position in space and its orientation relative to a reference frame. The movement model depends on the agent carrying the mobile node (e.g. the movement model for a human carrying a laptop computer would be considerably different from that of a wireless enabled robotic vacuum cleaner). The measurement model, on the other hand, is largely a function of the environment and of the location of the access points.

4.1. Measurement Model for the Particle Filter

A typical wireless communication system consists of two nodes exchanging information with each other. For the proposed localization approach to work, it is necessary that one of these nodes be at a fixed location at all times and we require a setup where the mobile node, or target, communicates with one or more wireless access points. Such a setup is typical in most buildings and homes where wireless network access is available via IEEE 802.11x, Bluetooth, or other technologies. E.g., a WiFi access point in such a setup will typically respond to a *probe packet* from a node with a *probe response packet*. The node can then extract the Received Signal Strength Indication (RSSI) reading from this probe response packet to build our measurement model.

Wireless Maps: To estimate the location of a mobile node from a Received Signal Strength Indication, a statistical representation of the same across the indoor environment is necessary. Building such a representation involves collecting a number of RSSI readings from each access point at every possible location in the indoor environment. These readings represent a *wireless map* of the environment and form the measurement model for the particle filter. Since it is infeasible in practice to collect readings at every possible location the mobile node may be in, it is necessary to discretize the physical area of the environment by dividing it into cells. This introduces a trade-off between precision in localization and cell size.

Since we are also interested in estimating orientation of the mobile node, we need to construct such wireless maps for every orientation the node may take. Again, this is practically infeasible and thus it is necessary to discretize orientation.

We represent a wireless map tuple by one set of readings from each access point per cell per orientation: $(x, y, \theta, \{AP_1, AP_2, \ldots, AP_k\})$ where:

- x & y represent the Cartesian coordinates of a physical point on the map
- θ represents the orientation at that physical point
- AP_1, AP_2,…, AP_k represent vectors containing a set of readings collected from access points 1, 2,…, k

4.2. Movement Model for the Particle Filter

A typical movement model representing the motion of a mobile node generally consists of velocity and/or acceleration parameters. Construction of such models is straightforward, considering that models representing human or robot motion are readily available.

For our purposes, we assume that the target's movement follows a Gaussian velocity model. Following this assumption, we pick a normally distributed random variable to update the location of each particle during the model update step.

Figure 2 shows the probability of particle displacement if the current location of the particle is the center of the shaded circle. Darker regions here indicate higher probabilities that the particle moves to that location after the measurement update step. Since the target node cannot cross walls, the particles are restricted from crossing walls as indicated in the figure.

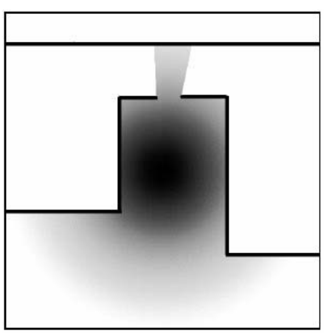

Figure 2. Particle displacement distribution

5. Implementation and Experimental Results

5.1. Experimental Setup

To validate the presented approach, a test network was set up on the at The University of Texas at Arlington (third floor, Nedderman Hall). The environment consists of four corridors, one lounge, and two wireless access points. The entire area was divided into 88 cells in order to derive the wireless maps. Two wireless access points are set up at the ends of one hallway to achieve coverage of the entire area and to reduce the structural symmetry in the environment. While we use an IEEE 802.11b wireless Ethernet network, the proposed method works with any wireless technology that provides RSSI readings as part of standard operation. The environment with the access point locations and cells is as shown in Figure 3.

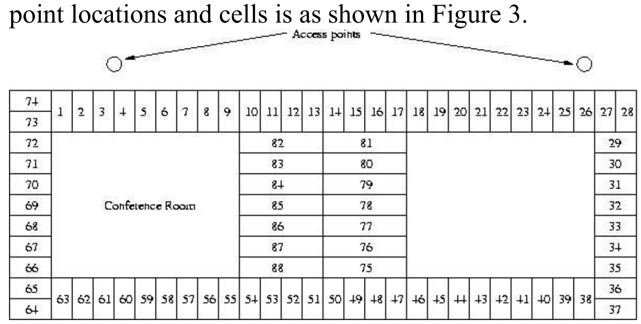

Figure 3. The environment

5.2. The Training Phase – Building the Wireless Map

The training phase consists of building a wireless map of the environment and has to be executed only once for a given environment if the access points remain in the same location. We build a wireless map of the environment by sampling the space and gathering data at various predefined points in the indoor environment.

This map forms a statistical representation of the environment based on the two access points. To build the map, the floor area forming the indoor environment was measured and divided into cells of known dimensions as shown in Figure 3. Sample sets of 100 RSSI readings from each access point are collected in each cell. Readings from multiple access points are collected concurrently so that covariance measures between readings from different access points are valid. Since the human body absorbs some of the energy of the radio waves, the orientation of the operator with respect to the access points while collecting readings can significantly affect the map. Therefore, we collect readings for eight different orientations in each cell. This sample set forms the data for computing the wireless map.

Figure 4 shows a wireless map of the environment developed using the top right access point. Signal intensity is denoted by shading in the environment: darker shades indicate regions with higher intensity.

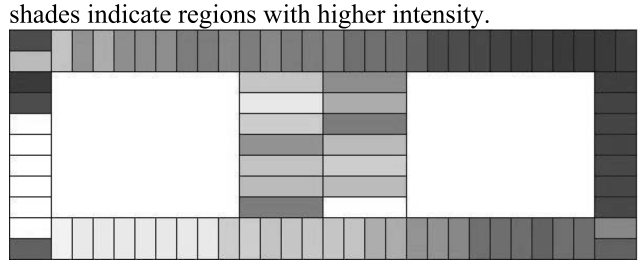

Figure 4. Wireless map for the top right access point

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5.3. The Localization Phase

To use the particle filter, we first initialize all three dimensions of the initial particle using uniform distributions. Subsequently, the particle filter uses the new RSSI readings to update the probability distribution for the location of the target across the environment.

To facilitate the measurement update using the wireless maps in an efficient manner and to account for readings that did not occur during the training phase, we represent the actual entries in each cell of the wireless map by a multivariate probability density function representing the set of readings. Readings within a cell seem to follow a Gaussian distribution as shown in Figure 5 and therefore, we use the Gaussian probability density function:

$$p(x) = \frac{1}{\sqrt{(2\pi)^k |V|}} \cdot e^{\left[-\frac{1}{2}(X-\overline{X})^T \cdot V^{-1}(X-\overline{X})\right]}$$

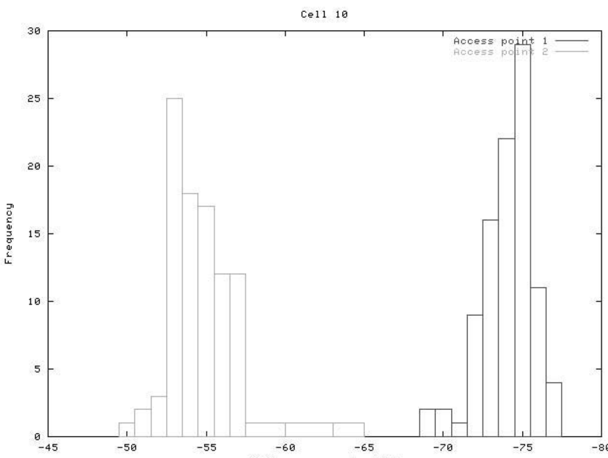

Figure 5. Signal strength distribution in a cell

In this function,

- $|V|$ denotes the *determinant* of the covariance matrix: $V = \begin{pmatrix} \sigma_1^2 & \cdots & \sigma_{1k}^2 \\ \vdots & \ddots & \vdots \\ \sigma_{k1}^2 & \cdots & \sigma_k^2 \end{pmatrix}$ with σ as the standard deviation, and σ_{lm}^2 the covariance between *l* and *m*, i.e. $\sigma_{lm}^2 = \frac{\sum_i \left(d_l^{(i)} - \overline{d}_l\right)\left(d_m^{(i)} - \overline{d}_m\right)}{n-1}$
- *X* are the RSSI readings: $X \equiv (d_1 \cdots d_k)^T$
- $\overline{X}$ is the mean of *X*
- $d_k^{(i)} = AP_k^{(i)}$ is the i^{th} reading in the set of readings taken from access point *k*, After computing this density value for the current reading, it is used as the weight of each particle.

Once the measurement update is performed, all three dimensions of the particles are updated based on a zero-mean Gaussian movement model. If, during this resampling, one or more particles are found to “cross” a wall or other physical barrier, they are simply deleted and new particles are added to substitute them. We then resample the particles based on their new weights.

While the particle filter generates a posterior distribution of particles, it is up to a user to extract a desired estimate from this distribution. We have implemented three such estimates:

Estimate 1: Sum of the Inverse Distances: This method computes the estimation weight of each particle with respect to its distance from all other particles. The inverse of the distance from one particle to another provides a weight with respect to that particle. The cumulative weight of a particle with respect to all other particles is used as the final estimation weight. Finally, the particle with the highest weight is chosen as the best estimate.

Estimate 2: Highest Particle Density in a Circle with Given Radius: Here a different estimation weight for each particle is computed; the particle with the highest weight is chosen as the best estimate. To compute the weight, circles with a constant radius are centered on each particle. The number of particles in each circle is determined and used as the weight. In our experiments a radius of 1m is used.

Estimate 3: Mean of All the Particles: Unlike the two methods above, no estimation weights are computed in this method. The value of each dimension of the particle is averaged across all particles and the resulting numbers are used as the best estimate. The advantage of this method is that it runs in O(*n*).

In the following we will show results for the first two estimates. The reason for choosing these is that, while the mean can lead to good results in terms of average error, it will frequently fall on impossible locations in the case of multimodal probability distributions in the particle filter.

5.4. Results – Simulated Walkthrough

In this section, we present results of our experiment using simulated RSSI readings. The movement path of the mobile node, which simulates a node moving with non-constant velocities, is as shown in Figure 6. Figure 7 shows snapshots of the simulation program’s graphical display while it is running. We see that after an initial phase of finding the mobile node, the particles (population:3000) are able to follow the node. The actual mobile node’s location is represented by a white circle, particles are represented by small dots, and the various estimates discussed above are represented by shaded circles.

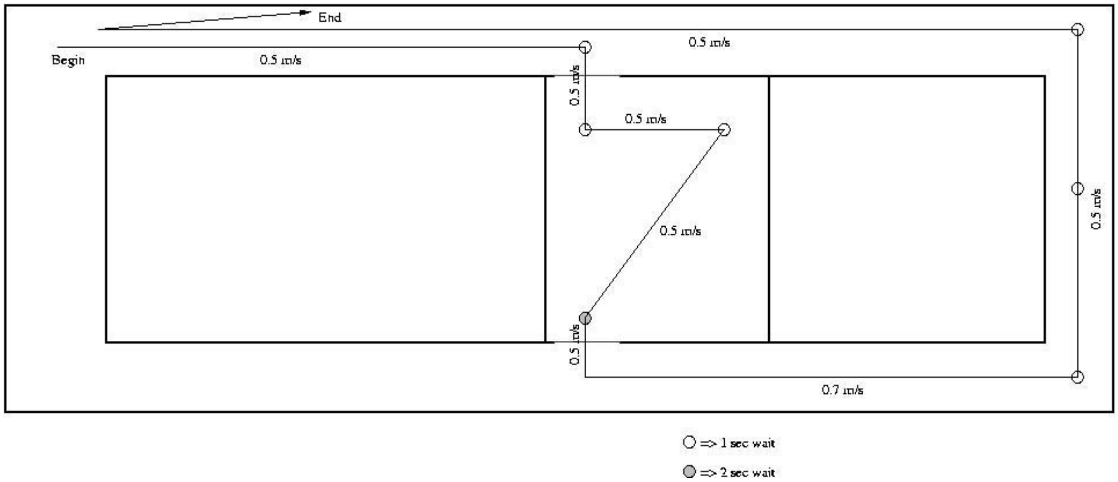

Figure 7. Movement path for the simulated walk through with velocities

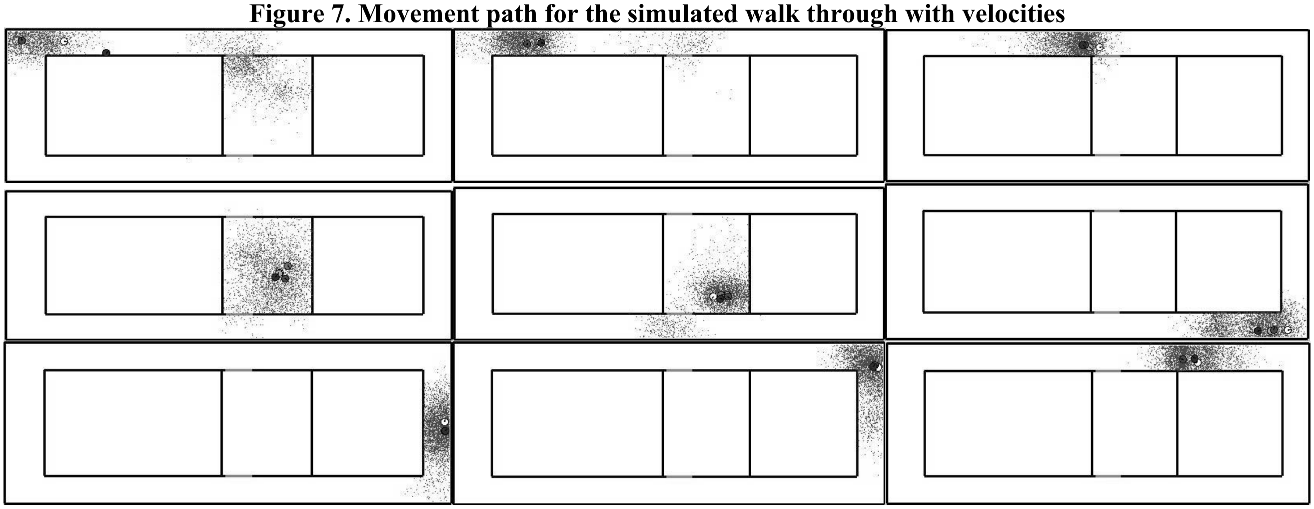

Figure 6. Simulation snapshots (simulated walkthrough mode)

As can be observed from the GUI snapshots, even with the assumption that the RSSI readings in a cell follow a basic Gaussian distribution, the system performs well at tracking the target

Estimation Errors

Data from the various location and orientation estimates was collected during the run and errors in estimation are determined by computing the difference between the true location and orientation values and those produced by the estimates. Figure 8 shows an error plot of estimate 1 for one simulated walkthrough.

In order to analyze the number of particles required to obtain estimates with the desired precision, trial simulations were run with varying number of particles (200 through 10,000). Data from these runs was collected for eight trials for each particle number value, and error plots for the two estimates (average location error) are presented in Figures 9 and 10. The error bars in these figures represent one standard deviation showing that

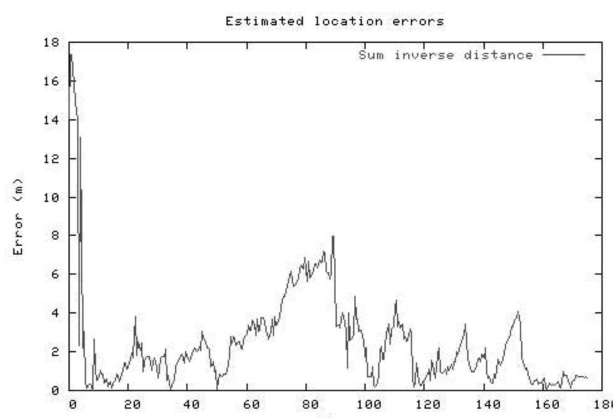

Figure 8. Location error

while the accuracy continues to improve when the number of particles is increased the magnitude of the improvement decreases significantly as the number of particles increases beyond 3000.

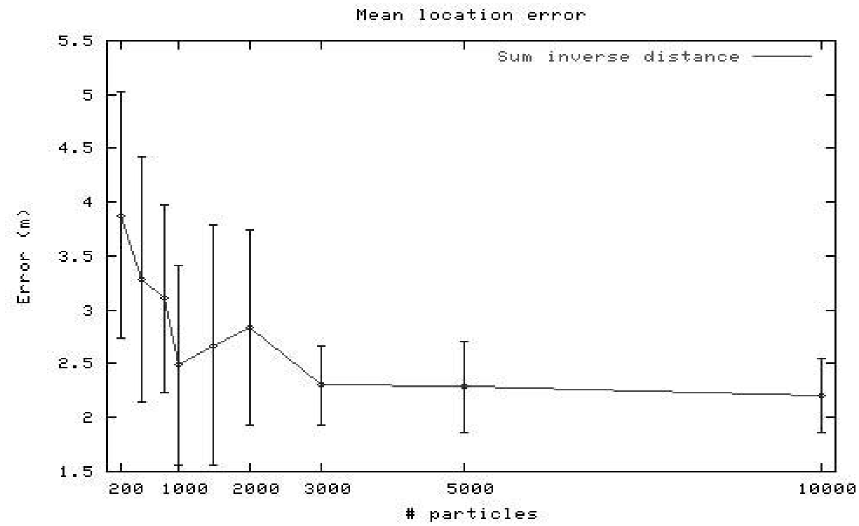

Figure 9. Average error in location (estimate 1)

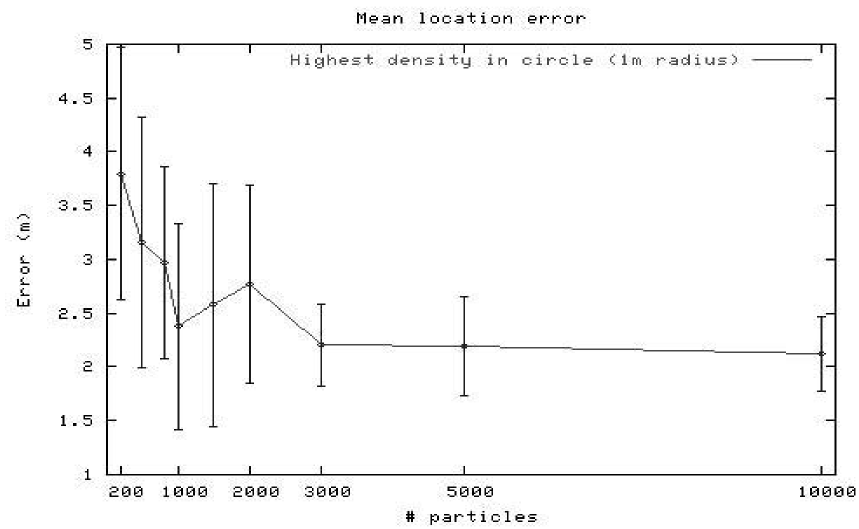

Figure 10. Average error in location (estimate 2)

5.5. Results – Real Walkthrough

In this section, we present results of experiments where RSSI readings from both access points were recorded during an actual "walk" through the environment. During the walk periodic RSSI measurements were taken from the network interface card and were stored on the computer. This recorded data was then used as the input to the simulation program and location estimates were derived using the particle filter. During the walk the user was following an engineered path so error estimates can be calculated.; this path taken by the walker is shown in Figure 11. Snapshots from the GUI of the simulation program are shown in Figure 12. Trial runs similar to section 5.4 were conducted with the recorded data; error plots are shown in Figures 13 and 14.

While the error is slightly higher than in the simulated walk through mode, the filter still tracks the mobile node correctly. The increase in average error is due mainly to systematic influences of the environment on the RSSI readings. These influences are caused by effects such as opened or closed doors and people or objects moving through the environment, which slightly alters the RSSI reading distribution in each cell.

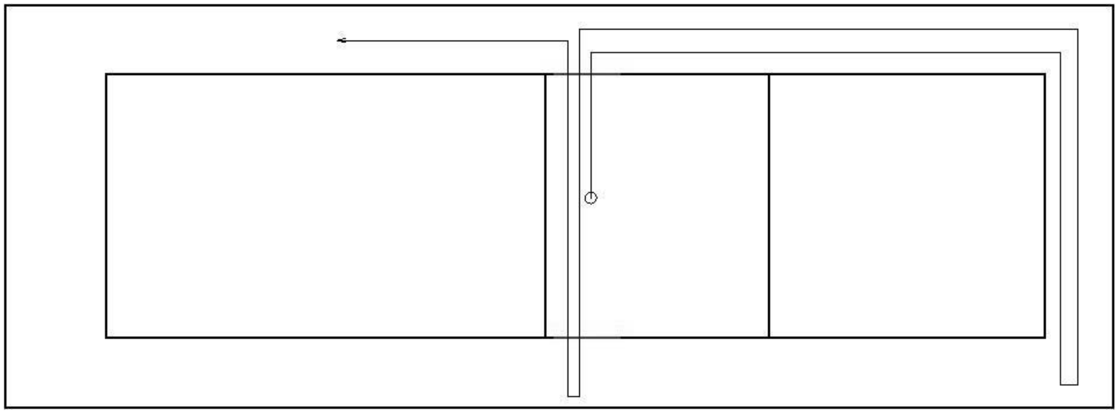

Figure 12. Movement path of the real walkthrough

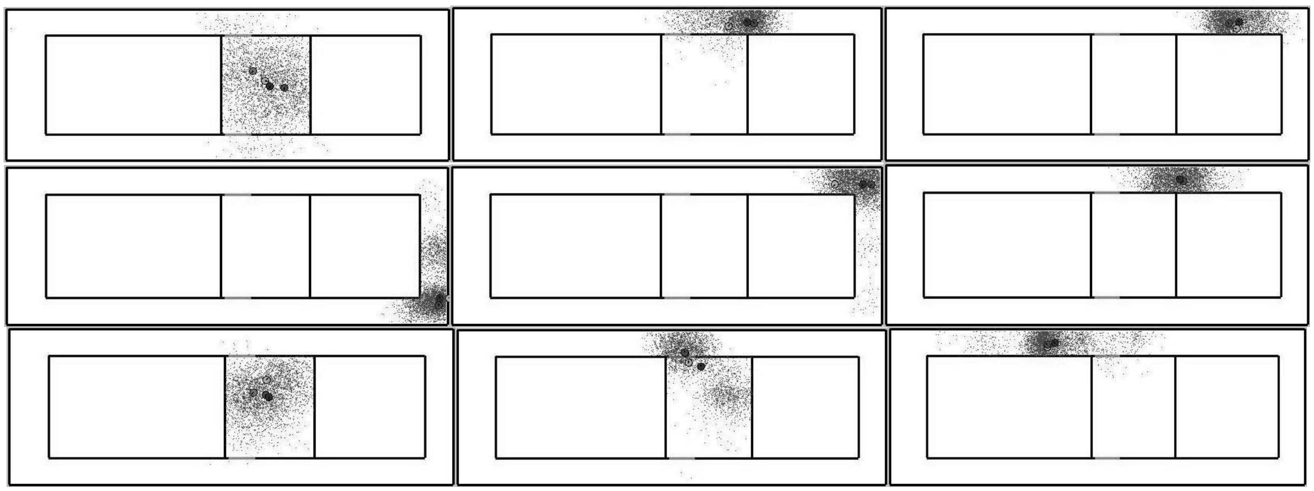

Figure 11. Snapshots of the localization interface during the real walkthrough

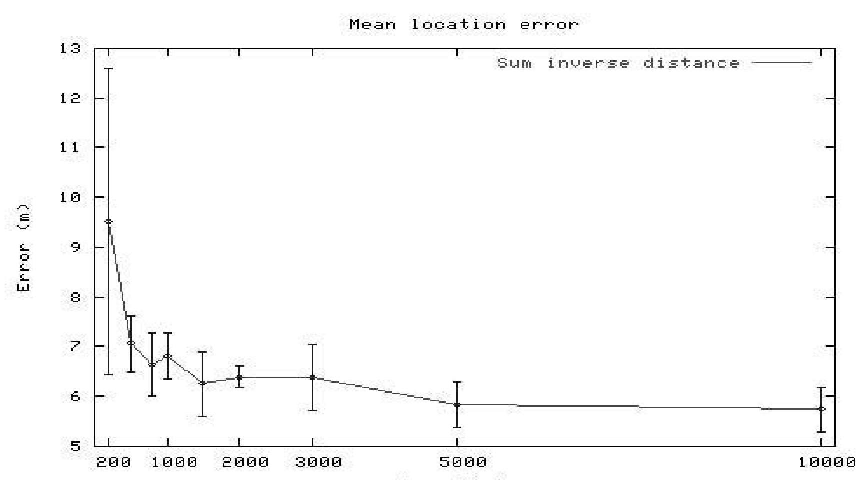

Figure 13. Average error in location (estimate 1)

6. Conclusions and Future Work

In this paper, we have presented a probabilistic approach to the localization problem using only RSSI readings, which almost all wireless devices are capable of measuring as a part of their standard operation. We have demonstrated the performance of the proposed approach through simulations and real life experiments performed in an indoor environment with two access points. These demonstrations show that even with all the required approximations, the system was successful at tracking the mobile node with a reasonable amount of precision. This illustrates the potential of our approach in enabling location awareness among existing devices with no additional infrastructure.

To improve the performance of the system, many of the approximations could be improved upon through research and study. The distribution of RSSI readings in a given cell under various conditions needs to be studied in detail to construct a better wireless map of the environment. Also, the movement model used has potential for improvement by using additional sensors which may easily be integrated with the existing particle filter.

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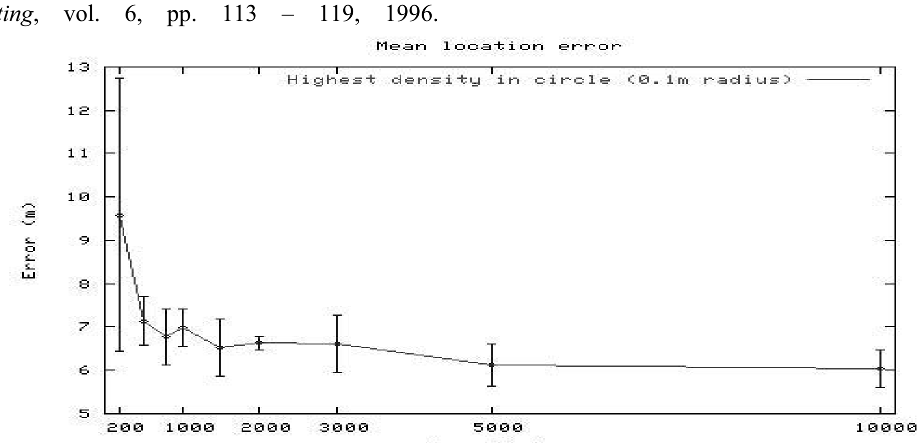

Figure 14. Average error in location (estimate 2)