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An RFID based indoor tracking method for navigating visually impaired people

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Abstract

This paper tackles the RFID based tracking problem in an obscured indoor environment. The proposed solution is an integral part of a navigation aid for guiding visually impaired people in a store. It uses RF signal strengths and is based on the Bayes Decision Theory. An observation vector is formed by received radio signal strength indication values, transmitted from three transmitters at distinct frequencies in the UHF band. The indoor area is divided into square grids, where each grid is considered as a class. The problem of tracking is expressed as classifying the observed radio signal strengths to the most likely class. A classification rule is formulated by incorporating a priori assumptions appropriate for the studied model. The proposed approach is tested in a laboratory environment. The results prove that the proposed approach is promising in tracking especially when the tracked person is guided by a system.

Key Words: *Tracking, location estimation, RF signals, Bayes, RFID, classification.*

1. Introduction

Several studies have been conducted to improve the navigation of visually impaired people in both indoor and outdoor environments [1-8]. A major challenge of navigation devices lies behind the requirement for a reliable positioning method in order to be able to guide the user in the correct direction. Location estimation algorithms are particularly exploited by services providing navigation aids, or by those tracking a person or an object in a certain environment. The technology used in location estimation and tracking depends on the type of the subject environment (indoor, outdoor, large scale, etc.) and also on the application. For example, Global Positioning System (GPS) or Geographic Information System (GIS) based systems are often utilized for large scale outdoor environments [1,2]. On the other hand, a pair of AM radio signal transmitters and a receiver, producing beep sounds when triggered, is preferred for the sake of simplicity and low cost, when a person wants to know the location of a particular object in a small scale outdoor environment [3]. For indoor environments, multiple ultrasound or infrared transmitters mounted on the walls or at the ceiling can be used [1,4]. Such a system enables estimation of the location of the receiver, by using received signal strength. However, line-of-sight requirement of ultrasound and infrared sensors limit their use in obscured environments. Use of passive Radio Frequency Identification (RFID) tags in a grid like structure is another alternative to track or estimate the location with respect to the nearest transmitter [5]. The radio signals do not require line-of-sight, and radio signal transmitters are easy to integrate into wireless networks. Hence, they have been particularly used for network based location estimation and tracking purposes [6-9]. By the term "network based" we refer to monitoring the location of a subject through a network.

Several localization and tracking systems proposed in the literature utilize distance measurement functions [10,11]. The distance measurement function measures the distance between a receiver and a transmitter. The Time Difference of Arrival (TDOA), the Time of Arrival (TOA) and the Received Signal Strength (RSS) are among the functions used for distance estimations. Takizawa et al. [10] state that TDOA distance measurement requires two different wireless media such as sound and radio waves and TOA distance measurement needs highly accurate time synchronization technology. On the other hand, RSS exploits either theoretical or empirical calculations for mapping the signal strength measurements to distance. However, radio signals are subject to reflections, diffractions and scattering in obscured environments. These result in multipath effect and time variance of the observation, hence performance decrease in the estimation. Statistical modeling approaches are incorporated for improving the performance in such cases [7-14]. These approaches include maximum likelihood [6,7,13] and Bayesian methods [8,9,12,14]. Generally, a radio signal propagation model is assumed first, and then statistical approaches are used to estimate the model parameters. The model and the formulations may change according to the application. For example, in order to estimate the distance to access points, the parameters of log-distance path loss model is extracted using the Bayesian Theorem in [8]. A hierarchical Bayesian graphical model improves the performance, when Wi-Fi signals collected by multiple terminals are processed for tracking device and personnel in a three floor building [9].

In this work, a medium scale obscured indoor environment is focused on. The aim is to monitor the location of a visually impaired person, by processing RSS indication (RSSI) levels sensed by an RFID tag carried by the visually impaired person. The tag collects signals from three RF transmitters broadcasting at distinct frequencies. The user is guided to follow a certain route by a tactile compass. The directions pointed out by the compass are exploited as a priori information by the location estimation algorithm. The subject environment and data collection system studied in this work are described in Section 2. Next, we introduce the path loss model and compare the measured RSS values with empirically generated ones in Section 3. The developed Bayes decision based tracking algorithm and its performance are presented in Sections 4 and 5, respectively.

2. Subject environment and data collection

Location estimation and tracking systems are often composed of two units: data collection and data processing. Data collection hardware can be composed of active or passive sensors such as infrared, ultrasound, RF or Wi-Fi transceivers. The selection depends on the type and scale of the environment and whether line-of-sight is required or not. Infrared and ultrasound sensors require line of sight which is not appropriate for large scale or obstacle filled environments [15]. In this work, we use radio signal transmitters and a single active RFID tag, which do not require line-of-sight. An RFID tag is an object that can be carried by being attached to or incorporated into a product, object, animal, or person for the purpose of identification using radio waves. RFID tags can be programmed to store and transmit data to be used for market or location sensing applications. There exist passive and active tags, where passive tags require no power source, and active tags do [16]. LANDMARC [17] is an RFID based location-sensing system which exploits a number of active tags separately for reference and tracking purposes. Its location reference tags are used to help location calibration, whereas tracking tags are attached to objects. The accuracy of the system is one to three meters. However, considering that four RFID readers are used for an indoor area in the scale of 36m^2, the expense of RFID readers will not justify deploying the system in a larger scale. Moreover, the placement and number of reference tags should be carefully designed since they affect the system performance.

In this work, we assume that an active RFID tag is attached to a compact portable hardware unit, and that unit is carried by a visually impaired person. The visually impaired person is navigated around in an indoor environment and is directed to follow a certain route. The environment considered in this work is a laboratory in the scale of (6.8, 19.5, 2.9)m. The area includes obstacles, which cause scattering and reflection of radio waves. Obstacles are walls, windows, wooden tables with 73 cm height and steel shelves (180x60x192cm), etc. One side of the room is covered with windows and the room walls are made of concrete blocks while the room ceiling is made of concrete with 2cm plaster and floor of concrete with 4cm chipboard. Measured data include recordings of RSS indicator (RSSI) levels from three UHF transmitters. RSSI measurements are carried out with the use of an active RFID tag and reader, and 3 transmitter-beacons. Each of the three transmitters is located at distant locations of the subject environment as in Figure 1, on the walls, in a way to form a triangle. The coordinates of TX1, TX2 and TX3 are (5.75, 0, 2.35)m, (1.2, 10.5, 2.9)m and (5.75, 19.5, 2.35)m, respectively. Each transmitter transmits RF signals at UHF band, with distinct frequencies (433.056 MHz, 433.344 MHz and 433.680 MHz) and with -10dBm. The tag is assumed to be carried by the person to be tracked, and it collects signal strengths from the three transmitters. The RSSI sensed by the tag is transferred to a computer via RFID reader by use of proprietary data collection software, and is processed by the computer (data processing system). RSSI values are directly proportional to the RSS levels; hence they possess a correspondence to the distance between the tag and the transmitter.

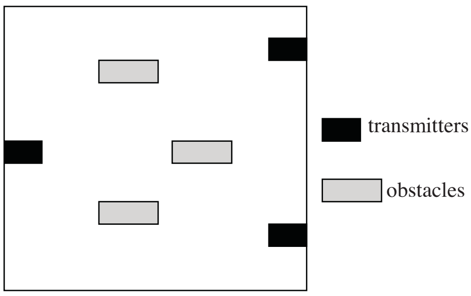

Figure 1. An example indoor environment and positioning of transmitters.

Special attention is required for adjusting the power levels of the transmitters. If the power level is too high, RSSI readings at the neighboring locations may become indistinct. If the power level is too low, RSSI readings from the most distant locations will be at noise level. As the scale of the subject environment exceeds the coverage of the transmitters, number of transmitters can be increased so that at least three transmitters have coverage at all locations. However, increase in number of transmitters may increase the duration of RSSI readings and hence may limit the responsiveness of the system. A high performance system can be designed by increasing both the number of the transmitters and the readers for larger scale environments.

3. Path loss model for indoor environment

RSS is location dependent as it is affected by factors such as attenuation due to the distance from the transmitter and existing obstacles. Buildings represent a complex environment of very large dimensions compared to wavelength. Reflection, diffraction and scattering of radio waves by structures inside a building result in the transmitted signal to reach the receiver through more than one path [18]. There are several approaches to indoor propagation prediction. In one approach, electromagnetic theory is applied using ray-tracing techniques. In this method, propagation predictions can be applied without performing propagation measurements first. However, computation times on personal computers can be long, and then, the predictions cannot be obtained interactively or with algorithms for estimating user locations. In the alternative approach, propagation models related to those for describing free-space propagation are empirically or statistically fitted to the measurement data. The resulting models are generally straightforward to apply, and prediction results can be computed quickly [18].

Note that RSS is a measure of the power received by the RFID tag from a transmitter and provides information as to location of the person carrying it. The received signal consists of direct, reflected, scattered and diffracted waves. According to Friis' formula, RSS is expressed in the following form:

$$P_r = P_t - P_L + G_r + G_t \tag{1}$$

where P_r is the received signal power (dB), P_t is the transmitted signal power (dB), $P_L(d)$ is the path loss (dB), and G_r and G_t are receiving and transmitting antenna gains, respectively.

For indoor environments, log-distance path loss model, among different path-loss models, in its simplest form often used for electromagnetic signals can be expressed as:

$$P_L(dB) = P_L(d_0) + 10n\log(d/d_0). \tag{2}$$

In (2), n is the path loss exponent depending on the building and surrounding medium, which indicates the rate of path loss with the increase of distance; d_0 is the reference distance, and d is the distance between the transmitter and the receiver. In our system, convenient empirical model equation is used, making the following assumptions [19]

$$P_L(dB) = A + B\log(d) \tag{3}$$

where A and B are unknown values. Some location estimation techniques in the literature aim to estimate the unknown parameters of (2) or similar log-distance path loss model, by use of statistical approaches [20,21]. The RADAR system uses the nearest neighbor method to infer a user's location [22]. Each signal strength sample is compared against the radio map and the coordinates of the best matches are averaged to give the location estimation. The accuracy of RADAR is about three meters with fifty percent probability. In this work, we start with estimating A and B values in equation (3) to form the empirical path-loss expression. For this purpose, we used an extensive set of measurements collected at 192 different locations in the subject environment. Figure 2 shows the measured RSS levels (through a spectrum analyzer) and the plot obtained by substituting empirically driven parameters in (3), for a single transmitter. The solid line refers to the plot generated through (3), and the stars refer to the measured levels. The plots exhibit similar behavior for the other two transmitters. Figure 3 represents the distribution of errors between empirically generated and experimentally measured RSS levels. The plots show that although the expected value of the error between the measured values and the empirically generated ones is close to zero, the standard deviation is unacceptably high. The average percentage of error is 32, 59, and 45, respectively for the three transmitters. The deviations are due to the fact that radio waves are affected by reflection, diffraction and scattering, and the subject environment is designed with many obstructions. As the distance between the tag and the transmitter increases, the deviation gets higher, due to increased probability of obstacles in between. As a result, the accuracy of location estimation will be very low if merely the path loss model and the nearest neighbor methods are used. This calls for the development of a new approach, where a priori information can be incorporated.

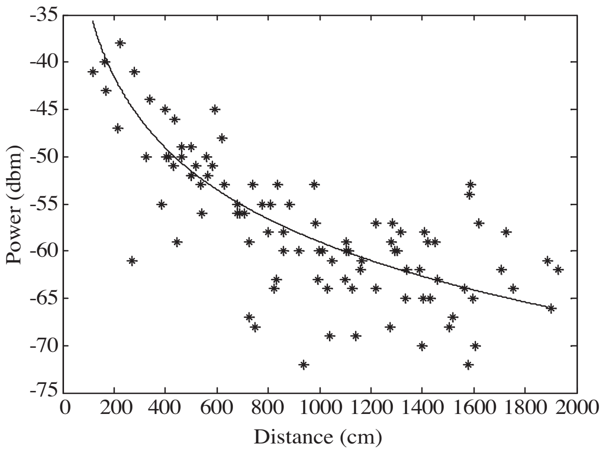

Figure 2. Comparison of experimental and empirically generated signal strength values.

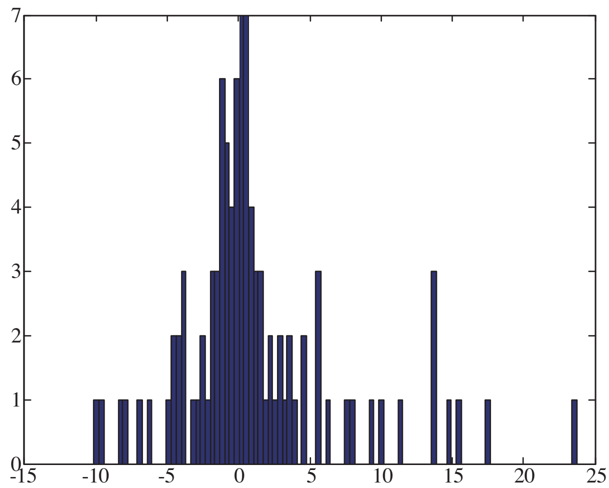

Figure 3. Histogram of error between the experimental and empirically generated signal strength values.

4. Location estimation with bayesian approach

When the signal propagation environment differs significantly from ideal conditions, RSS measurements are unreliable. In order to overcome this problem, we try to incorporate statistical signal processing techniques.

4.1. Bayes Decision Theory

The Bayes Theorem is essentially an expression of conditional probabilities. Consider an experimental study where the outcome (observation) is a feature vector x corresponding to a pattern. Assume that there exist N classes $C_1, C_2, ..., C_N$ where the observed pattern belongs to either one of these classes. The problem is stated as finding the class C_i, to which the observed pattern is most likely to belong [23]. For this purpose, often a discriminant function g(x) is used as:

classify x in C_i if gi(x) $>$ gj(x) $\forall j \neq i$.

The discriminant function gi(x) is often defined as;

$$g_i(\mathbf{x}) = \ln\left(p(\mathbf{x}\,|C_i)\cdot P(C_i)\right) = \ln\left(p(\mathbf{x}\,|C_i)\right) + \ln\left(P(C_i)\right) \tag{4}$$

where $p(\mathbf{x}\,|C_i\,)$ and $P(C_i)$ refer to conditional probability density function and probability of the ith class, respectively. Equation 4 is known as the maximum aposteriori (MAP) decision rule since it chooses the hypothesis which has the highest posterior probability.

4.2. Problem formulation

Let us assume that the received signal strength identification levels from the three transmitters by the RFID tag constitute feature vectors x. Equation (4) shows that a probability model for the feature vectors of each class is required. For this purpose, the indoor environment shown in Figure 4 is divided into 120cmx120cm (2λx2λ) square grids. The degree of signal attenuation especially depends on the dominant signal path (line-of-sight path). The power of the line-of-sight path decays with distance squared [18]. Hence, in our application a signal level change occurs with less than 2^2 from the center of a grid to the center of a neighbor grid.

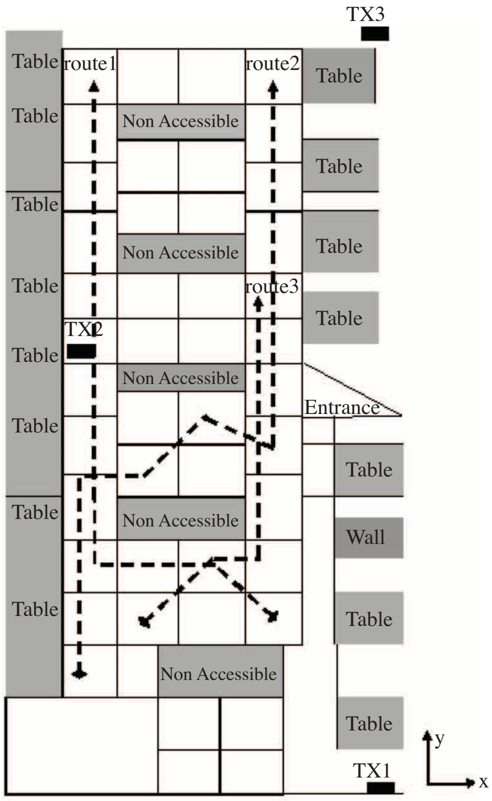

Figure 4. Part of the subject environment. ■ 's represent transmitters.

We assumed each grid as a class. For each class, we recorded 52 measurements from each transmitter, at the corners and at the center of the class, and when the person carrying the tag, and hence the tag's embedded small-sized spiral dipole antenna is facing in different orientations. A helical antenna is attached to each transmitter. We investigated the histograms of these recordings for each class and decided to use the Gaussian distribution assumption. As displayed in Figure 5, the Gaussian probability density function does not always perfectly match the RSSI distributions, but will be a good enough assumption for our application, when the number of samples is sufficient.

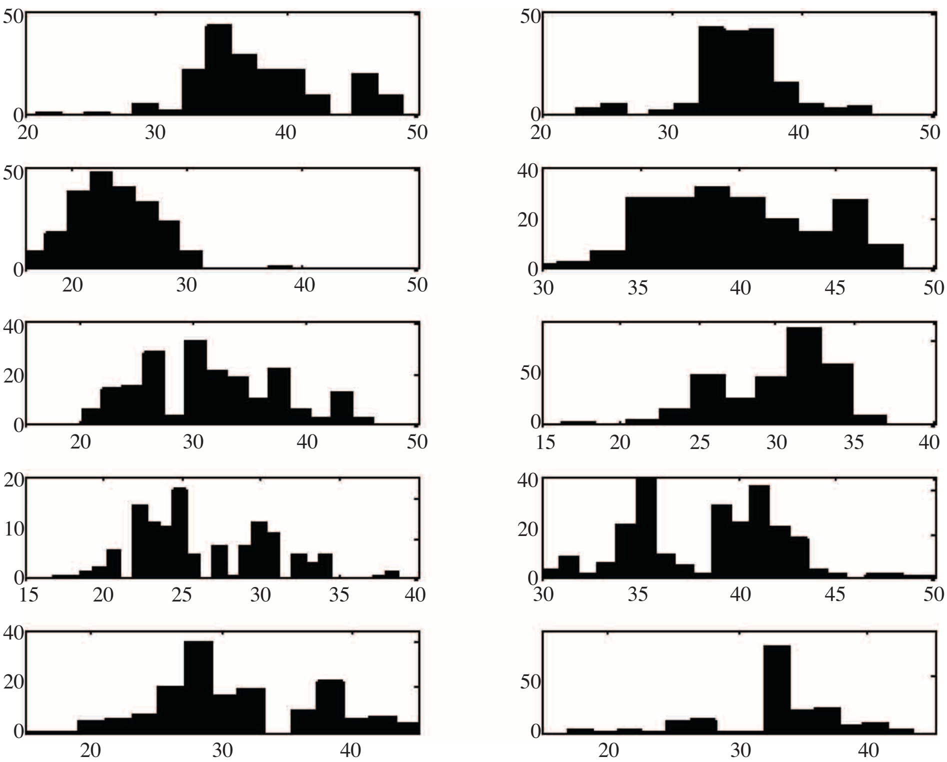

Figure 5. RSSI distribution for some of the classes for different transmitters, where x axes refer to RSSI levels and y axes refer to number of occurrences.

Then, the conditional probability distribution model for the feature vector x given class C_i will be

$$p(\mathbf{x}\,|C_i\,) = \frac{1}{(2\pi)^{3/2}\,|\Sigma_i|^{1/2}} \exp\left(-\frac{1}{2}(\mathbf{x}-\mu_i)\Sigma_i^{-1}(\mathbf{x}-\mu_i)^T\right), \tag{5}$$

where Σ_i and μ_i refer to the conditional covariance matrix and conditional mean vector of the feature vector x given class C_i, respectively. Note that the signal strength transmitted by each transmitter is independent. Hence, the covariance matrix becomes diagonal and the joint probability density function (5) can be expressed as;

$$p(\mathbf{x}\,|C_i\,) = \prod_{l=1}^{3} \frac{1}{(2\pi)^{1/2}\sigma_{li}} \exp\left(-\frac{1}{2\sigma_{li}^2}(x_l-\mu_{li})^2\right) \tag{6}$$

The statistics σ_{li}^2 and μ_{li} are evaluated by computing sample variances and sample means for each class and each transmitter, by use of the recorded measurements. We assume that the person carrying the RFID tag starts navigating in the environment from a known location at time $t = 0$. This is the location where the navigation aid will be presented to the user and will be activated. The observations (feature vectors) are received at constant time intervals Δt (around 1 sec). At every Δt interval, the previous location of the person is assumed to be known. Note that the RSSI levels are collected by the tag and are transmitted to a remote PC through a wireless channel. The remote PC executes the Bayes Theory based tracking algorithm to estimate the current position of the user, and determines the direction (out of 8, north, south, east, west and the ones in between) that the user should follow in his/her next step in order to reach his/her destination. That direction is signaled to the user via a tactile compass, of which knob is sensed by the thumb of the user. Hence, we also assume that the user is most likely to follow this signaled direction than moving to an unpredictable direction. Based on this assumption, (4) is updated as;

$$g_i(\mathbf{x}) = \ln\left(p(\mathbf{x}\,|C_i)\,\right) + \ln\left(P(C_{ik})\right) \tag{7}$$

Substituting (6) into (7), we obtain the decision function as

$$g_i(\mathbf{x}) = \sum_{l=1}^{3} \ln\left[\frac{1}{(2\pi)^{1/2}\sigma_{li}} \exp\left(-\frac{1}{2\sigma_{li}^2}(x_l - \mu_{li})^2\right)\right] + \ln\left(P(C_{ik})\right) \tag{8}$$

where $P(C_{ik})$ refers to the transition probability, that is, probability that the user used to be in class Ck (where k is the index of the class that the user is in) in the previous time of reading and displaced to class Ci (where Ci are the accessible classes near to Ck), at the current time of reading. Two different ways on how to assign $P(C_{ik})$ in our case is proposed in the next section. Our proposal can also be used for more general cases where a user is being guided by a system via directions. x_l is the observed RSS at the current location for the lth transmitter. Then, given the previous location of the RFID tag, the current location of it is estimated as the Ci that achieves

$$g_i(\mathbf{x}) \geq g_j(\mathbf{x}), \quad \forall i, j \in A, \quad i \neq j \tag{9}$$

where A refers to the set of available classes.

A similar work which is based on Bayesian approach and carries out indoor localization by using wireless Ethernet is presented in [14]. It aims localization in hallways of a building where locations in the hallways are spaced roughly 1.5m apart. Aiming different application areas and using wireless Ethernet, the work in [14] has a quite different hardware setup than our work. Although the observation in their case consists of pairs of base station addresses and signal strengths that are similar to our work, the number of replies is different from the number of base stations (each base station may not reply at all or may reply up to four times at each reading). As a result, [14] incorporates number of counts in their probability model and does not include a priori information in the form of a direction to a certain orientation as in our case. Hence, we come up with a different state space model and a different decision function than the proposal of [14]. Yet, being based on similar principles we compare our results with that of [14] in the next section.

5. Experimental results

The proposed method is tested in the indoor environment presented by Figure 4 with the following a priori information and assumptions:

- The statistics (conditional mean and conditional variance) of each class are available.
- The user's displacement at Δt time interval is limited.
- The locations of NON ACCESSIBLE classes are known by the tracking system.

- The initial location of the user is known. This is reasonable since the portable hardware unit carried by the user will be presented at a certain location. That location can safely be considered as the initial location where the device will be turned on and the tracking algorithm will start to execute.

The tracking system is executed on a computer, which receives RSSI levels from the RFID reader. The statistics (mean and variance values) of each class is pre-computed from the pre-collected data, and are stored in the computer together with the map of the subject environment. A set of routes between different cells are defined. The tracking algorithm performance is tested on these routes for two different cases. 9 routes are tested for the subject environment. Three of the tested routes are presented in Figure 4. Route 1 and route 2 starts from one end and ends at the other end of the environment where route 3 starts at one end and ends in the midway of the environment. In the first case, transition probabilities between the classes are assumed to be equal except for the current class. The probability of staying at the same class is assumed to be lower (half the probability of each other transition) than the probability of displacement. In the second case, it is assumed that the user is navigated to follow a certain route; hence a bias favoring a certain class exists (considering that the tactile compass will be guiding the user). Then, the transition probabilities between classes are arranged according to the following principles

- the probability of staying at the same class is a/2
- the probability of transition from the previous class to the directed class is 2a
- the probability of transition from the previous class to all other accessible classes is a
- the sum of all transition probabilities add up to 1.

Note that there exists an underlying assumption that the user cannot displace faster than a class between two readings.

We recorded estimated and actual positions of the user along each route. Then, we calculated the error between the estimated and actual locations. In [14], similar tests are carried out where the actual and estimated positions are recorded while walking up and down the hallways of the tested building. Since the plot of error along the route cannot be compared to the test results of others, we preferred to present cumulative probability plots for measured error between the actual and estimated positions. Figure 6-7 present test results (cumulative probability plots) as compared to the listed test results of the algorithm presented in [14] for two hallways. Note that the plots corresponding to the results of [14] are the same both in Figure 6 and Figure 7. Figure 6 shows the performance of our proposed method without any bias compared to that of [14]. Figure 6 shows that without any bias, the user can be tracked from one end to the other end of the area, with at most 3.8m error, which is similar to the best listed case in [14] although the overall performance is slightly worse than the best of [14]. When a bias favoring the directed class exists (Figure 7), the tracking performance increases significantly (at most 3m error). This performance increase illustrated in Figure 7 shows that use of direction information as a bias contributes significantly to the estimation problem.

The experimental results show that statistical processing of the RSS levels enables compensation of noisy measurements in a tracking application, especially when a bias favoring a certain direction of displacement exists. In order to comment on the robustness of the method with respect to environmental changes, there has been a period between the collection of data and conduction of experiments where small changes in the environment such as number of persons present in the environment (changed only by three or four), replacement of small furniture such as chair or boxes have occurred. Yet, it should be noted that major changes such as replacement of big shelves or walls will require a recollection of data and recomputation of the statistics.

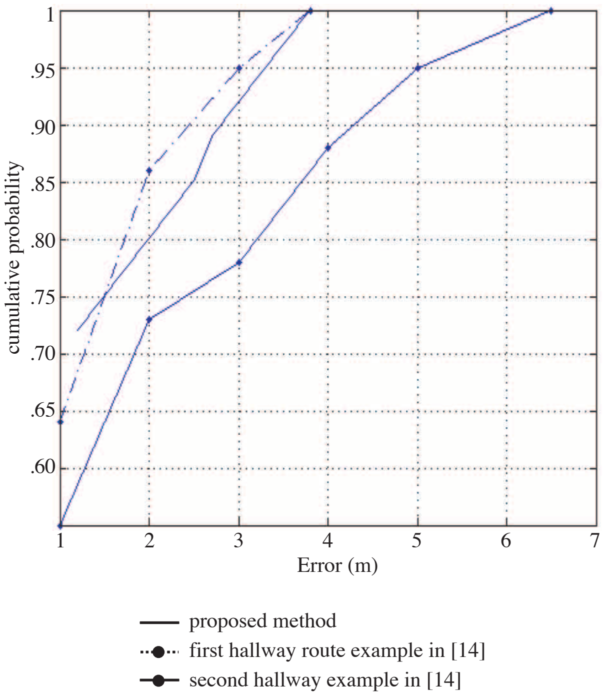

Figure 6. Cumulative probability vs error with no bias.

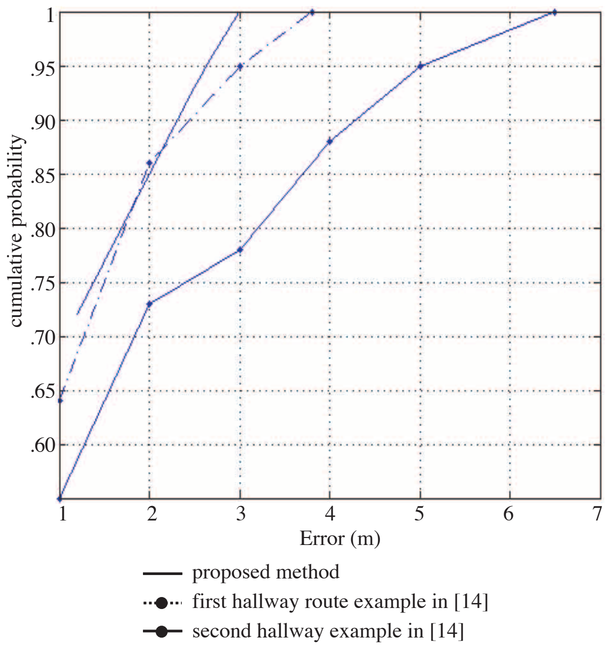

Figure 7. Cumulative probability vs error with bias.

6. Conclusions

An indoor tracking method for obscured environment is proposed. The method is developed as an integral part of a navigation aid for guiding visually impaired people. The method is based on the Bayes Decision rule, where an observed feature vector is classified to a class among the set of available ones. The classes are modeled as accessible square grids in an indoor environment. The feature vector is composed of signal strength indicator levels received from three transmitters working at distinct frequencies in the UHF band. The technique is tested by using an extensive set of recorded measurements. The performance of the tracking method is tested for different routes in the environment. The increase in tracking performance with the assumption of a bias guiding the user to a certain direction is recorded.

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