PASSIVE INDOOR LEVELED RFID LOCALIZATION ALGORITHMS

by

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Abstract

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by

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One of the most sought-after innovations in RFID technology is the ability to accurately locate stationary objects and track moving entities in real time. The author proposes three multi-leveled detectable count RFID localization algorithms (nearest-neighbor, multilateration, Bayesian inference) to accomplish these tasks using UHF passive RFID tags—chosen due to low cost and efficient implementation—by affixing them onto the floor as known reference nodes. Simulations are conducted to examine the accuracy and performance of the algorithms to locate stationary and mobile objects. Furthermore, experiments are carried out to test the localization of stationary objects in a real world setting such as a laboratory environment. The outcomes from the simulations and experiments are analyzed. The results are remarkable and most importantly, when the proper parametric values are considered, such as reference tag density and detection range, the accuracy performance of the algorithms achieved are impressive which confirms that the proposed methods are highly preferable when accurate, efficient and cost-effective passive RFID localization systems are to be implemented. Future directions of the study include exploration of different ratios for the three power levels of the RFID reader, use of other reference tag spacing pattern besides square such as hexagon, examination of other multi-level approach beside tri-level such as

quad-, penta- or dual-level, experimentation with different kinds of RFID reference tags besides the passive Alien type G, as well as field tests of methods for mobile entities in a realistic real-world settings such as a laboratory.

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Chapter 1

Introduction

Radio Frequency Identification (RFID) has been widely utilized for the automatic identification, inventory, and tracking of animals, pharmaceuticals, supply chains, merchandise, library books, and other objects [11,13,40]. As both the financial cost of the manufacturing and the physical size of the RFID transponders have been decreasing dramatically over the past two decades, their increasing impact on the utilization of the technology in the academic [23-26], industrial and commercial sectors has been tremendous. The capability and capacity to identify, store and retrieve large amounts of data embedded in these tiny—and sometimes almost invisible—tags, coupled with the speed and accuracy to determine the object's estimated location, make RFID tags much more powerful and efficient, compared to the traditional technology that requires physical contact and/or line-of-sight such as the ubiquitous barcodes.

Most of the current basic RFID systems are capable of providing location information. Though they are coarse-grained—they can tell whether the object is present or absent in the proximity—the technology can be used to identify the proximity of any tagged objects. As more accurate of the location information of tagged objects is becoming available, more breadth and depth of the application of the RFID technology can be developed. Real time localization of objects (for example, a huge quantify of merchandized items in a massive warehouse) and living things such as farm animals, household pets, and human beings (for example, new born infants or inpatients in a large medical facility) is highly desirable and provides the underpinning for many potentially critical and beneficial applications. Hence, an effective, efficient, low-cost and accurate RFID localization system will be invaluable.

1.1 An overview of RFID technology

As both an enabler and enhancer of the IoT (Internet of Things), RFID undertakes the crucial function for recognizing an entity and for furnishing the coarse-grained positional data in addition to other details and information regarding an entity. Working in tandem with the infrastructure of the Internet, it sets in motion the possibility and capability of communicating and connecting from everything to everything else at anytime and from anywhere.

There are three major components in a modern day RFID system [22,37]: the transponder (commonly called the tag), the reader (transceiver, or interrogator), and the backend server. The tag can be passive (a small antenna connected to a microchip without integrated power source, which harvests energy emitted by the reader to operate and communicate with the reader by backscattering), active (powered by a internal battery, it transmits an RF signal in response to the reader, rather than backscattering the reader's signal), or semi-passive (using a battery to power up the microchip and also using backscatter to communicate with the reader). The reader is located between the tag and backend server. The reader sends and receives information to and from the tag and also communicates with the backend server as well as updates its database. The backend server, at the highest level of RFID infrastructure, runs applications, hosts databases, processes information from the reader, and connects to the enterprise network. In a sample RFID system, as shown in Figure 1.1, we use ALR-8780 RFID reader, antennas and passive EPC Class 1 UHF ALL-9338 RFID tags manufactured by Alien Technology Corporation.

Figure 1.1: A typical RFID system and its components

1.2 Overview of the dissertation

In addition to this introduction chapter, the rest of the dissertation is organized as follows. In Chapter 2, we first discuss the propagation models of radio frequency, which can be negatively impacted due to obstructions and interferences in an indoor setting. We then cover localization techniques for both outdoor environments and indoor settings, which can be RF-based or non-RF-based [50]. We also introduce RFID localization systems and discuss the basic localization methods in the literature. Lastly, selective noteworthy localization systems are examined in detail.

In Chapter 3, we describe the three proposed mobile leveled indoor localization methods that utilize passive RFID technology. We explain why we choose not to use RSSI, and instead employ the detectable counts of RFID querying. We also discuss the setup of the approaches, which require passive UHF RFID tags to be affixed onto the floor of the indoor space in a certain pattern and the antennas of the RFID reader be attached to the target, both for stationary object and mobile entity.

In Chapter 4, we choose a specific location for a fixed target and also develop computer simulation programs to examine the feasibility and validity of the proposed approaches. We test our methods through varying the values of two parameters: the density of the passive RFID reference tags that are laid onto the floor and the length of the detection range of the reader. We decide to maintain the ratio of the three power level detection ranges at a fixed proportion (4:3:2). Simulation results are obtained and analyzed in detail for the three proposed algorithms.

In Chapter 5, through computer simulations, we develop an actual path for the mobile entity in order to examine the proposed methods. The path is U-shaped so that we can test whether our methods can track the moving entity when it makes turns, including sharp ones in real time. The starting and ending positions of the entity in a large room are chosen. The number of steps as well as the distance of each step are determined. The parameters for the tests are also discussed. Lastly, the Mean Localization Error of the methods are computed and analyzed in detail.

In Chapter 6, we perform experiments in a laboratory environment to test the validity of our approaches. We describe the equipment and space used to carry out the experiments. The setup of the experiments and issues with sensitivity and orientation of the passive RFID tags are covered in detail. We examine four actual cases of localization of stationary objects in the experiments. The outcomes of the four cases are also analyzed.

Lastly, the dissertation is concluded in Chapter 7 with discussions of major findings and future directions of this study.

Chapter 2

RF propagation models, localization, and RFID

In Chapter 2, we introduce RFID localization systems and discuss the basic localization methods in the literature.

2.1 RF propagation models

Indoor static obstructions, furniture, dynamic human movements could block, absorb radio signal, and also cause fading. Moreover, signal reflection and refraction can cause the severe multipath. Therefore, indoor radio frequency (RF) propagation model is quite different from the ones of outdoor or free space. When RF-based localization approaches are used in indoor settings, the RF model must be adjusted according to the location and time inside the building.

The basic theoretic RF propagation model in free-space is the Friis transmission formula [12,39] that relates the receiving power to the distance:

$$P_r(d) = P_t G_t G_r (\lambda / 4\pi d)^2 = P_t G_t G_r (c / 4\pi d f)^2 , \qquad (1)$$

where $P_r(d)$ is the power available at the receiver antenna, P_t is the power fed into the transmitter antenna, G_t is the transmitter antenna gain, G_r is the receiver antenna gain, d is the distance between the two antennas, λ is the wavelength, c is the speed of light in free space (3×10^8 m/s), and f is the frequency of the radio carrier. The path loss between the transmitter antenna and receiver antenna is (if f in MHz, d in meter) [47]:

$$L(d) = 10\log(P_t / P_r) = 20\log f + 20\log d + 32.45. \qquad (2)$$

Therefore, considering the path loss, we can have $P_r(d) = P_t - L(d)$. We can see that equation (1) will not hold for $d = 0$. Therefore (1) is for $d > d_0$, where d_0 is a close-in distance, as a known received power reference distance [12]. In the non-free space environment, the path loss is usually determined by $L \propto (d/d_0)^\gamma$, where the path loss exponent γ is usually not equal to 2, as in free-space scenario. In an indoor settings, the path loss will be caused by reflection, refraction, diffraction and scattering. The log-distance path loss model for indoor settings will be [47]

$$L(d) = L_0 + 10\gamma \log(d/d_0) + X_g, \qquad (3)$$

where X_g, a normal random variable with zero mean, reflects the attenuation caused by fading. L_0 is the path loss at the reference distance d_0 given by $L_0 = G_t G_r (\lambda / 4\pi d_0)^2$. In the case of shadow fading, [12] gives an indoor path loss for 2.4GHz as

$$L(d) = L_0 + 10\gamma \log(d/d_0) + \sum PAF, \qquad (4)$$

where PAF is the partition attenuation factor, for example, $\sum PAF = 2.3$dB if the receiver and transmitter are separated by one wall, and $\sum PAF = 2.3 + 15 = 17.3$dB if the separation is two walls.

2.2 Localization

The following is a brief overview of localization techniques. Localizing techniques can be classified into RF-based and non-RF-based [50]. GPS (Global Positioning System) [34,47] is a successful RF-based example for positioning outdoor objects. The system is based on two-dozen satellites and a few ground monitoring centers. Four or more satellites broadcast the RF signals to a GPS receiver, then it uses TOA (time-of-arrival) of signals to calculate the 3D geographic position information (latitude, longitude, and altitude) of the receiver. However, GPS receivers in general do not work in indoor settings because the satellite signals are heavily attenuated by the building walls and floors.

RF-based localization approaches also include wireless local area network (WLAN), wireless sensor network (WSN), and RFID localizations. In WLAN localization, a WLAN device can be localized based on beacon signal strength information between the device and access points. Some of the major studies on WLAN localization can be found in [4,38,41,49]. Generally speaking, WSN localization techniques are based on AOA (angle-of-arrival), TDOA (time-difference-of-arrival), and RSSI (received signal strength indication). WSN localization is an important area of research and many studies have been reviewed in [2,29,35]. RFID localization techniques are surveyed in [1,20,50]. They are similar to other RF-based localizations in principle; the main advantages over WLAN and WSN approaches are the inexpensiveness and easiness of deployment [50]. We will address RFID localization in detail in the subsequent sections. Non-RF-based localization techniques employ acoustic, vision, ultrasonic [36], infrared [46] and laser as measuring signal. These techniques typically are built on TOA and triangulation or multilateration algorithms.

2.3 RFID localization systems

LANDMARC [30] is one of the most regarded and highly cited RFID localization prototypes where active RFID tags are localized based on received signal strength (RSS) measurements. A multi-level approximation of the location is achieved by dynamically changing multiple readers' transmitter powers in multiple levels and k-nearest neighbor reference tags. LANDMARC has been used to facilitate the management of hospitals in locating patients, staff, and equipment [28]. SpotON [21] is another indoor localization system based on RSS measurements to estimate inter-tag distances. RG [27], robotic guide, is a RFID-based indoor navigation robot with the help of passive RFID tags deployed in the environment. RG navigates in the building using potential fields and by finding empty spaces around itself. WLPS [42], wireless local positioning system, is intended for the design of intelligent vehicles to improve road safety by avoiding collisions. Using active RFID tags, WLPS estimates the location based on the time-of-arrival and direction-of-arrival. R-LIM [14-16], RFID-based library information management, is used to help find displaced library books in real-time. R-LIM is based on the aging-counter method which, in essence, is the nearest neighbor and proximity approach. RFID localization systems are generally implemented based on two classes of algorithms [1]: (Class-1) using RF propagation models to estimate the distance, e.g. RSS and TOA; (Class-2) without using RF propagation models. The Class-2 algorithms can be further classified into two sub-groups: (1) calibrate the RF distribution and then estimate the location, e.g., multilateration and Bayesian inferences; (2) direct estimate location, e.g., nearest neighbors, proximity, and kernel-based learning.

2.4 Selective noteworthy localization systems

2.4.1 A modified and improved kNN RFID localization method

In [17], Choi et al. propose a novel modified RSSI (received signal strength indicator) based scheme that significantly improves the performance of kNN in stationary object localization based on inexpensive RFID technology. k-Nearest Neighbor (kNN) algorithm is first put forward by Ni et al. [30] who try to take advantage of the low cost of RFID infrastructure to localize objects in an indoor setting.

During the in-depth investigation conducted by Choi et al. [17] of the behaviors of RFID tags under both the same and varied conditions, they conclude that there are three major issues regarding the usage of passive RFID tag for the purpose of localization:

i. Even for the same model numbered RFID tags of the passive type that are produced from the same single factory, they often do not behave consistently.

ii. Numerous environmental circumstances can affect the values of RSSI read which often cause the system to have unsatisfactory result in the endeavor of computing the position of an object.

iii. A single identical RSSI measurement can point to several different locations in the area that is being surveyed.

To mitigate the shortcoming of those issues, they propose the following two techniques: the correction of the measured RSSI values and the purging of the superfluous reference tags.

2.4.1.1 Correction of the measured RSSI

The discrepancy of RSSI values among the tags can be quite large even during normal uniform condition and it plays a key role in the less than satisfactory performance of pure kNN approach. They examine fourteen tags and find the discrepancy ratio to be in the excess of few percentage points and all the way up to over 89 percents. Therefore it is sensible that the discrepancy issue be addressed and be corrected to the best possible way. To ensure accuracy, a very large number of samples (twenty thousand) of RSSI values of each tag are measured under the same identical condition and the average RSSI value for each tag is used for the correctional procedure. Then the RSSI-corrected figure for a specific reference tag is the average RSSI value of that tag divided by the RSSI discrepancy ratio of the same reference tag over the target tag. An example provided by Choi et al. [17] is that if the average RSSI of a reference tag is 1.99815e-06 mW and its discrepancy ratio is 1.89, then its RSSI-corrected is 1.05722e-06 mW.

2.4.1.2 Purging of the superfluous reference tags

The key idea of this technique is that when tags are positioned in similar locations, their readabilities tend to be also similar. On the other hand, tags that are physically located distant from each other tend to have very different readabilities. Therefore, reference tags that are very far from the target tag's neighborhood may not provide useful guidance to the exact location of the target tag and may instead introduce noise and localization estimation error. Hence, their exclusion may be quite beneficial to the accuracy of the localization scheme. The example Choi et al. [17] provided is that if the target tag is situated at a distance of two and half meters from the antenna of the RFID reader and the ratio of scanning rate between the target object's tag and the surrounding reference tags are more than or less than fifty one percent, which also happens to be the standard deviation number from their experiments, then those reference tag should not be included from the computation of the target position when using kNN as their extreme dissimilarity in readability will render them not useful in the determination of the accurate location of the target object.

2.4.1.3 Remarks

By adopting the original kNN approach with their performance enhancement and error reduction techniques, Choi et al. [17] in their experiments are able to obtain a localization error of only 20.89 cm. That is thirty four percentage points better the 33.15 cm localization error of the pure kNN method. Clearly their investigation, analysis, and the pursuing corrective techniques provide a remarkable improvement to the accuracy of RFID localization over the pure kNN method for the localization of indoor object via the utilization of cost effective passive tags.

2.4.2 Phase difference and RFID localization

In [19], Hekimian-Williams et al. investigate whether the difference of phase of the radio waves received by the two antennas of wireless signal receivers can be harnessed to provide a more accurate measurement of RFID based localization when it is integrated with the established methods that utilize received signal strength indicators. They construct a prototypical system to test and validate their idea.

In general, a common typical frequency used by battery powered active RFID tags is 433.92 MHz and they usually have a relative long range (over ninety meters). They also likely to be energy efficient and the battery often last more than seven years. To communicate with the RFID reader, the radio waves are sent in burst mode at regular internals, as continuous-mode sending will be highly energy inefficient and will run out the battery quickly. For each radio wave burst, a certain quantity of pulses is sent at equal magnitude so that each tag can be uniquely identified. Essentially the shape of each pulse of radio wave sent is the same of the mathematical sine function wave. The distance of the path the radio wave undertakes from the tag to the wireless signal receivers will impact the waveform the receiver captures. Given that two receivers are using the exact same sampling clock, the phase difference that captured can be used to compute the difference of the path distances and that can be utilized to assist in the localization of a tagged entity.

Hekimian-Williams et al. [19] conduct experiments in an ideal lab setting and are able to obtain 0.954 degree as the standard deviation for the phase difference. The number translates to a potential accuracy of localization of 0.18 centimeter ((0.954/360)×299792458/433920000 meter; speed of light: 299792458 m/s, RFID freq: 433.92 MHz). Moreover, through further testing and examination, they are also able to predict and estimate the phase difference reliably and confirm that it is also discriminating. That is, whenever the active tag is moved, the phase differences also reflect the movement through smooth changes.

In conclusion, the results of their numerous experimentations conclude that the phase difference of the radio waves of a moving tag can be captured and measured robustly and accurately and the technique can be combined with schemes are based on received signal strength to significantly advance the accuracy of localization that is based on active RFID technology.

2.4.3 RFID localization via readability and power level

In [48], Wilson et al. propose that the patterns of readability of passive RFID tags under different reader's power levels can be exploited to aid in the computation of the localization of tagged entities. The readability patterns can be recorded during sample trial runs and stored into a database where future tagged objects' distances and positions can then be calculated. One of motivations of their study is that not relying on RSSI (received signal strength indicator) may provide a better performance in localization accuracy.

From their preliminary testing, they confirm with previous researches that materials of metal nature tend to have an interference effect on RFID reading. Prudently, they remove all possible surfaces made of metal from the testing environment and use wood to construct the objects that are being tagged. The reader and tags they employed in the experimentation are manufactured and provided by the industrial leader Alien Technologies (reader model 9780, passive tag ALL-9338-02).

The main idea of Wilson et al.'s study is that the successful read count of a passive RFID tag under different power levels will provide a clear indicator of the distance between the tag and the antenna of the reader [48]. To confirm their principle, they place a tag at a fixed distance from the reader's antenna and vary the power level of the radio signal; then they measure the successful read count out of one hundred scans. The fixed distances they use are from one foot to five feet, with half a foot as the step. Furthermore, they adjust the reader's power level from zero to one hundred sixty dB, at a step of ten dB each. They also perform the experiments using three different orientations of the tags (front, back and side-facing) to examine the possible impact they might have on their approach. Lastly, they test the idea of employing the method of writing to tag, instead of just reading from it, as in general writing tends to be more demanding than just scanning it.

The results of their findings indicate that lower power level tends to give a higher readability rate, more so than that of the distance between the tag and the antenna. And when power level goes too high, the readability drops precipitously. For example, when the distance is at two feet, the peak readability of high ninety percentages is achieved when the power level is between twenty and thirty dB but then it drops to zero percentage when power level reaches one hundred dB. All the measurements of the characteristic curves of the behaviors of the tag readings under the testing environment are stored in a database and any future tags with unknown distances can be readily computed as long as it is within the range of the study. Then with the deployment of multiple readers, a tagged entity's position can also be obtained. Moreover, their experimentations also indicate that front-facing orientation of the tags seems to produce a slight better result even though back and side-facing work satisfactory too.

The conclusion of their study is that the characteristic curves of the readability of low cost passive RFID tag under different reader's power levels can be efficiently utilized to locate an object within the query range of their study and the technique of writing to tag instead of just using the reading count will provide a sharper resolution but at the cost of reduced range.

2.4.4 RFID localization based on power-distance relationship

In [8-10], Chawla et al. propose a novel approach in tackling the challenging task of localizing a stationary or moving entity based on RFID technology. Utilizing the physics principle of Friis transmission equation, they derive the power-distance relationship for RFID tag detection. That is, from the amount of power necessitated by the RFID reader to pick up the radio wave signal of a tag, one can infer the distance between them rather accurately. They also assert that "if the behaviors and responses of two tags are very similar, then their positions must be very close as well." Utilizing this assertion, they state any moving entity with a RFID tag that is detected near a stationary fixed reference tag must have a very close position relationship.

2.4.4.1 Pre-processing of the RFID tags

For their localization method, Chawla et al.'s study indicates that certain pre-processing is needed due to the less than stellar quality control and the nature of certain detection behavior of the regular stock passive RFID tags [8-10].

2.4.4.2 Tag sensitivity

From their investigation, Chawla et al. [8-10] conclude that the sensitivity of tags plays a key role in the detectability of a tag and hence also the performance of their approach. They conclude tag sensitivity is determined by what is the smallest amount of power required to scan a tag at a specific distance. They notice the sensitivity of tags differs considerable among the many individual tags of the same type mainly due to the variability in the manufacturing process. They decide it is sensible to use tags that have uniformly high tag sensitivity for their studies as that will most likely guarantee the reduction in the errors of their localization method.

2.4.4.3 Tag orientation, orthogonality and multi-tags

Chawla et al. [8-10] observe that numerous studies including their own have indicated that an orthogonal multi-tag platform most often will provide a much better performance than just a single individual tag and they decide to adopt the strategy to ensure their localization approach will have an optimized outcome. One of the trade-off is that the "tag" becomes a 3-D object as they put 4 tags vertically in a right angle to each other on a small Lego plastic block versus the traditional passive tag which is basically a thin piece of tiny paper (like a small sticker or paper label).

2.4.4.4 The real time localization process

Their actual real time localization process involves three major steps: two techniques plus the utilization of heuristics [9].

Step one:

They have the test area populated by fixed referenced tags of known positions. The reader loaded with the mobile entity will be able to detect the fixed tags that are closed to it when it traverses on a fixed track on the test area. The location of the detected reference tags will yield the approximate position of the moving entity.

Step two:

They adjust the power level of the fixed reader to find out the minimum power level required, that will give a good distance measurement between the reader and onboard tag. They perform the same technique from four different sides by placing four antennas on the test area of 2 meter by 4 meter.

Step three:

Even though the afore-mentioned steps provide a decently good estimate of the current position of the mobile object, they are able to fine tune it further by employing error reducing heuristics. An example of the heuristics employed is to utilize the difference in the reader power level between the onboard target tag and each one of the detected neighboring reference tag, that is:

i. compute the absolute difference of the reader power levels between the onboard target tag and each one of scanned neighboring reference tag.

ii. sum all the absolute difference for each one of the 4 readers.

iii. see which reference tag J has the minimum.

$$\mathrm{H}_1 : \underset{\forall J}{\mathrm{Min}}\left(\sum_{I=1}^{M} \Delta_I (R_J) \right)$$

$\Delta_I(R)$: |Power(T) – Power(R)| using reader I

R_J : Reference tag J

M : Number of readers

Power : Minimum detection power level for a tag

T : Target tag

2.4.4.5 Remarks

Although their method has a pretty good performance in term of localization error: an average of about 0.2 meter in a 2 by 4 meter testing area, it suffers from the following drawbacks:

i. Scalability issue: four decent size antennas are used on the four sides of the testing area of only 2 x 4 m as that is the range of the reader used. To expand to a bigger space, four antennas are mostly likely to be required for every 2 x 4 m space. The antennas also require cables and additional reader. The additional antennas and cables will become a moving obstacle or hazard as one wants to scale up the space traversed by the mobile entity.

ii. Even though the multi-tag platforms significantly enhance the outcome of the approach, it is essentially a three dimensional objects that hinders the movement of the testing entity which essentially cannot step on or roll over the multi-tag platform.

iii. In addition, their method requires too many and also densely populated tag platforms in a relatively small region, thirty three of them in a 2 x 4 m space.

iv. Their experiments employ a pre-defined fixed track for the moving Lego robot. It is generally considered unrealistic in a real world setting if a mobile entity can only confine its movement to a fixed pre-defined track. The robot should be allowed to roam around "freely" while the localization approach does its job in trying to ascertain its current position in real time.

2.4.5 Localization of a mobile robot via the read time of an RFID system

In [33], Park and Hashimoto propose a new method utilizing RFID technology in locating a moving robot in an indoor setting. Provided that that the robot is moving in a fixed speed, their approach uses the "read time" to compute the position and orientation of the mobile robot in real time. They define the read time as the time it takes for an RFID reader to scan and recognize a specific tag. In other words, the amount of time when the tag enters the reading range of the moving robot which is equipped with the reader. The RFID system they chose is based on the high frequency range (13.56 MHz), with the ant-collision feature not enabled; i.e. only a single tag can be scanned at a given time. When the robot is instructed to move from point A to point B which are positioned on the two far sides of a 6.2 x 4.2 meters indoor space, the read time method can accurately measure the robot's current location and orientation, even though the initial orientation of the robot is varied.

Their method claims that when a robot is traversing at a certain fixed speed, the angle of the robot's movement will distinctly determine the RFID read time. For example, if the angle of the trajectory of the mobile robot is 90 degrees (in reference to the x-axis) when moving at 12.2 cm/s, then the read time is about 2.7 seconds. On the other hand, the read time is about 0.95 second if the angle is between 40 to 49 degrees. By measuring the different read times for the different angles of movement in advance, one can then accurately compute the orientation of the robot during the actual runs. The pattern of the tags that are being laid on the floor for the testing area is integral to the performance of their system. A square grid like pattern is chosen as it is both simple and effective. All high frequency RFID readers have limited range and the scanning range of the reader of the proposed system is about 17 cm. Hence the tags are being spread 34 cm from one another. When the robot is moving from one detected tag onto the next detectable tag, its position can also be ascertained as the locations of all these fixed tags are already known. Furthermore, the current orientation of the robot can be obtained using classic trigonometry calculation as both the x and y coordinates of the previous detected tag and the current one are already known. Their experiments confirm that the system is both robust and accurate. They are able to achieve a localization error of only 6 cm and 5.3 cm on average for the x and y-axis respectively. The error of orientation angle of the moving robot is also impressive and comes in about 10 degrees on average.

Chapter 3

The three RFID localization algorithms

In Chapter 3, we describe the three mobile leveled indoor localization methods that utilize passive RFID technology.

3.1 The leveled nearest-neighbor

The proposed scheme is to combine the nearest-neighbor method [30] with multi-leveled signal strength indication to enhance accuracy. Instead of directly using RSS, which is difficult to measure by the current RFID readers, especially in the real world environment due to noises and interferences [32], we will use detectable or non-detectable counts in place of the RSSI. The nearest-neighbor means that the target tag's signal strength should be similar to that of its closest neighbors, and so is its location. In order to increase the accuracy, we expand the nearest-neighbor method into levels [5]. The setup is as follows.

The reference passive RFID tags are deployed in a grid. The reader (mobile or quasi-mobile) has three different discrete power levels - high, medium, and low - with high-level having the longest reading range, and low-level the shortest range. The algorithm is illustrated in Figure 3.1. The black dots are reference tags located on the grid with known coordinates. The solid-line square is the target. When the high-level power is used, there are four nearest neighbors: *a*, *b*, *c* and *d*, which are detectable in the large radius. The location estimate of the target is the center of *abcd*, i.e., the black dash-line square. When the power is switched to medium-level, there are two detectable neighbors, *b* and *c*, in the red dash-line radius. The new estimated location for the target is the red dash-line square. To keep the calculation simple, we just move the first estimate to the right of the half distance of the center of *abcd* to line *bc*. Finally when the low-level power is used, only the single neighbor *c* is detected. Therefore the algorithm moves the second estimate down half distance of the center of *abcd* to line *cd* to get the last estimate of the target, i.e., the black solid-line square. The estimate of the target location gradually gets more accurate.

We can also see that the leveled nearest-neighbor algorithm is indeed a weighted average approach [31], i.e., the closer the reference tag, and the more weight it will get. We can use a formula to express the estimate as

$$(x, y) \approx (\hat{x}, \hat{y}) = \left(\frac{\sum_{i \in N} w_i \cdot x_i}{\sum_{i \in N} w_i}, \frac{\sum_{i \in N} w_i \cdot y_i}{\sum_{i \in N} w_i}\right). \quad (1)$$

In Figure 3.1, neighbor set $N = \{a, b, c, d\}$, (x_i, y_i) are the coordinates of the reference neighbors, where $i = a, b, c$, or d. The weight w_i equals to the number of being detected. In the example in Figure 3.1, reference tags *a* and *d* are detected once, therefore $w_a = w_d = 1$; *b* is detected twice, hence $w_b = 2$; and *c* is detected three times, thus $w_c = 3$.

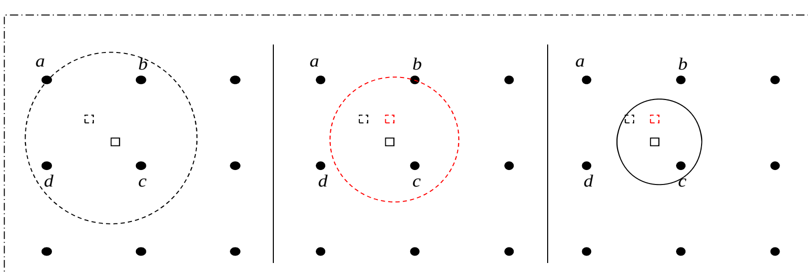

Figure 3.1: Leveled nearest-neighbor algorithm by three levels

3.2 The leveled multilateration

The multilateration algorithm is a mature approach to locate objects; it requires calibrating the RF signal distribution first. On a two-dimensional plane, given at least three reference points with known coordinates and their respective distances to the target, then the target's location can be ascertained (Figure 3.2).

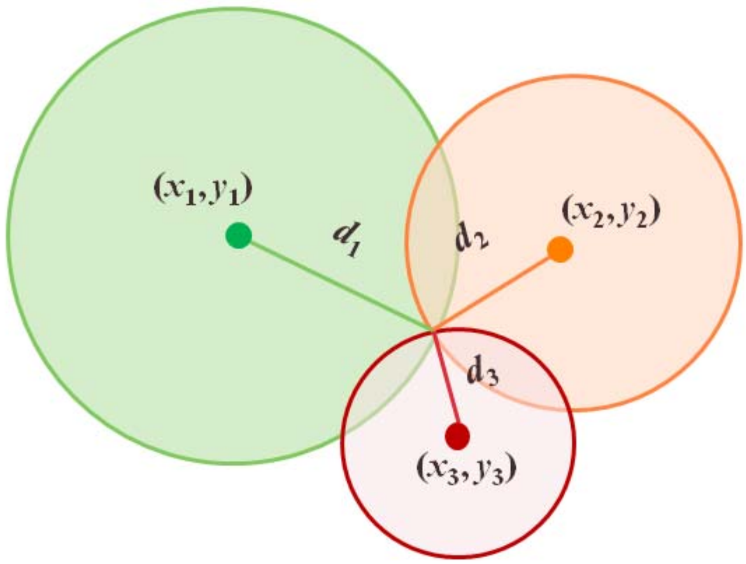

Figure 3.2: Three reference nodes with known distances to the target

For example, let there be *n* reference points (or beacons) with known distances:

$$\begin{cases} d_1^2 = (x - x_1)^2 + (y - y_1)^2 \\ d_2^2 = (x - x_2)^2 + (y - y_2)^2 \\ \dots \\ d_n^2 = (x - x_n)^2 + (y - y_n)^2 \end{cases}$$

where d_i is the distance between the target and beacon *i*, (x_i, y_i) is the coordinates of the beacon, and (x, y) is the target's position.

To linearize the system of the *n* equations above, one will subtract any single one equation from the rest of the other equations. It is common to just use the first equation to subtract from the others. Therefore, we have:

$$\begin{cases} (x_1 - x_2)x + (y_1 - y_2)y = b_{21} \\ (x_1 - x_3)x + (y_1 - y_3)y = b_{31} \\ \ldots \\ (x_1 - x_n)x + (y_1 - y_n)y = b_{n1} \end{cases}$$

In matrix form, the equations become: $M\ T = b$, where

$$M = \begin{bmatrix} x_1 - x_2 & y_1 - y_2 \\ x_1 - x_3 & y_1 - y_3 \\ \ldots & \ldots \\ x_1 - x_n & y_1 - y_n \end{bmatrix}, \ T = \begin{bmatrix} x \\ y \end{bmatrix}, \ \text{and } b = \begin{bmatrix} b_{21} \\ b_{31} \\ \ldots \\ b_{n1} \end{bmatrix}$$

Usually *n* (the number of reference points) is larger than three, so the system of equations becomes over-determined. To obtain the coordinates of the target node, one transfers the equations to a linear least squares problem: $\text{Min}\|\ M\ T - b\ \|^2$.

In this proposed algorithm, obtaining the weights (detectable counts as in Figure 3.1) is the calibrating process [43]. A larger number of detectables indicate stronger signal strength. The distances from all detected reference tags in the neighbor set *N* of our example in Figure 3.1 of Chapter 3.1 are replaced with the inverses of corresponding squared weights. The system of equations for the general multilateration algorithm [13] can then be re-written as

$$\begin{cases} \dfrac{1}{w_a^2} = (x - x_a)^2 + (y - y_a)^2 \\ \ldots \\ \dfrac{1}{w_d^2} = (x - x_d)^2 + (y - y_d)^2 \end{cases}$$

where w_a and (x_a , y_a) are the weight and coordinates of tag *a* respectively. Reference [3] provides further details for how to solve the system of equations by a standard least-square (LS) approach.

3.3 The leveled Bayesian inference

In essence, the approach of Bayesian inference [49,50] is to estimate optimally the posterior probability of the hidden or unknown states recursively in a system that is of the nature of Markov, as incomplete measurements or observations become available in a Bayesian network, which integrates the rule of Bayes ($p(A|B) = p(B|A)p(A)/p(B)$) and a directed graph. The edges of the graph are used to represent conditional dependence and information flow. We estimate the posterior probability of the target tag *t* (for simplicity, with *t* also representing its location (*x*, *y*)) when a series of *n* signal strengths s_i (i = 1,..., *n*) of its reference tags (*a*, *b*,...) transmitted to *t* are available [5]. As an example, Figure 3.2 demonstrates how the posterior probability is inferred for the case of Figure 3.1. The strengths of the three measures by the readable of reference tags (*a*, *b*, *c*, *d*) are s_1 = (1, 1, 1, 1), s_2 = (0, 1, 1, 0), and s_3 = (0, 0, 1, 0), where 1 means presence and 0 means absence of the corresponding reference tag. Since the system is assumed to be a Markov process, hence given t, the probabilities of s_i are independent of each other. The probability of target tag position t, given the series of measurements of its neighbor strengths $p(t|s_1,\ldots, s_n)$, can be calculated by the following recursive equation (see [49] for details)

$$p(t|s_1,\ldots,s_n) = \alpha p(s_n|t) \times p(t|s_1,\ldots,s_{n-1}), \qquad (3)$$

where α is a normalizing factor. $p(s_i|t)$ is the probability of signal strength of measurement i given the target t. Here, the signal strength will use the detectable counts as Chapters 3.1 and 3.2. In the case of moving targets, Equation 3 involves multi-dimensional integrals, in which Kalman filters, particle filters, and Monte Carlo methods [18,44,45], among other techniques, need to be utilized to approximate the solution.

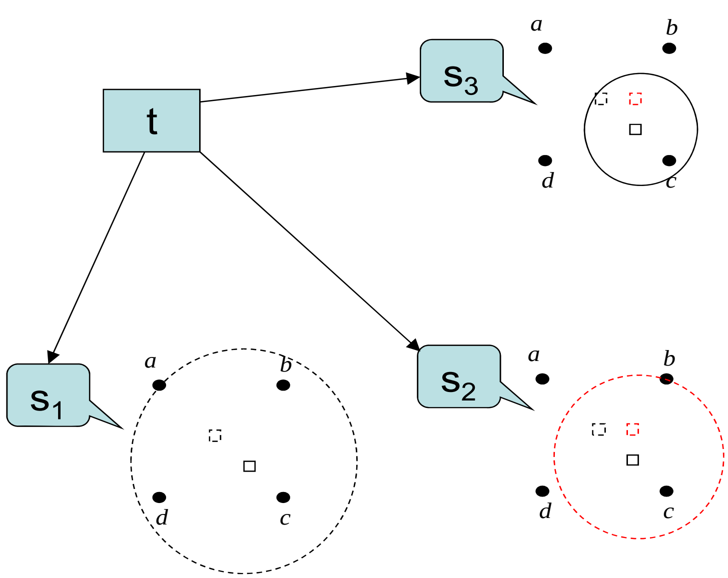

Figure 3.3: Leveled Bayesian inference by three levels

For solving the recursive Equation 3, we need to determine the *a priori* probability $p(t|s_0) \equiv p(t)$ for the target t, which represents all available information known about the target beforehand. As we only know the boundaries about the target in advance, we will use the uniform distribution probability for $p(t|s_0)$ since it is the least biased [50]. Therefore, $p(t|s_0) = p(t) = 1/N$, where N is the total number of reference tags in the region of the target tag. In our leveled algorithm, we make three measures, *i.e.*, $n = 3$. If we take account of the initial s_0, the Equation 3 will become

$$p(t|s_0, s_1,..., s_3) = \alpha p(s_3|t)p(s_2|t)p(s_1|t)p(t). \quad (4)$$

In the case of Figure 3.3, $N = 9$ and we get the following equations for each reference tag:

$$p_a(t \mid s_0, s_1, \ldots, s_3) = \alpha p(s_3 \mid t)p(s_2 \mid t)p(s_1 \mid t)p(t) = \frac{1}{7} \times \frac{1}{6} \times \frac{1}{4} \times \frac{\alpha}{N} \quad (5)$$

$$p_b(t \mid s_0, s_1, \ldots, s_3) = \alpha p(s_3 \mid t)p(s_2 \mid t)p(s_1 \mid t)p(t) = \frac{2}{7} \times \frac{2}{6} \times \frac{1}{4} \times \frac{\alpha}{N} \quad (6)$$

$$p_c(t \mid s_0, s_1, \ldots, s_3) = \alpha p(s_3 \mid t)p(s_2 \mid t)p(s_1 \mid t)p(t) = \frac{3}{7} \times \frac{2}{6} \times \frac{1}{4} \times \frac{\alpha}{N} \quad (7)$$

$$p_d(t \mid s_0, s_1, \ldots, s_3) = \alpha p(s_3 \mid t)p(s_2 \mid t)p(s_1 \mid t)p(t) = \frac{1}{7} \times \frac{1}{6} \times \frac{1}{4} \times \frac{\alpha}{N} \quad (8)$$

Then, we obtain $\alpha = 126$ from the following normalization equation

$$p_a + p_b + p_c + p_d = \alpha(1 + 4 + 6 + 1)/(7 \times 6 \times 4 \times 9) = 12\,\alpha/1512 = 1. \quad (9)$$

Therefore, we have $p_a = p_d = 126 \times 1/1512 = 0.083$, $p_b = 126 \times 4/1512 = 0.33$, $p_c = 126 \times 6/1512 = 0.50$.

Chapter 4

Simulations of leveled RFID localization for indoor stationary objects

In Chapter 4, simulation results are obtained for the proposed methods.

Using a computer simulation program (see Appendix) and the target location *t* = (4.1, 3.6), we compute the location errors of the proposed multi-power level approaches with regard to different reference tag densities from 1 to 5 meters (with 1 meter step), and different radius ratios of the detection range of the high-level power which varies from 70% to 150% of the "default *R* (radius)."

The "default *R*" used is the radius of the high-level power detection range when the reference tag density is at 4 meters; i.e. 3/4 of the length of the line *ac* = 4.2426 meters (see Figure 3.1). In other words, 150% of default *R* is 4.2426 x 1.5 = 6.3639. However, when R is too small (70% of the default = 4.2426 x 0.7 = 2.9698) and the tag density is too low (5 meters), none of the reference tags gets picked up by any of the multi-level detection ranges, so no location estimate of the target tag can be ascertained.

The current ratio of the radii of the set of three detection ranges used is 4 : 3 : 2, i.e. the small detection range is half of the large one and the medium one is the average of the large and the small. For each case when the large R changes (from 70% to 150% of the "default *R*"), the ratio of the three detection range radii remains unchanged at 4 : 3 : 2.

4.1 The simulation results of the three leveled RFID localization

4.1.1 The leveled nearest-neighbor

As demonstrated by the Figures 4.1 and 4.2, the results (localization error at: 0.0414, 0.0970 meter) of the proposed leveled nearest-neighbor method are impressive when the reference tag density is at one meter and the large detection range is at 80% and 90% of "default *R*" (3.3941, 3.8183 meters). Furthermore, even the results at default *R* are quite good.

However, when the reference tag density is too low while the detection range is also too small, results can be disappointing; e.g. when the density is 5 or 4 meters and the radius is 80% of *R*, the errors are 1.9026 and 0.9848 meter respectively. The problem is that only the high power detection range is able to read the reference tags, but the medium and small detection ranges fall short to do so.

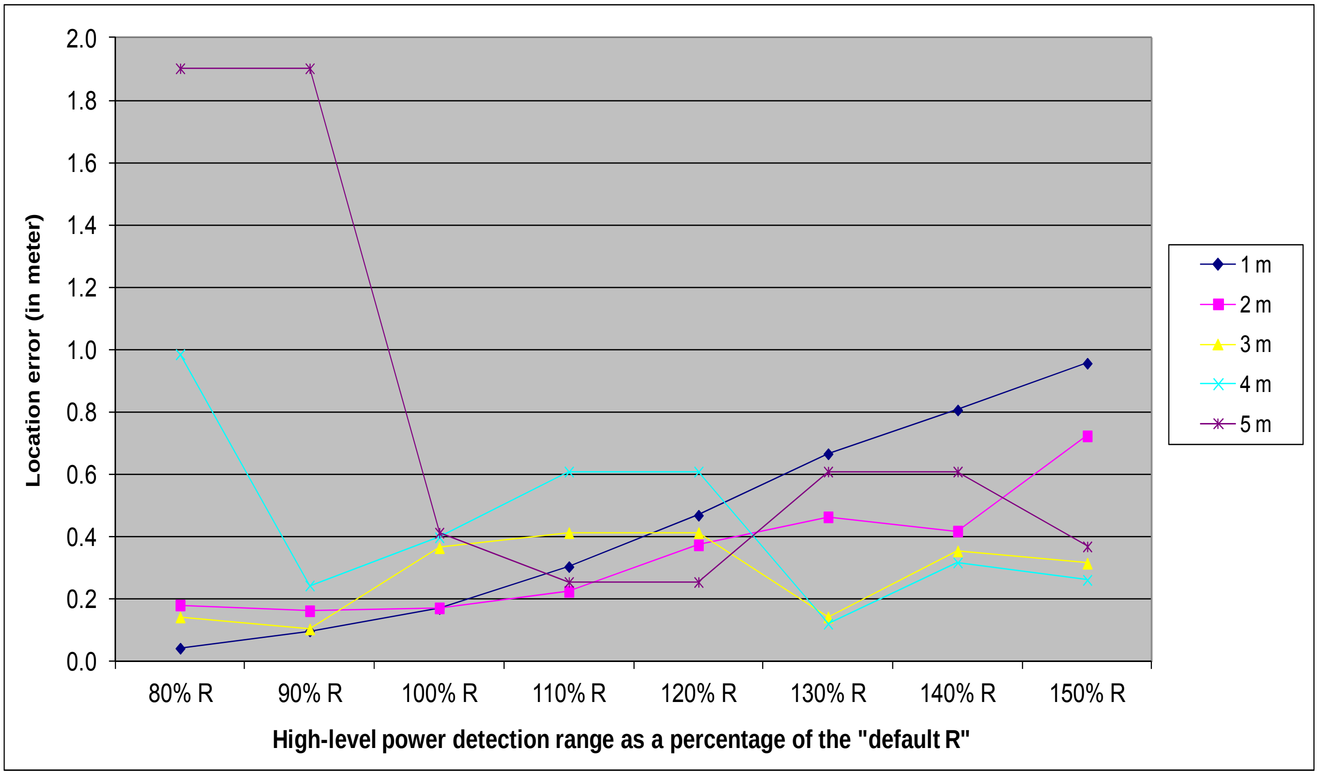

Figure 4.1: Leveled nearest-neighbor simulation results for different radius ratios

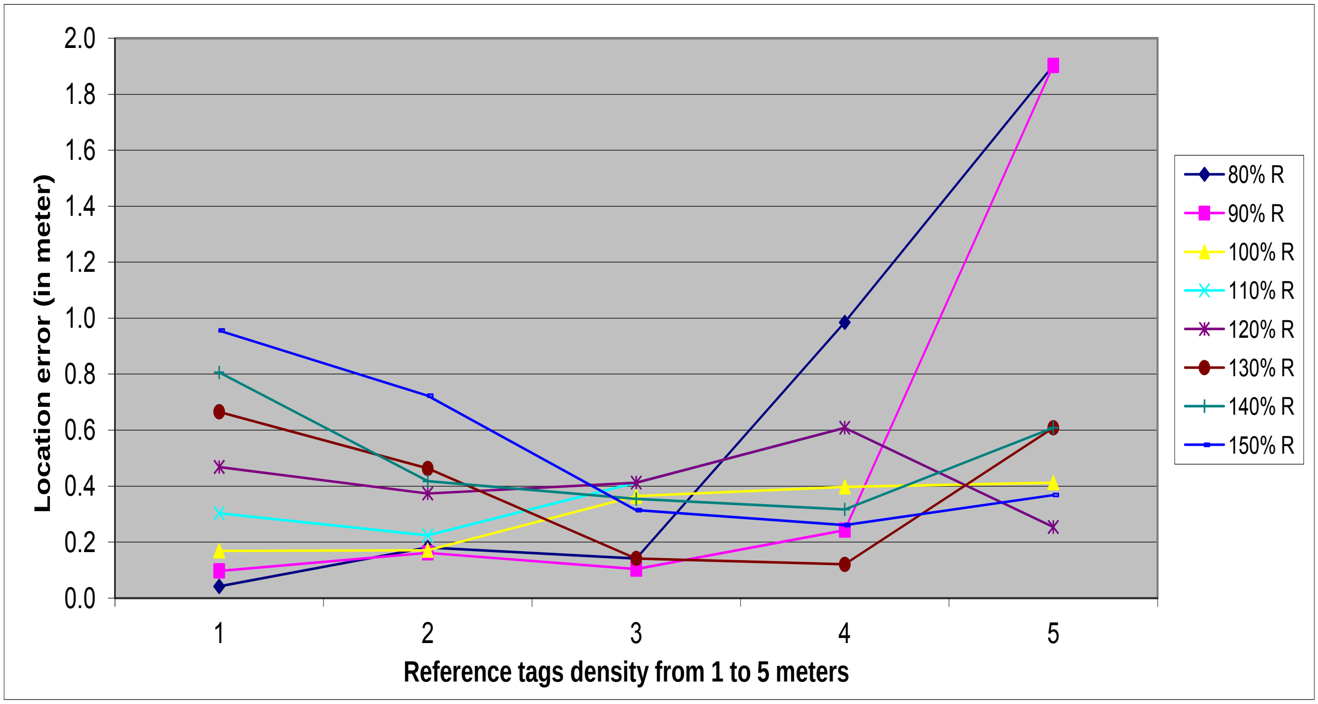

Figure 4.2: Leveled nearest-neighbor simulation results for different reference tag densities

4.1.2 The leveled multilateration

As indicated by the graphs in Figures 4.3 and 4.4, the overall localization accuracy performance of the proposed leveled multilateration scheme is quite satisfactory. Furthermore, Figure 4.4 shows that in general the higher the reference tag density and with the greater power level of the RFID reader (which produces a larger radius of the detected zone), the better is the accuracy performance in the estimation of the location of the target entity. Nonetheless, there is always the possibility of overshooting the peak performance. When the RFID reader's power level employed is too high, as seen in Figure 4.3, the accuracy starts to degrade when the radius of the detection range reaches 1.5 x *R* (= 6.3639 meters). Lastly, Figure 4.5 reveals that when the parameters of the reference tag density and power level are "optimized", the results of the proposed leveled multilateration algorithm (0.1003, 0.0408 meter) can be exceptional (the radius at 1.40 x *R* (= 5.9396 meters) and the reference tag density at one or two meters).

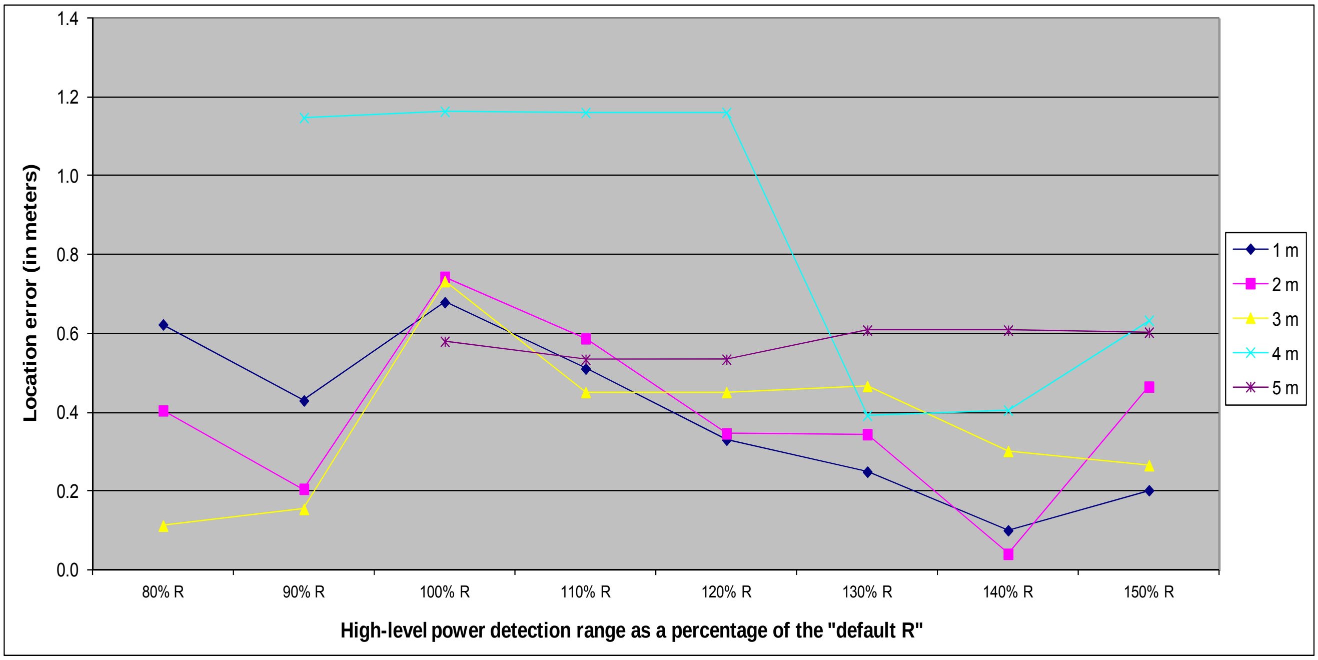

Figure 4.3: Leveled multilateration simulation results for different radius ratios

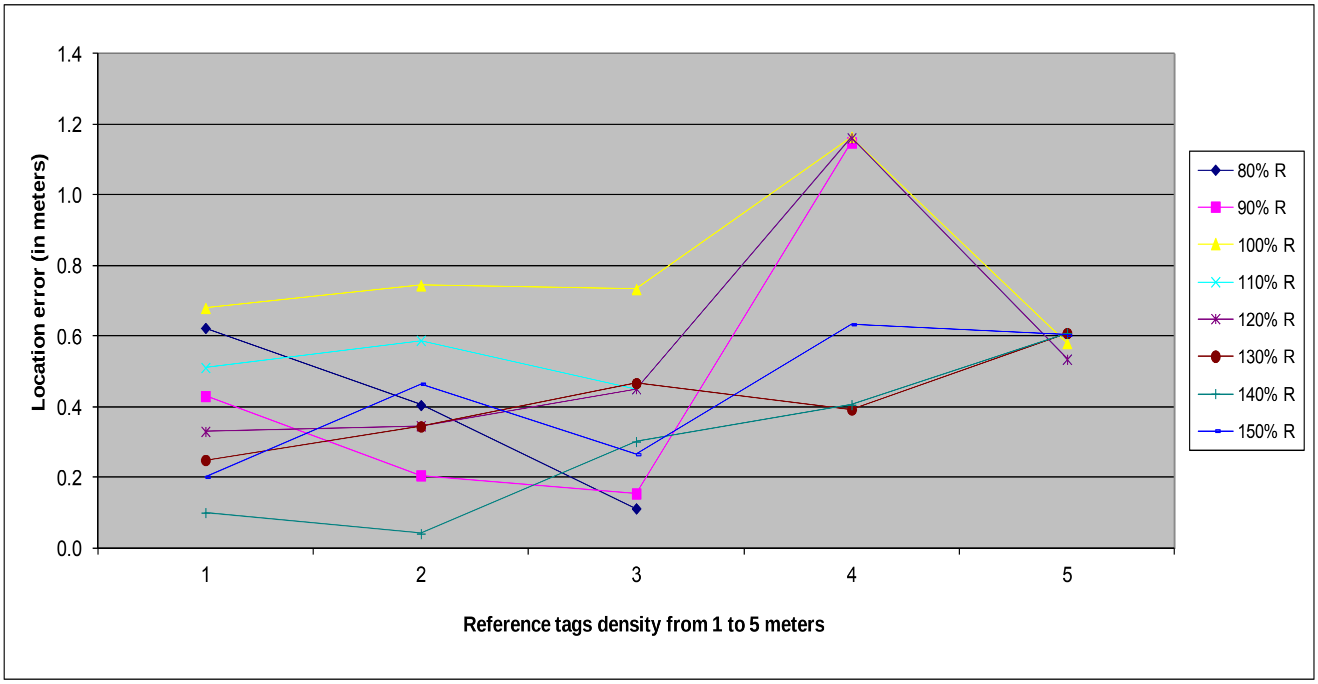

Figure 4.4: Leveled multilateration simulation results for different reference tag densities

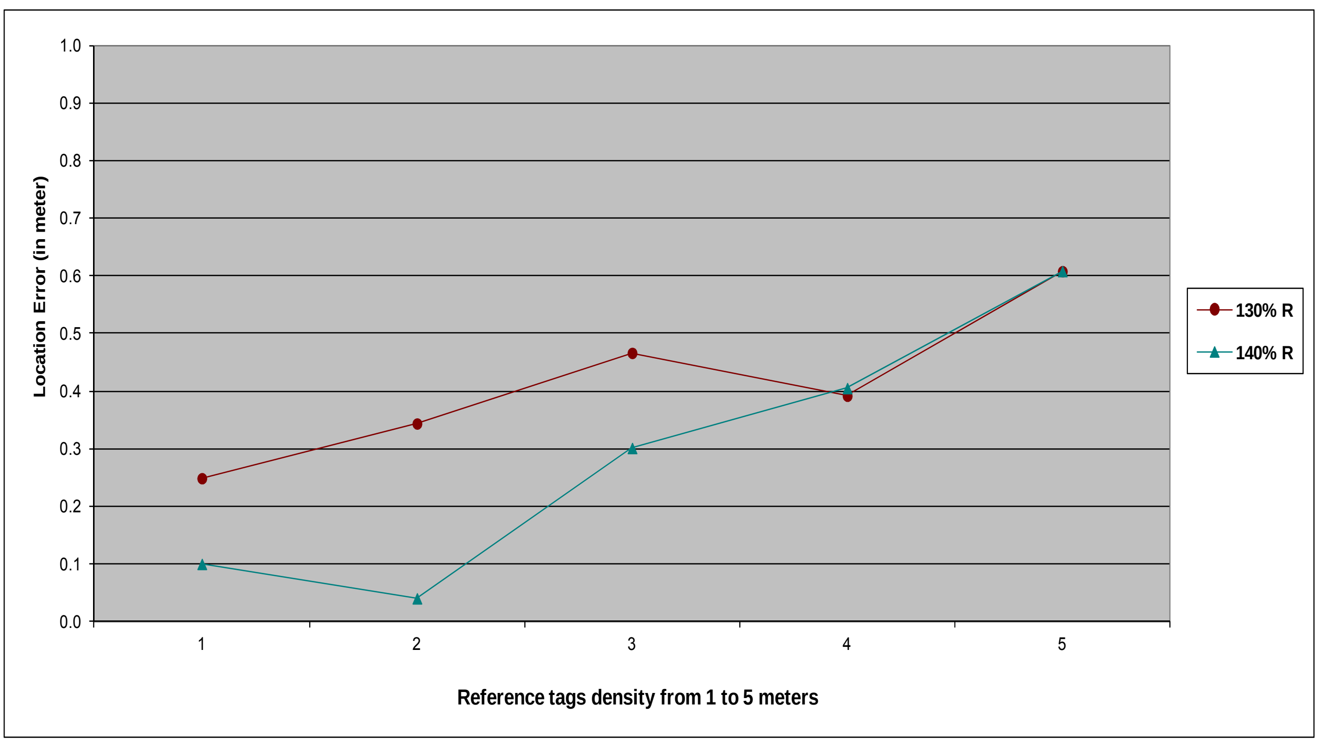

Figure 4.5: Leveled multilateration simulation results for different reference tag densities

4.1.3 The leveled Bayesian inference

Akin to the performance of the leveled nearest neighbor and multilateration methods, the leveled Bayesian inference algorithm performs quite well with highly satisfactory outcomes (Figures 4.6 and 4.7). More importantly, the results (0.0389, 0.0660, and 0.0871) are excellent when the high power detection ranges employed are relatively short (80% to 100% of the default *R*) and the reference tag density is high (at one meter). On the other hand, problems similar to that of the leveled nearest neighbor scheme can occur when the tag density is too high but the detection range is overly short. That causes the failure in the detection of any reference tags as they are outside the interrogation zone of the mid- and low-power levels of the RFID reader and the performance of the scheme will be significantly jeopardized.

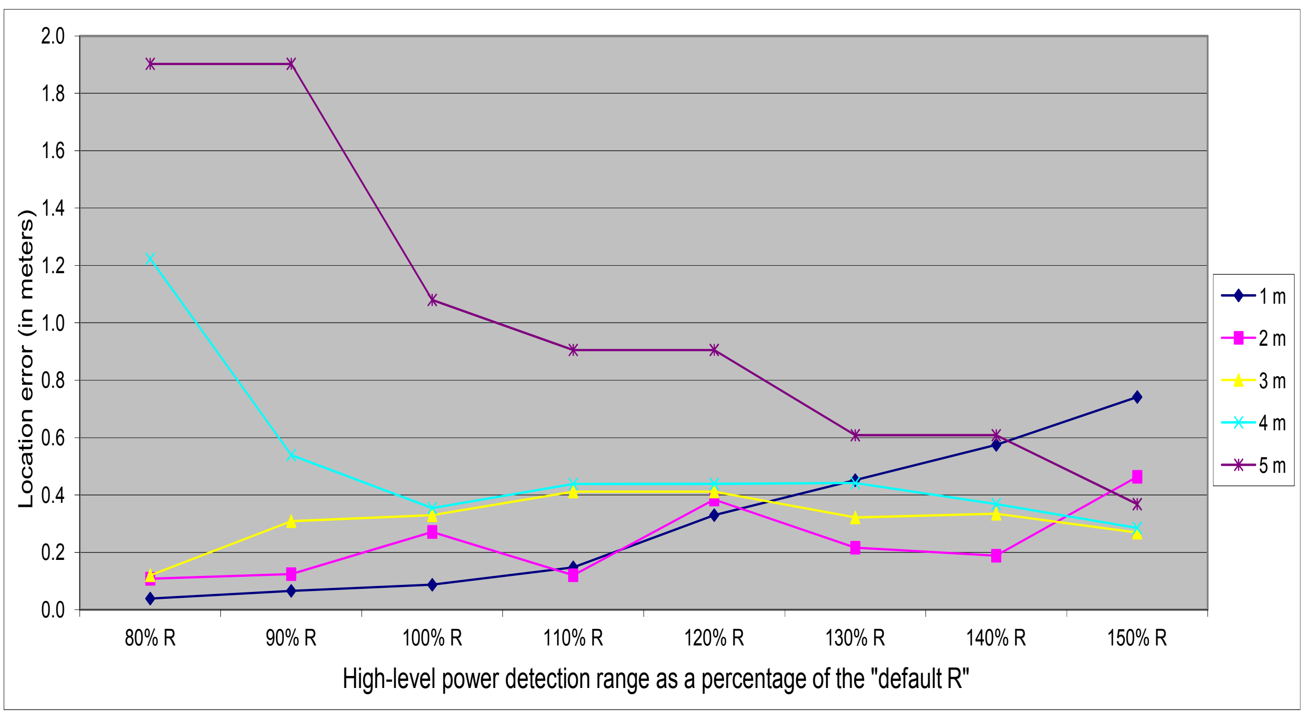

Figure 4.6: Leveled Bayesian inference simulation results for different radius ratios

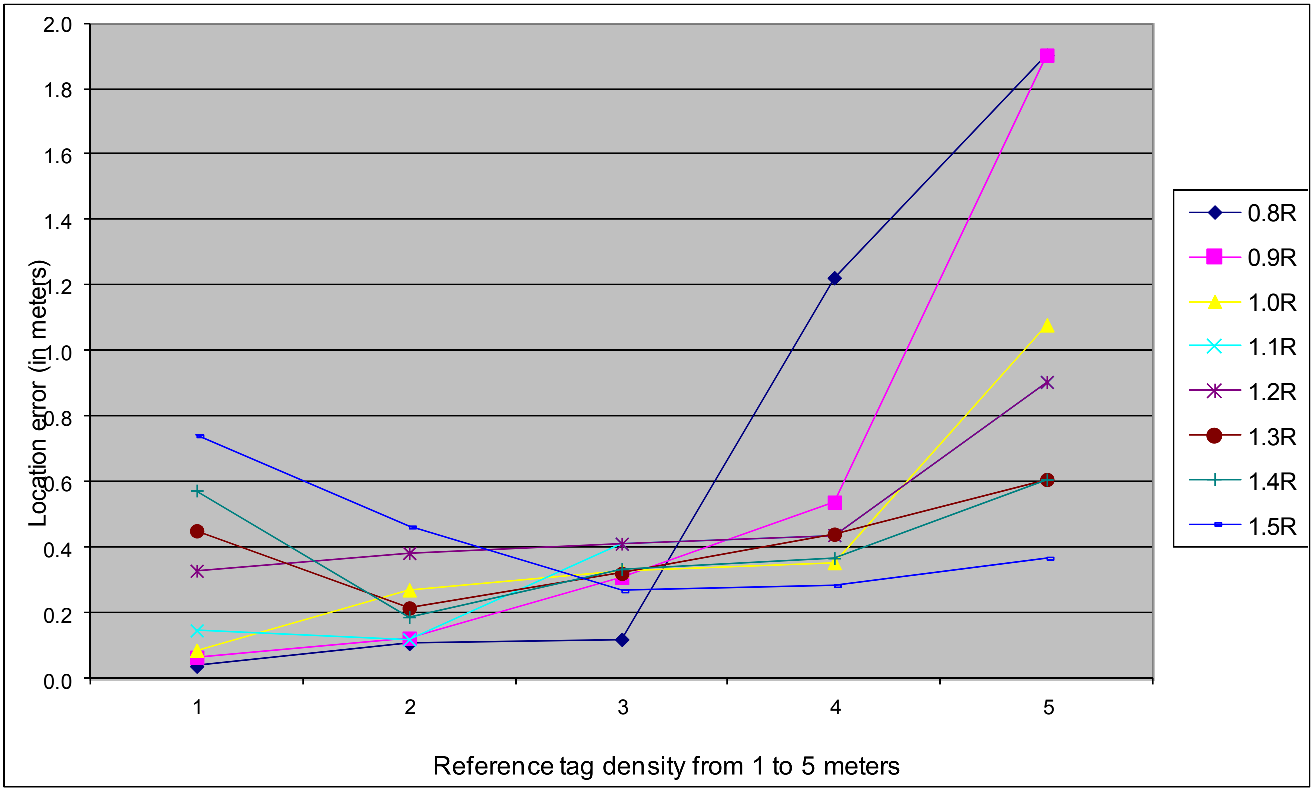

Figure 4.7: Leveled Bayesian inference simulation results for different reference tag densities

4.2 Analysis

Overall as illustrated by the outcomes of the computer simulations, all three multi-level RFID localization algorithms perform quite well as long as the extreme parameter values are handled properly. Figure 4.8 demonstrates that the LNN (leveled nearest-neighbor) and LBI (leveled Bayesian inference) schemes obtain similar outcomes when the reference tag density used is at one meter while the LML (leveled multilateration) result has a more distinct pattern. Furthermore, the LNN and LBI methods generate localization results (0.0414 meter, 0.0389 meter) that are much more accurate than that of LML (0.6228 meter) when the tag detection range utilized is small (80% and 90% of default *R*) and the reference tag density is high (at one meter). On the other hand, when the detection range is large (150% x *R* = 6.3639 meters), LML does significantly better than both the LNN and LML at the one meter tag density. As indicated by Figure 4.9, when the reference tag density employed is adjusted to three meters, all three proposed methods have comparable localization results and perform quite well even when the tag detection range used is at maximum (150% of the default *R*).

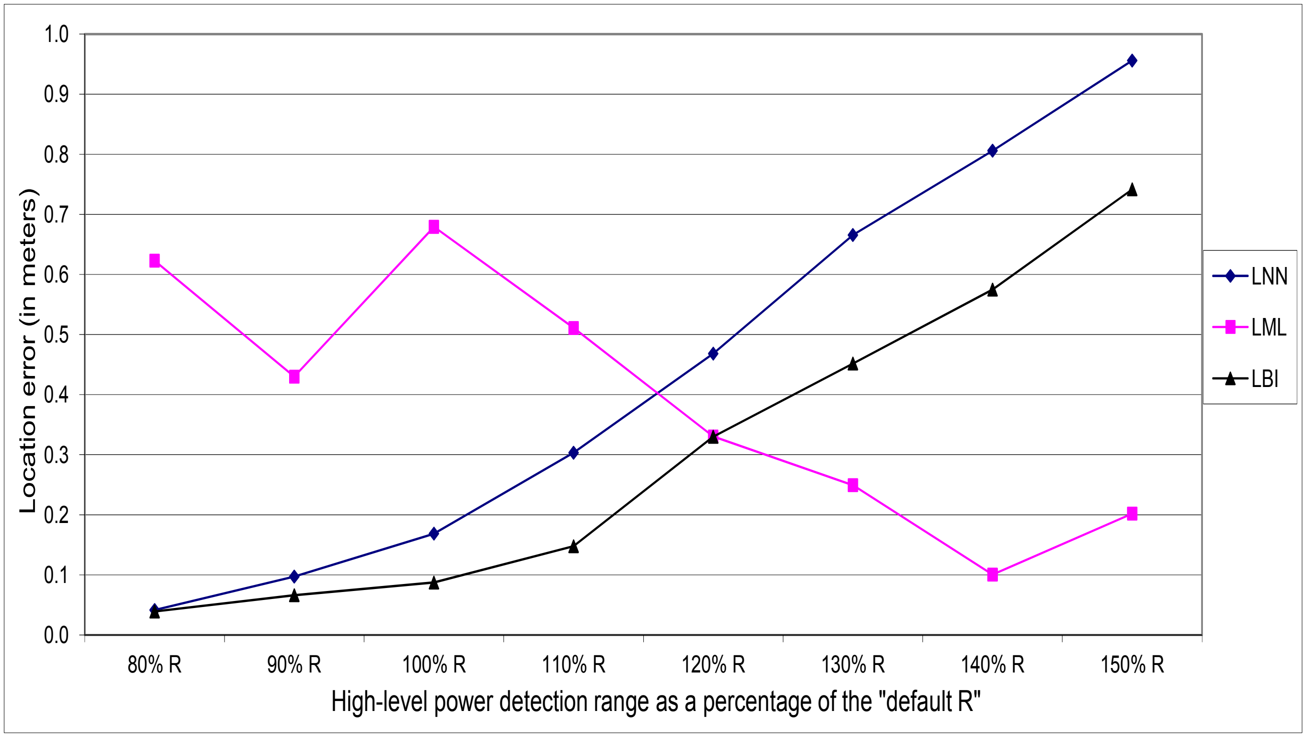

Figure 4.8: Proposed three algorithm simulation results at 1-meter tag density for different radius ratios

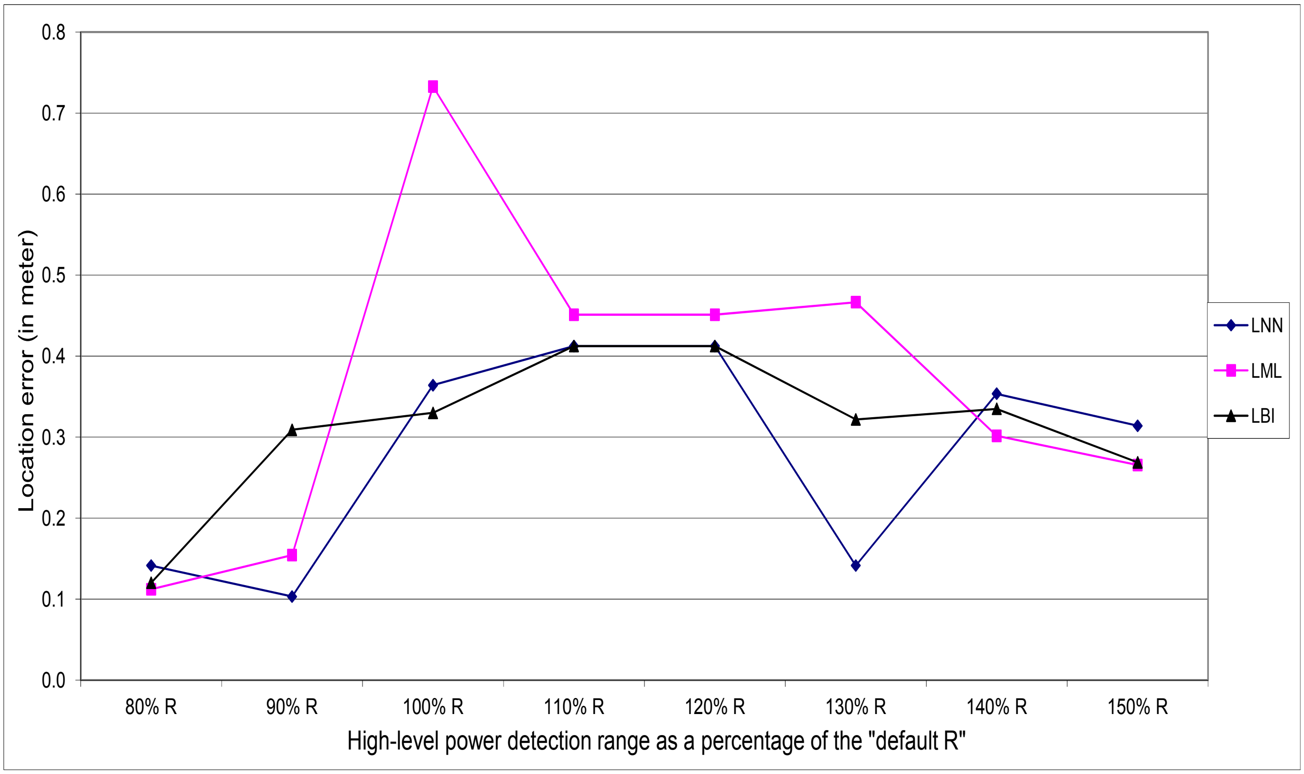

Figure 4.9: Proposed three algorithm simulation results at 3-meter tag density for different radius ratios

Chapter 5

Simulations of leveled RFID localization for mobile entities

In Chapter 5, we examine the methods on mobile entities through computer simulations.

The author proposes to apply the efficient, cost-effective, interference-resistant leveled RFID localization methods [5] to compute the estimated position of a moving entity in real time within an indoor environment. For the proposed RFID location tracking algorithms [6], the size of the room used is 30 times 30 squared meters. The actual path of the mobile object chosen is that of a U-shape (Figure 5.1). The path elected demonstrates that the proposed methods are able to track the movement of the entity as it makes sharp turns. The starting position of the moving target is (x, y) = (5, 15) and the ending location is about (22, 14). Moreover, the distance of the object travelled per "time step" or iteration is fixed at a constant length of three quarters of a meter.

Using a computer simulation program with the proposed schemes, the location of the object is estimated at every time step and is compared with its actual position. The distance between the estimated location and the actual position is the estimate error for that location. Since the object travels forty steps from its starting point, the distance errors from each step are summed up and then divided by the number of steps to give the average distance error for the whole path travelled, i.e. the Mean Localization Error (MLE).

The various reference tag densities tested are from 1 to 5 meters (with half meter steps), and the different radius ratios of the detection range of the high-level power of the RFID reader vary from 80% to 150% of the "default *R* (radius)." The "default *R*" used is the radius of the high-level power detection range when the reference tag density is at 4 meters; i.e. 3/4 of the length of the line *ac* = 4.2426 meters (see Figure 3.1). In other words, 80% of default *R* is 4.2426 x 0.8 = 3.3941 meters. The current ratio of the radii of the set of three detection ranges used in the methods is 2 : 3 : 4, i.e. the large detection range is twice of the small one and the medium one is the average of the small and the large. For each case when the *R* changes (from 80% to 150% of the "default *R*"), the ratio of the three detection range radii remains unchanged at 2 : 3 : 4.

The implementation of proposed methods is that if for any move when the location of the object cannot be estimated due to either no or insufficient reference tags detected for that parameter setting, we assume the result will not be generated for that parameter setting. For example, when the tag density is 5 meters and 80% of default *R* is used, zero tag is detected for a move using both the mobile leveled nearest neighbor and Bayesian inference methods. In addition, for the mobile leveled multilateration method, when the tag densities are low (5 to 3.5 meters) and the radii of the detection ranges are short (e.g. 80% and 90% of default *R*), less than three reference tags are detected for certain moves; so results are not generated for those parametric values as with only two or less detected reference points, multilateration cannot estimate those positions of a moving object at those steps.

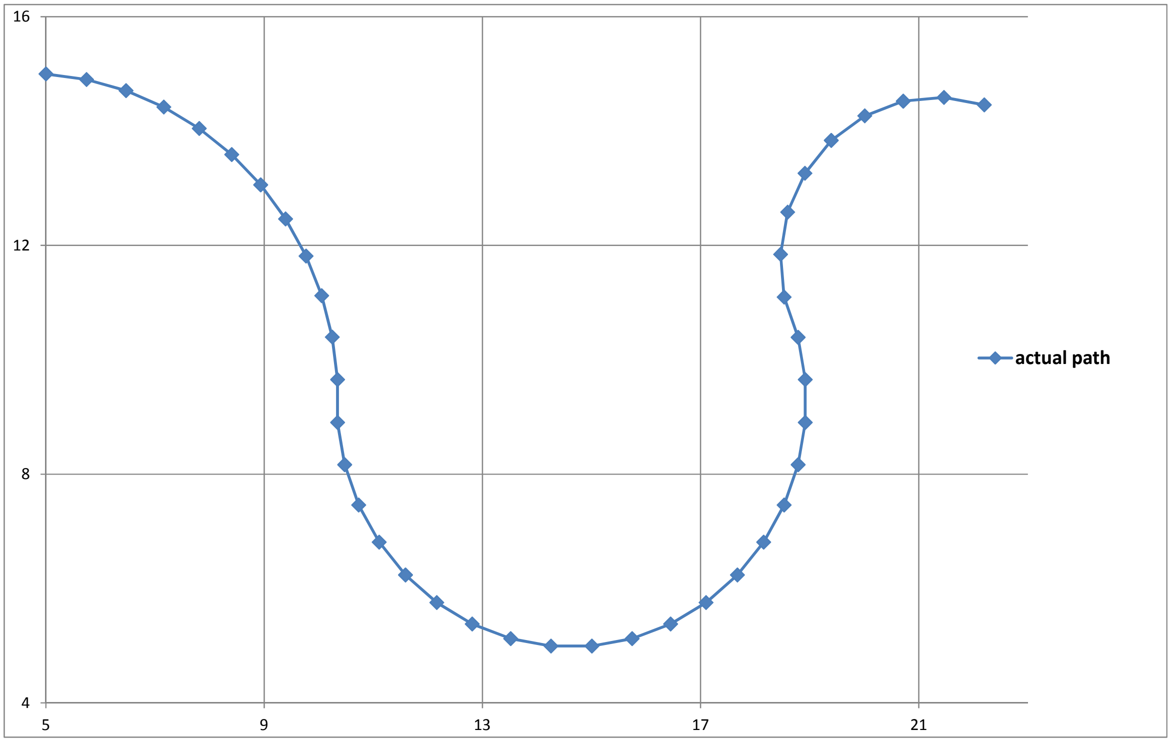

Figure 5.1: Actual path of the moving entity

5.1 Simulation results of the three mobile leveled algorithms

5.1.1 The mobile leveled nearest-neighbor

As indicated by the graphs in Figures 5.2 and 5.3, the results (MLE at 0.0442 and 0.0517 meter) of the proposed mobile leveled nearest-neighbor (MLNN) method are remarkable when the reference tag density used is at one meter and the large detection range is at 120% and 90% of "default *R*" (5.0911 and 3.8183 meters). However, when the reference tag density is too low while the detection range is also too small, results can be disappointing; e.g. when the density is 5 or 4.5 meters and the large detection range (radius) is 90% or 80% of default *R*, the MLEs are 0.8982 and 0.6276 meter respectively. The problem is that only the high power detection range is able to read the reference tags, but the medium and small detection ranges fall short to do so. In general, the higher the reference tag density, the better the tracking performance regardless of the range of the high power detection (the *R*) used as the MLE obtained at high tag density is quite small.

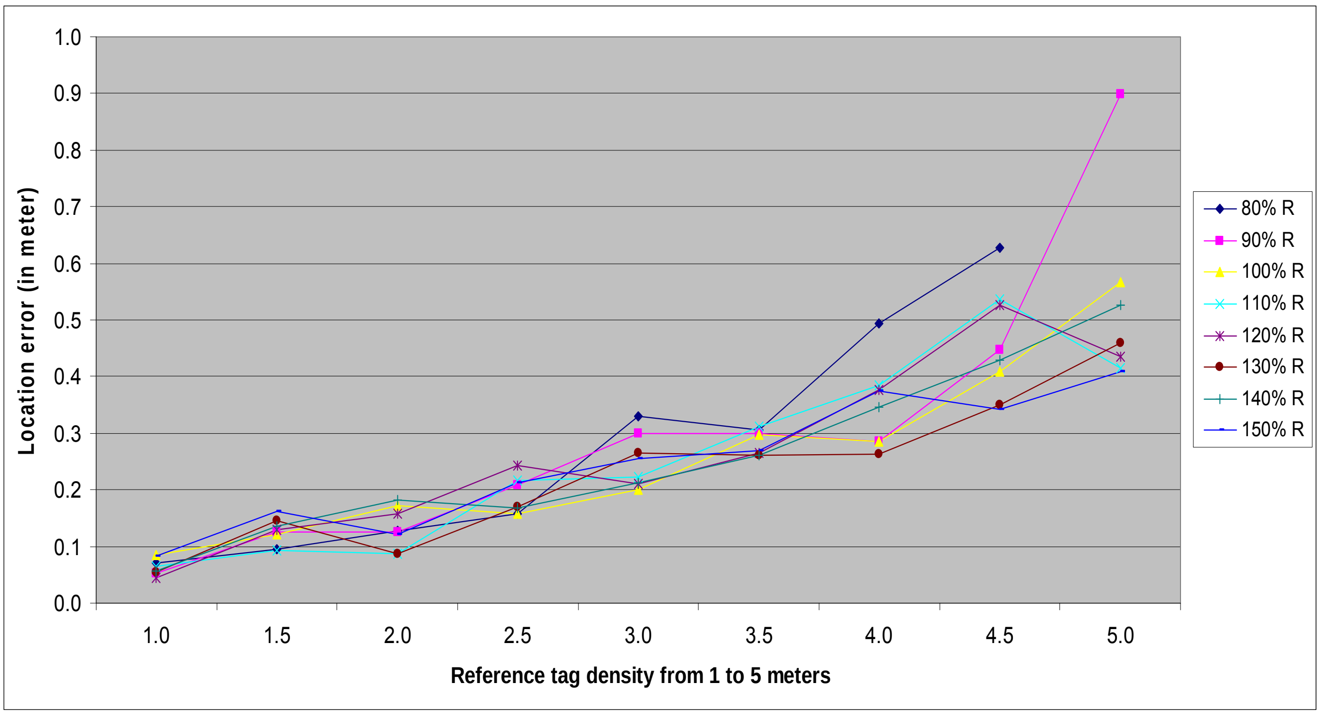

Figure 5.2: Mobile leveled nearest-neighbor simulation results for different reference tag densities

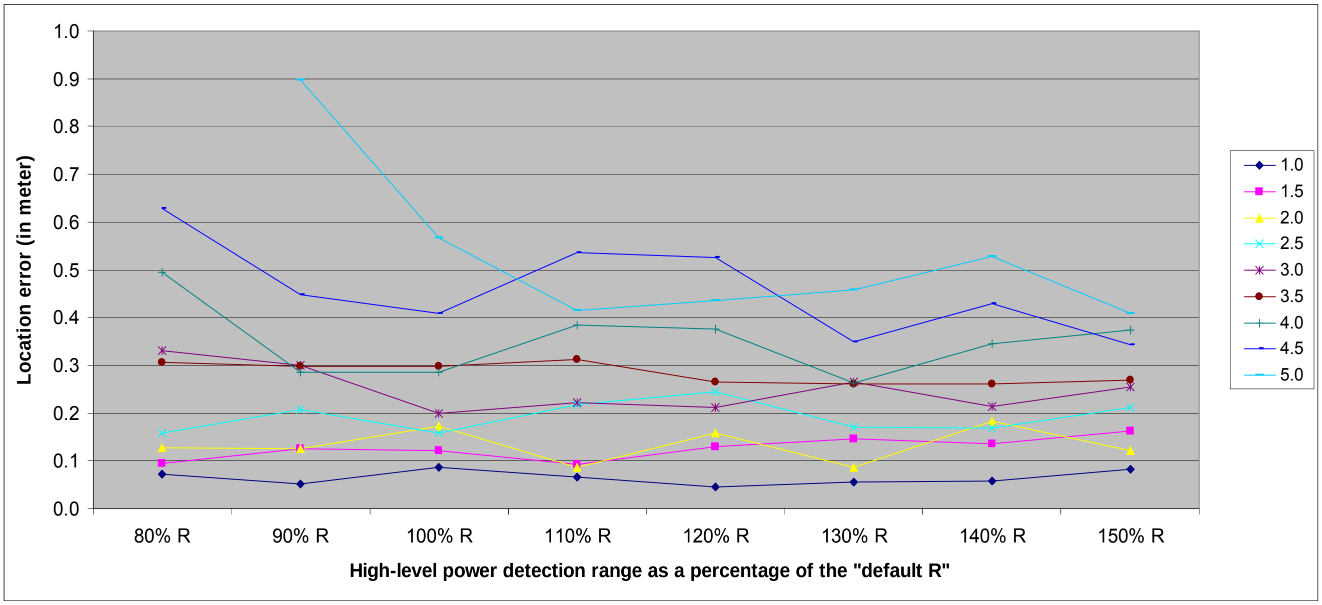

Figure 5.3: Mobile leveled nearest-neighbor simulation results for different radius ratios

5.1.2 The mobile leveled multilateration

As demonstrated by the Figures 5.4 and 5.5, the location tracking accuracy performance of the proposed mobile leveled multilateration (MLM) scheme is quite satisfactory when the proper reference tag density and *R* are chosen. The median MLE is 0.6982 meter when 2-meter reference tag density and 120% of the default *R* are selected. Moreover, the best MLE is 0.3529 meter whilst 2.5-meter tag density and 80% of the default *R* are used and this kind of performance is quite respectable. Finally, unlike the MLNN method, the power level of the RFID reader seems to play a bigger role for the MLM approach as it tends to have a better performance when the power level of the RFID reader used is smaller (which produces a shorter radius of the detected zone) and the reference tag density is higher (1 to 2.5 meters).

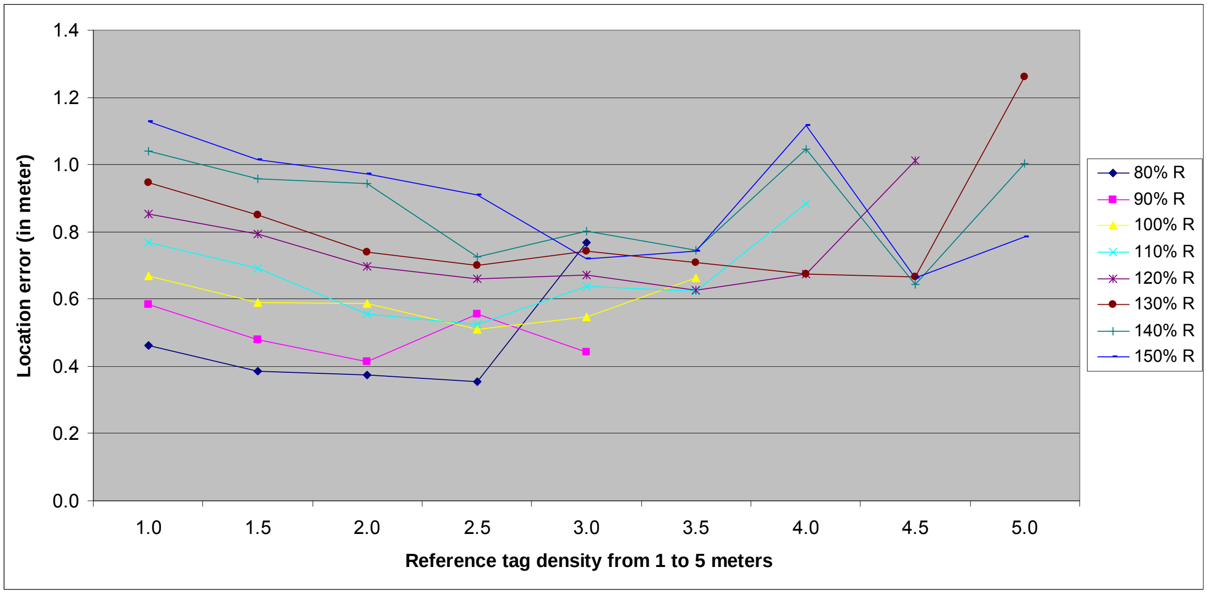

Figure 5.4: Mobile leveled multilateration simulation results for different reference tag densities

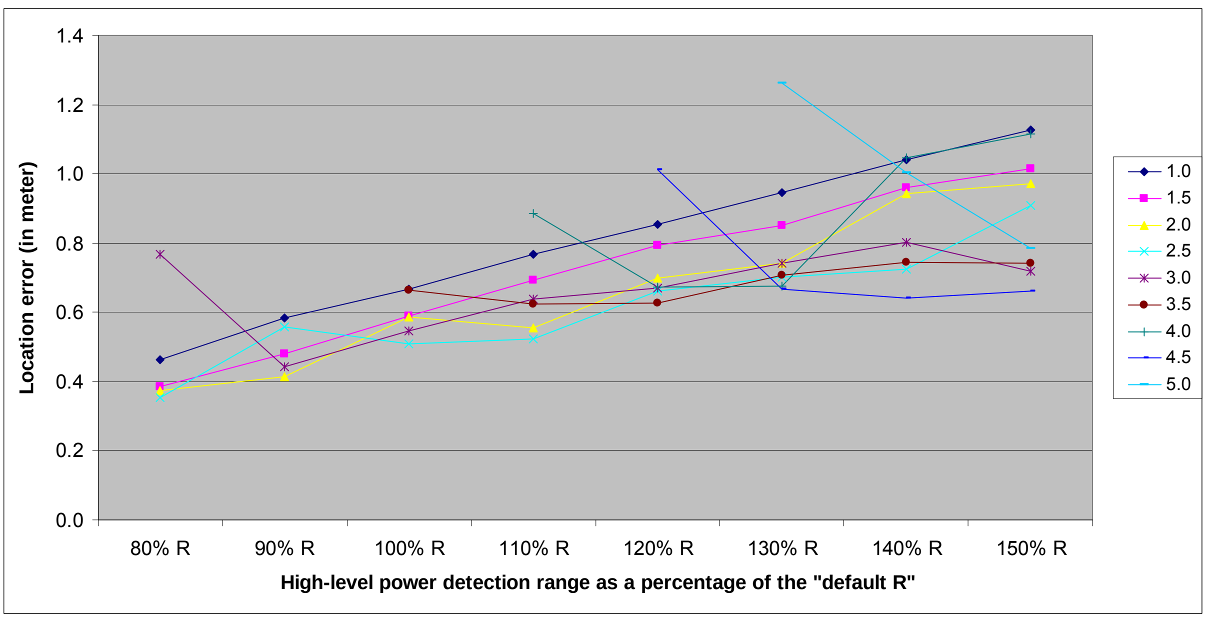

Figure 5.5: Mobile leveled multilateration simulation results for different radius ratios

5.1.3 The mobile leveled Bayesian inference

Similar to the performance of the mobile leveled nearest neighbor, the mobile leveled Bayesian inference algorithm performs quite well with highly satisfactory outcomes (Figures 5.6 and 5.7). More importantly, the results (0.0418 and 0.0419 meter) are impressive when the high power detection ranges employed are relatively long (120% and 140% of the default *R*) and the reference tag density is high (at one meter). On the other hand, problems similar to that of the mobile leveled nearest neighbor scheme can occur when the tag density is too low and the detection range is overly short. That causes the failure in the detection of any reference tags as they are outside the interrogation zone of the mid- and low-power levels of the RFID reader and the performance of the scheme will be significantly jeopardized (e.g. 1.05 meters MLE at reference tag density 5 meters and 90% *R*).

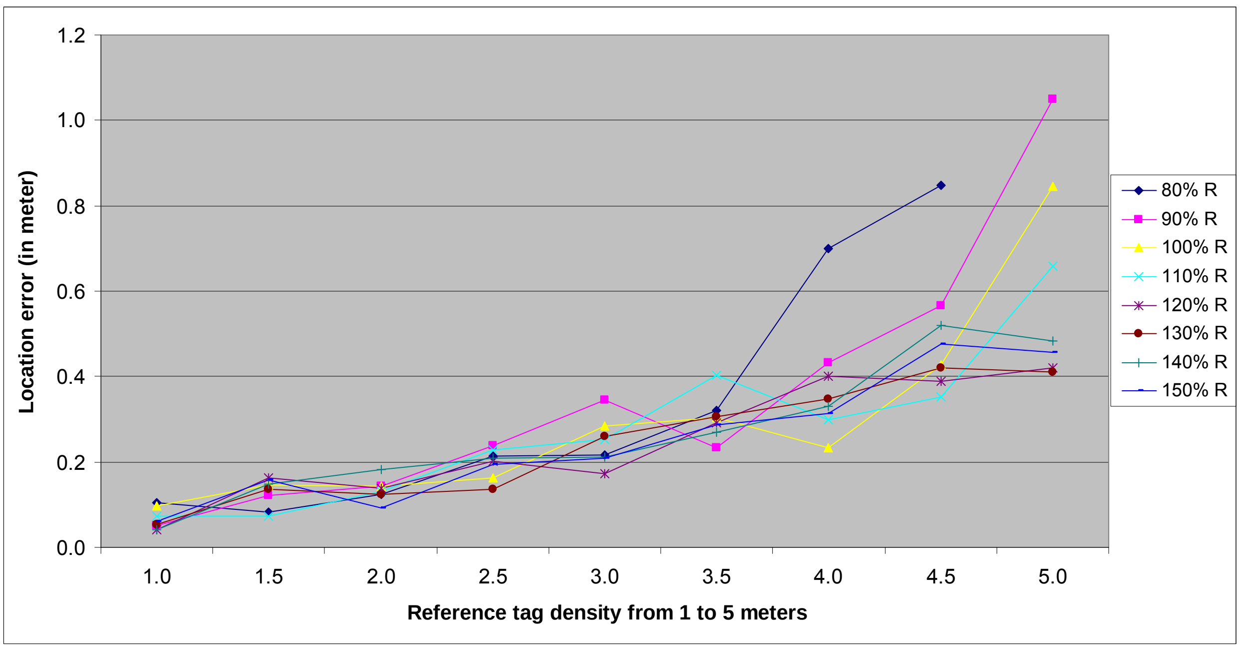

Figure 5.6: Mobile leveled Bayesian inference simulation results for different reference tag densities

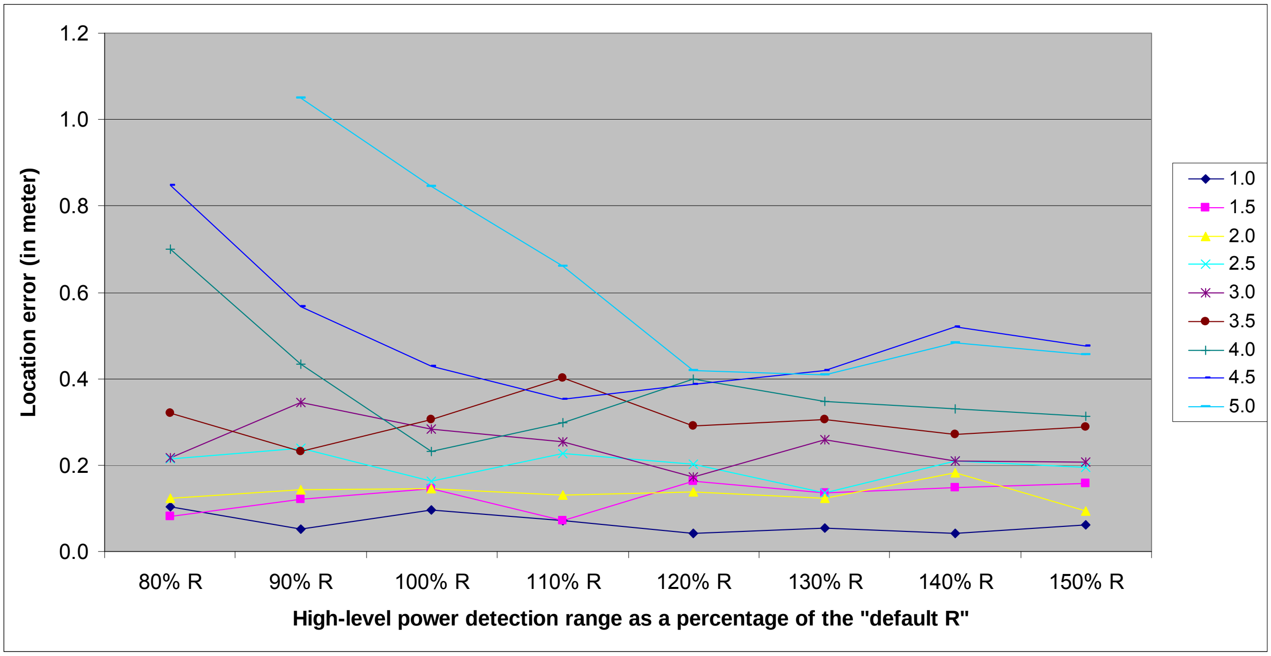

Figure 5.7: Mobile leveled Bayesian inference simulation results for different radius ratios

5.2 Analysis of simulation results of mobile leveled RFID localization

Overall, as indicated by the results of the computer simulations, all three multi-level mobile RFID localization algorithms perform quite well as long as the extreme parametric values are dealt with appropriately (the median MLEs obtained are 0.2435, 0.6982, 0.2321 for MLNN, MLM, MLBI respectively). Figures 5.8, 5.9 and 5.10 show that the proposed methods are able to follow the movement of the object quite nicely as it makes sharp turns along its U-shaped path. Even with the worst parametric values that are tested, the three methods are still able to track the general direction of the motion of the entity (MLEs 0.8982, 1.2606, 1.0500 using the following tag density and percentage of default *R*: 5 m, 90% *R*; 5 m, 130% *R*; 5 m, 90% *R*).

The best results of both MLNN and MLBI (0.0442 and 0.0418 meter) are much more accurate than that of MLM (0.3529 meter); the reference tag density and power detection range used are 1 meter, 120% *R* for both MLNN and MLBI, and 2.5 meters, 80% *R* for MLM. Though the performance of MLM is a bit less satisfactory as the deviation of its best computed path from the actual path is far from perfect but somewhat noticeable. But with the optimal parameter setting, the resulting best computed paths of MLNN and MLBI are very close to that of the actual path of the moving entity. In general, both MLNN and MLBI perform better as the chosen reference tag density approaches a higher value. Lastly, MLM does better when the range of the high power level of RFID reader used is shorter.

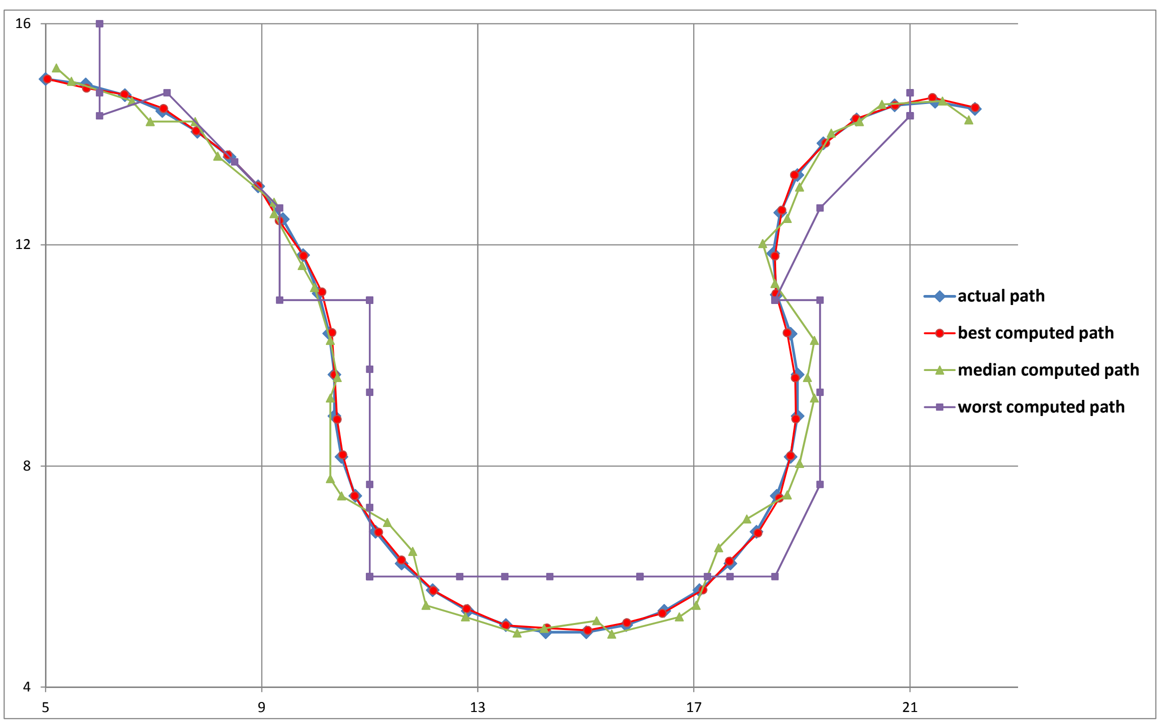

Figure 5.8: Actual path, best, median and worst computed paths of the mobile leveled nearest-neighbor method

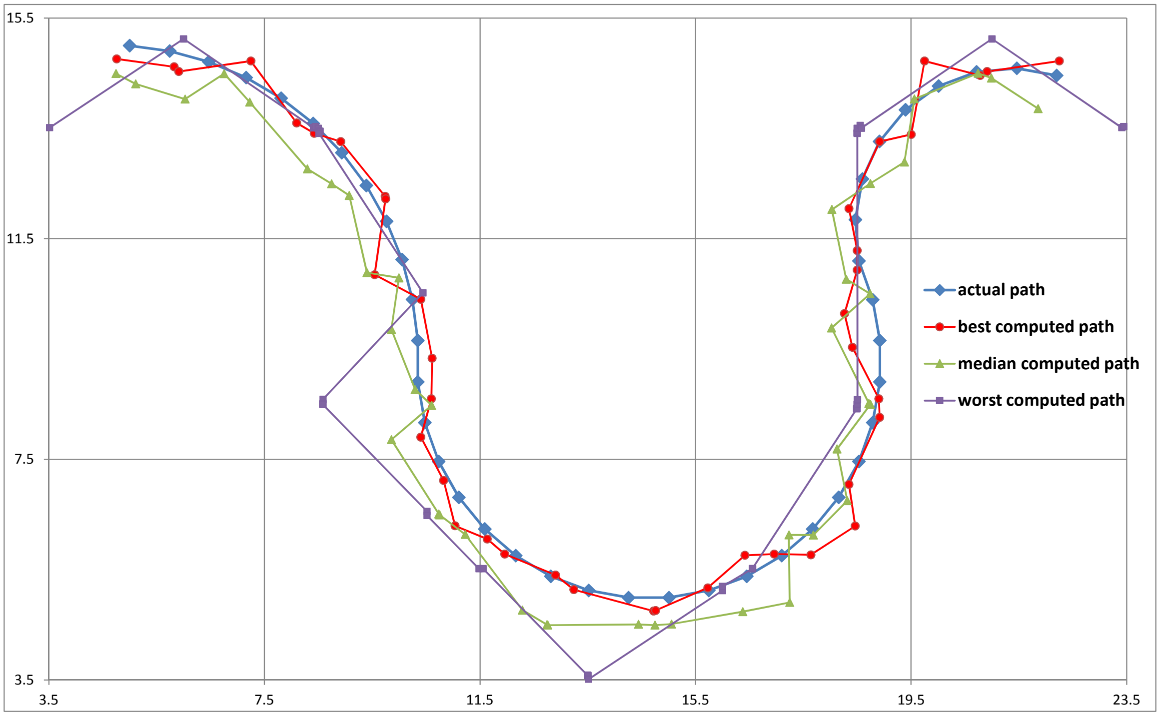

Figure 5.9: Actual path, best, median and worst computed paths of the mobile leveled multilateration method

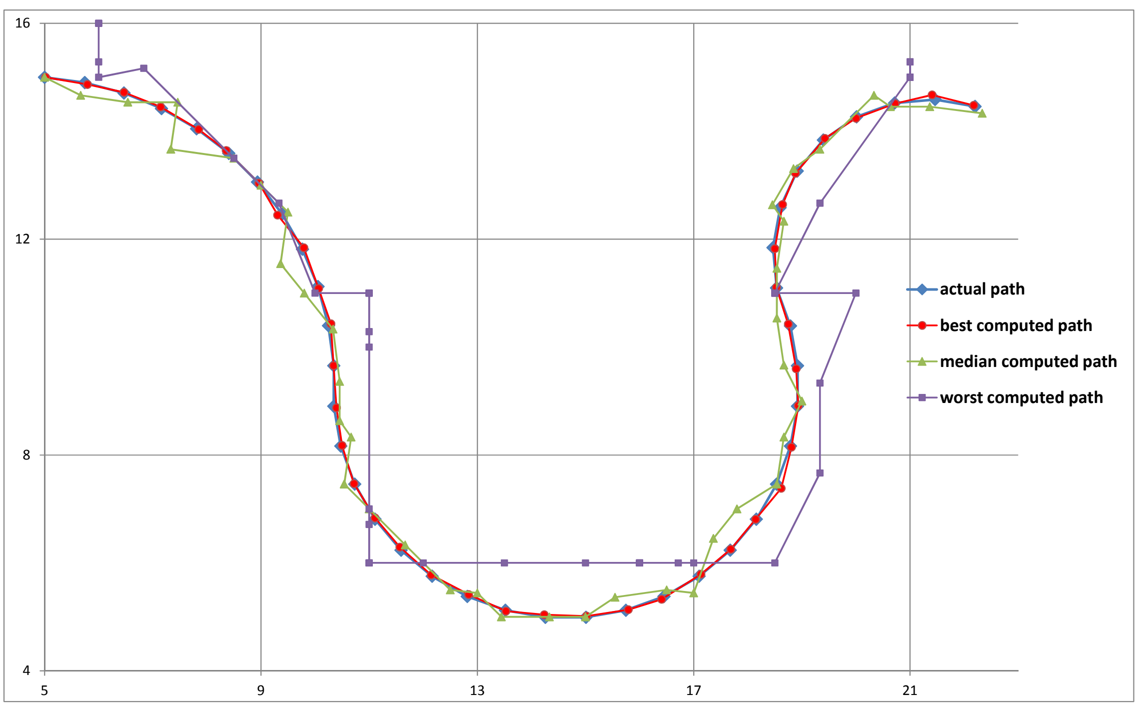

Figure 5.10: Actual path, best, median and worst computed paths of the mobile leveled Bayesian inference method

Chapter 6

Testing the leveled methods in a laboratory experimental setting

In Chapter 6, we perform experiment in a laboratory environment to test the validity of our approaches.

In order to examine the proposed methods in a realistic circumstance, we decide to carry out experiments in the environment of a laboratory [7]. The reader we chose to employ is the ultra-high frequency RFID reader made by Alien Technology (ALR-9900+), together with a pair of the Alien ALR-8696-C antennas; and the passive RFID tags used are Alien type G tag (ALN-9654) (see Figures 6.1 to 6.3). The size of inlay of the tag is 96.5 x 23.2 mm^2 (3.8 x 0.9 squared inches).

Figure 6.1: A single Alien ALR-8696-C antenna

Figure 6.2: RFID reader of Alien Technology (model number is ALR-9900+)

Figure 6.3: Backside of passive Alien type G RFID tag (ALN-9654)

6.1 Sensitivity and orientation of RFID tags

As other researchers have indicated, tag sensitivity and quality is an important issue when one attempts to implement a RFID localization scheme. We examine every tag that we have acquired to weed out the outliners, those that are very sensitive or too insensitive. Basically we choose the tags that belong to the "middle of the pack" category; i.e. they have normal and average sensitivity for that type of tags we are using.

In general, the best orientation of a tag for the purpose of detection is that it faces the antenna in a parallel fashion. But as the antenna is normally standing vertically, it is highly not advisable to also have the tag standing up as that kind of setup will likely interfere with the movement of an entity when mobile localization is required to be implemented. Hence the next best approach is to have the tag lie flat on the floor but in a parallel orientation in reference to the footprint of the antenna.

But since the tags are placed all over the floor of the testing area in a square grid pattern, and even with four antennas used, there is no guarantee that a tag which is within the detection range of an antenna will be parallel to an antenna. To enhance the likelihood that the detectable reference tag's orientation is at zero degree from an antenna, we put two tags in a cross pattern at every single reference point in order to increase the detectability of that reference point.

6.2 Experimental setup

The probability of detection of a tag in the quarter-ish region directly in front of the antenna is almost very high, usually between 90 to 100%, i.e. if an RFID tag is in that region not too far from the antenna and when the reader scans for the tag, the successful read counts out of the 100 scans is at least 90. To ensure that the full circular region (i.e. 360 degrees) around the target has similar detection likelihood and capability, we need to employ four antennas at 90 degrees to each other, a single antenna turning 90 degrees four times, or two back-to-back antennas turning 90 degrees once for scanning. We elect the last option as it is the least cumbersome to implement and execute.

To ensure that the surface is highly clean, free of dusts or debris, we decide to put brand new paper poster boards on the floor before we lay down the passive RFID tags with the pair of RFID antennas placed at the center the testing area within the lab room. The tags are placed on the floor in a square grid pattern with each cross pattern tag pair positioned a half meter from one another (see Figures 6.5 and 6.6). The size of the testing area in the laboratory that is used for the experiments is forty two and a quarter squared meters (a square region of 6.5 x 6.5 sq. m.). We do not place the RFID tags on the testing region's boundaries; hence the first pair of cross tags are laid at the location of *x*, *y* coordinates of 0.5, 0.5 (meter) while the last pair is at 6.0, 6.0 (meters). All together, one hundred and forty four pairs of RFID tags are placed in the testing region with the target (i.e. the pair of back-to-back antennas) located at the center of the area (*x*, *y* = 3.25, 3.25).

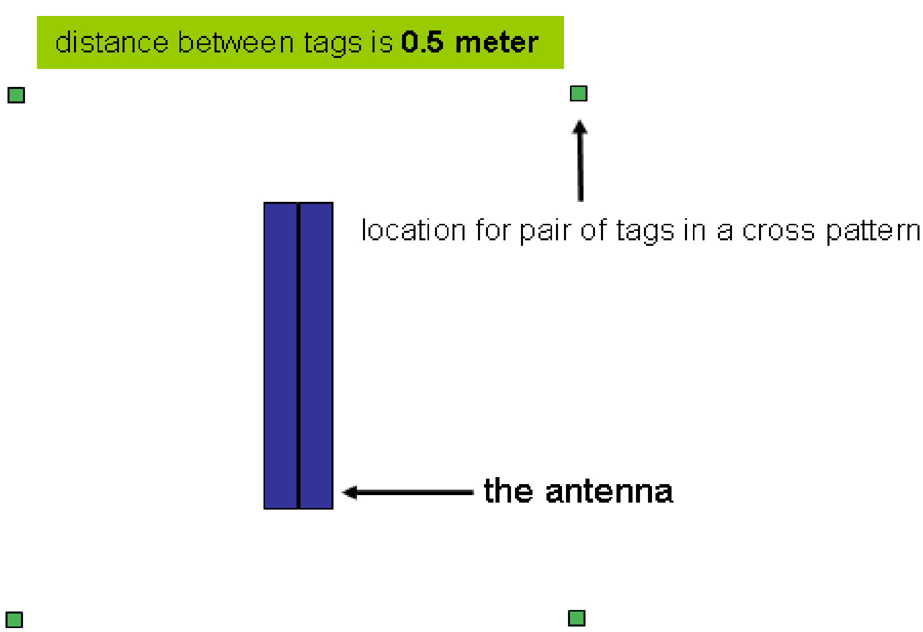

Figure 6.4: Schematic top view of the center of the testing area

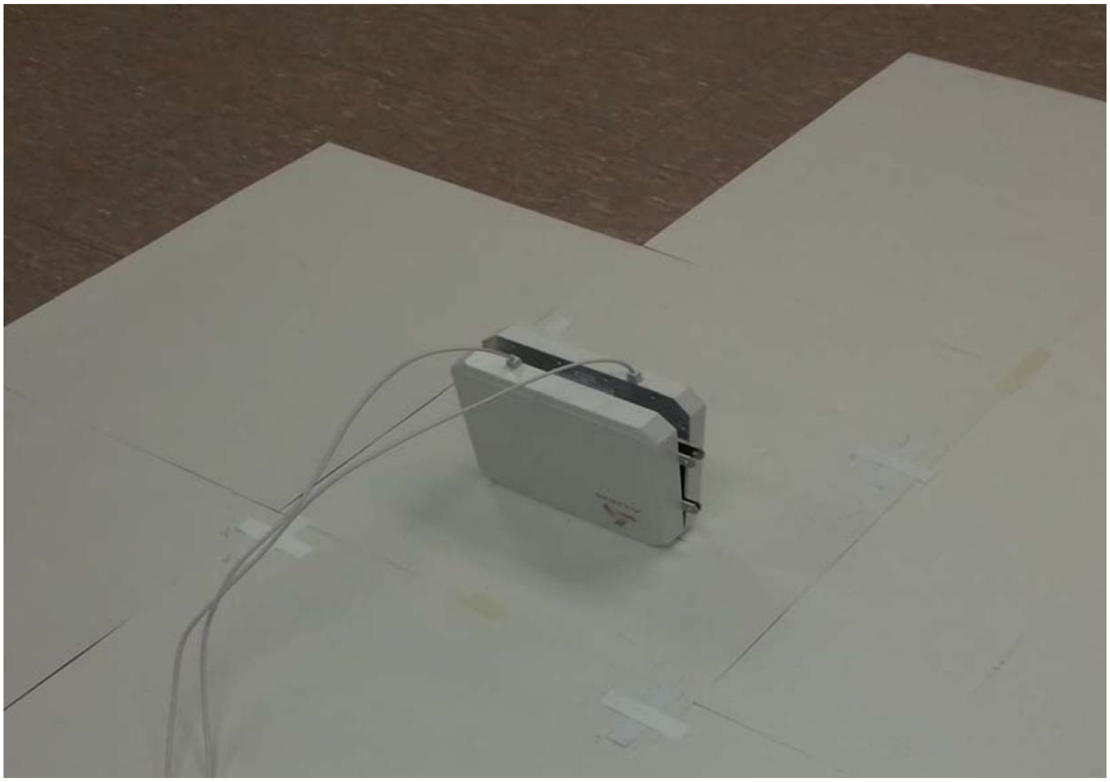

Figure 6.5: Setting up the testing area with the antennas at the center

Figure 6.6: Testing region with 144 pairs of RFID tags (half meter apart)

Through the adjustment of the power attenuation of the RFID reader, we can control the detection range of the reader for the tags that are being queried. Our approaches state that there are three detection ranges: large, medium and small; and the ratio of those ranges used in our simulations is 4 : 3 : 2. In the experiments, we test four instances with the same ratio for the three detection ranges:

i. 1.0 : 0.75 : 0.5 meter,

ii. 2.0 : 1.50 : 1.0 meter,

iii. 3.0 : 2.25 : 1.5 meters,

iv. 4.0 : 3.00 : 2.0 meters.

6.3 Experimental results and analysis

Based on the experiments and the results of computation, the estimated locations (*x*, *y* coordinates in meters) of the target for the three multi-leveled methods (Leveled Nearest-Neighbor, Leveled Multilateration and Leveled Bayesian Inference) are:

case number	**LNN**	**LBI**	**LML**
1	3.2917, 3.2083	3.2826, 3.2391	3.2677, 3.4747
2	3.3704, 3.2222	3.3700, 3.2100	3.4864, 3.4107
3	3.2128, 3.2234	3.2035, 3.2384	3.0637, 3.4821
4	3.2778, 3.1984	3.2582, 3.2049	2.9818, 2.7636

Table 6.1: Estimated locations of the target

Since the true actual location of the target in the experiments is at 3.25, 3.25 meters, we have the following results (errors in distance of estimate target location) and also the average of the four cases for the three multi-leveled methods (in meters):

case number	**LNN**	**LBI**	**LML**
1	0.058926	0.034373	0.225442
2	0.123534	0.126491	0.285888
3	0.045757	0.047943	0.297674
4	0.058591	0.045821	0.555448
average (of 4 cases)	0.071702	0.063657	0.341113

Table 6.2: Errors in distance of estimated target location

Generally speaking, it is apparent that the results of the proposed methods of localization experiments in the laboratory setting are consistent with that of the afore-mentioned results done in the computer simulations. Moreover, the average results for both the LNN and LBI (0.071702 and 0.063657 meter) are good. Even the LML's average result of 0.3411 meter is rather reasonable, given that the size of an indoor space can be extremely large (for example 500 x 500 squared meters). Finally, for the four cases and the three methods used, the best and the second best results of 0.034373 and 0.045821 meter (Leveled Bayesian Inference, case 1 and case 4) are impressive.

Chapter 7

Conclusion and future directions

For the computer simulations of our proposed methods to test the ability to accurately locate stationary objects, we vary the density of the reference tags, which are affixed onto the floor from one to five meters with one meter step. We also vary the range of the high power level of the RFID reader from 80% to 150% of the default *R* (4.2426 meters). The best result of the localization errors (at 0.0414 meter) of the proposed leveled nearest-neighbor method is excellent when the reference tag density employed is at one meter and the detection range of the high RFID reader power level is at 80% of default *R* (3.3941 meters). Regarding the proposed leveled multilateration algorithm, the simulation yields impressive result if the parameters are optimized (localization error of 0.0408 meter with two-meter reference tag density and 140% default *R* detection range: 5.9396 meters. Moreover, the best localization error result of the proposed leveled Bayesian inference method is remarkable (0.0389 meter with parameters of 80% default *R* and one meter reference tag density).

As the simulation results clearly indicated, the proposed leveled detectable count RFID localization methods produce outstanding accuracy performance, when the proper values of the reference tag density and detection range are elected in conjunction with the specific multi-power level approach. Of the three localization algorithms to locate stationary object, LNN (leveled nearest-neighbor) and LBI (leveled Bayesian inference) schemes obtain similar impressive outcomes when setting the reference tag density high with low detection range. LML (leveled multilateration) result has a more distinct pattern.

Simulations and experiments confirm that parameters such as reference tag density and detection range are critical to the implementation. In addition, both the computer simulations and the follow-up experiments of the study indicate and confirm that a localization error of less than four centimeters is attainable when we attempt to compute the estimated position of the stationary object. Furthermore, the simulation results of the mobile algorithms establish that our mobile methods are able to track moving entity in real time even when it undertakes sharp turns as the actual path of the mobile entity is that of a U-shape.

In contrast to other non-RFID schemes, utilizing passive RFID technology is a highly cost-effective means for the acquisition of indoor positional information of both stationary and mobile entities. Additionally, the deployment of RFID infrastructure is much less cumbersome and can be accomplished in a reasonably brief time frame. As it is well-documented in numerous RFID localization literatures, RSSI is quite susceptible to the interferences and noises in the environment, the author's adaptation of employing detectable counts significantly increases the resistance of the proposed algorithms to the various interference challenges imposed by the real-life circumstances of RFID localization applications.

In regard to the future directions of the study, we will:

- explore different ratios for the three power levels of the RFID reader, which is currently fixed at 4 : 3 : 2
- use other reference tag spacing pattern besides square: for example, hexagon

- explore other multi-level approach beside tri-level such as quad-, penta- or dual-level
- use other kinds of RFID reference tags besides the passive Alien type G
- field test the methods for mobile entities in a realistic real-world settings such as a laboratory.

Appendix: Leveled multilateration C simulation program

The following codes of the C language program implement the simulation for the detectable count multi-levels multilateration algorithm to compute the estimated location of a stationary object.

```
#include <stdio.h>
#include <math.h>

// max size limit of both the 1st and 2nd dimensions of the matrix used:
#define sz 88

struct pt { double x, y;  int w; };
// x,y is the co-or of a ref tag;
// w is the weight; i.e. the sum of the detectable counts at diff RFID
// reader's power level.
typedef struct pt Pt;

struct ans { double gap, error; };
typedef struct ans Ans;
// saving the answers for printout after the loop is done.


// do fn prototyping here and document/comment each fn.


// This fn updates the ref tags' weights based on the range of the reader
// If the distance between a ref tag and the center of the range < = the
// range of the reader, then it's detected by the reader.
// r is the range of the reader; depending on the power level.
void wtupdate( Pt p[], int np, double cx, double cy, double r )
{
  int i;  double dx, dy, ds, rs ;
  rs = r * r; // rs = radius square.

  // increment the weight of the ref tag if it is inside reader's range.
  for( i = 0; i < np ; i++)
  {
    dx = p[i].x - cx; // diff in x's from the center.
    dy = p[i].y - cy;
    ds = dx * dx + dy * dy; // ds = distance squared.
```

```
      // If the dist between a ref tag and the center of the range < = the
      // range of the reader, then it's detected.
      if( ds <= rs )
      {
        p[i].w++;
        // increment the weight since the ref tag is inside the range.
      }
    }
}

//  multiplies matrix a1 by a2; row by column.
//      parameters: int a1[][] -- left  matrix
//                  int a2[][] -- right matrix
//                  int a3[][] -- answer matrix
void mult( double a1[][ sz ] , double a2[][ sz ] , double a3[][ sz ], int
nr, int nc, int ncr ) // nr & nc is the size of the answer, eg 2 by 2.
{
   int i, j, k;
   for(i = 0; i < nr; i++) // num of rows of A.
     for( j = 0; j < nc; j++ ) // num of columns of C.
       a3[ i ][ j ] = 0; // init to 0.
   for(i = 0; i < nr; i++) // num of rows of A.
     for( j = 0; j < nc; j++ ) // num of columns of C.
       for( k = 0; k < ncr; k++ ) //  num of columns of A == # rows of B.
         a3[ i ][ j ] +=  a1[ i ][ k ] * a2[ k ][ j ];
}

// 2 by 2 square matrix only.  b is the inverse of a:
void inverse( double a[][sz], double b[][sz] )
{
  double det;
  int i, j ;
  det = a[0][0] * a[1][1] - a[1][0] * a[0][1];
  b[0][0] =  a[1][1] ;
  b[1][1] =  a[0][0] ;
  b[0][1] = -a[0][1] ;
  b[1][0] = -a[1][0] ;
  for( i = 0 ; i < 2 ; i++ )
    for( j = 0 ; j < 2 ; j++ )
      b[ i ][ j ] /= det;
}
```

```
// b will be the transpose of a:
void transpose( double a[][sz], double b[][sz], int nr, int nc )
{
  int i, j;
  for( i = 0 ; i < nr ; i++ )
     for( j = 0 ; j < nc ; j++ )
       b[ j ][ i ] = a[ i ][ j ];
}

int main()
{
 double cx, cy, dx, dy, ds ;
 double rL, rS, rM, r;
 int i = 0, j = 0, n;
 Pt p[ 99999 ];
 int np;
 // np = num of ref points.  each point represents a reference tag.

 // copy ref tags (points) that have weights into a new array q first:
 Pt q[ 99999 ];
 int nq; // # of ref tags that have weights (i.e. detected).

 int nr; // num of rows
 double a[ sz ][ sz ];
 double t[ sz ][ sz ];  // transpose of a.
 double m[ sz ][ sz ];  // m = tranpose (t) times a .
 double mi[ sz ][ sz ]; // mi is the inverse of m.
 double bm[ sz ][ sz ]; // b-vector's matrix.

 // compute A-transpose time vector b: answer in atbm
 double atbm[ sz ][ sz ];
 double ans[  sz ][ sz ]; // answer matrix.

 // compute the distance between every other detected reference tags with
 // the first detected ref tag and store into vector d (the squares):
 double  dsq[ 999 ];
 double  b[ 999 ]; // vector b.
 int wt1s, wtis;
 // square of the first weight, square of the i+1th weight.
```

```
double  tag1x, tag1y;
// save the first tag's x and y co-or for computation at the "end".

int sumw;
double sumx, sumy, estx, esty;
double x, y, initxr , inityr , gapr;
Ans A[9];
int numAns;

// for the real location of target t, we assume it's t = (4.1, 3.6).
cx = 4.1;
cy = 3.6; // co-or of target; target has the rfid reader.

// compute the default R:
// r = 3/4 the line ac.; see Chapter 3 for the details regarding default R
// 4 meters is the ref tag density.
r = 0.75 * sqrt( 2 ) * 4 ;

rL = r;       // default R is the range of hi power.
rS = rL / 2;  // range of low power is half of hi power's
rM = ( rL + rS ) / 2;  // the ratio of hi, mid and low is 4 : 3 : 2.

// test for the ref tag density from 5 to 1 meters with 1 meter step:
for( gapr = 5 ; gapr >= 1 ; gapr-- )
{
 initxr = inityr = 1; // the first ref tag's loc is at 1,1 meter.
 y = inityr;
 np = 0;    // init the index of the ref tag array to 0.

 // setting up the reference tag grid with 11 x 11 ref tags:
 for( i = 0; i < 11 ; i++ )
 {
   for( x = initxr,  j = 0; j < 11 ; j++ )
   {
      p[ np ].x = x; // using a 1-D array for the ref tags grid.
      p[ np ].y = y;
      p[ np ].w = 0; // init the weights of all the ref tags to 0.
      np++;
      x += gapr;
   }
   y += gapr;
 }
```

```
// check which ref tags are inside the RFID scanning range; then the
// detected ref tags' weights are updated:

// the hi power range:
wtupdate( p, np, cx, cy, rL );

// the mid power range:
wtupdate( p, np, cx, cy, rM );

// the low power range:
wtupdate( p, np, cx, cy, rS );

// copy the ref tags that have weights into the (new empty) array q:
for( i = j = 0 ; i < np ; i++)
{
  if( p[i].w > 0 )
  {
    q[ j ] = p[ i ];
    j++;
  }
}

// save the first tag's x and y co-or for the computation at the "end"
tag1x = q[ 0 ].x ;
tag1y = q[ 0 ].y ;
nq = j; // # of ref tags that have weights (i.e. detacted).

// create the matrix that is nq - 1 by 2:
nr = nq - 1; // num of rows. // num of col is 2.

// subtract every others rows by the first row (equation) and then save
// the result into matrix a.
for( i = 1 ; i  <=  nr ; i++ )
{
  // x sub i minus x sub 1. // col 1 for the x's.
  a[ i - 1 ][ 0 ] = q[ i ].x - q[ 0 ].x;

  // y sub i minus y sub 1. // col 2 for the y's.
  a[ i - 1 ][ 1 ] = q[ i ].y - q[ 0 ].y;
}
transpose( a, t, nr, 2 ); // t is the transpose of a.
```

```
// m = a-transpose times a.
// void mult( double a1[][ sz ] , double a2[][ sz ] , double a3[][ sz ],
// int nr, int nc, int ncr )
// nr & nc is the size of the answer, ie 2 by 2.
  mult( t, a, m , 2, 2, nr ); // nr is the ncr.

  inverse( m, mi ); // mi is the inverse of m.

// compute the distance squared between every other detected ref tags with
// the "first" detected ref tag and then store the result into the vector
// dsq.
// the distance between 2nd and 1st detected tag is = dist sub 21.
// distance squared between point 1 and point 2  is = ds = sq( x2 - x1 ) +
// sq( y2 - y1 ).
  for( i = 0 ;  i < nq - 1 ; i++ )
  {
    dx = q[ i + 1 ].x - q[ 0 ].x;
    // x of point i+1 minus x co-or of the first point.

    dy = q[ i + 1 ].y - q[ 0 ].y;
    dsq[ i ] = dx * dx + dy * dy;
    // dsq has the dist sq between all the other tags with the first tag
    // (detected ones).
  }
  // compute the vector b:
  // r means distance from the ref tag to the unknown target tag.
  // b sub 1  =  r sub 1 sq - r sub 2 sq + dist sub 21 sq.
  // b sub 2  =  r sub 1 sq - r sub 3 sq + dist sub 31 sq.
  // b sub 3  =  r sub 1 sq - r sub 4 sq + dist sub 41 sq.
  // r sub 1 sq == 1 / w sub 1 sq
  // r sub 2 sq == 1 / w sub 2 sq
  // r sub 3 sq == 1 / w sub 3 sq
  // int wt1s, wtis;
  // sq of the first weight.
  // sq of the i+1th weight.
  // using 1/weight as the distance.  so r sq = 1 / weight sq.
  wt1s = q[ 0 ].w * q[ 0 ].w;    // square of the first weight.
  for( i = 0 ;  i < nq - 1 ; i++ )
  {
    wtis = q[ i + 1 ].w * q[ i + 1 ].w ; // square the i+1th weight.
    b[ i ] = ( 1.0 / wt1s ) - ( 1.0 / wtis ) + dsq[ i ];
    b[ i ] /= 2.0 ;  // divide by 2.
  }
```

```
  // compute A-transpose times vector b:
  // we have t = a-transpose already.
  // need to change vector b to a matrix first due to coding.
  for( i = 0 ;  i < nq - 1 ; i++ )
  {
    bm[ i ][ 0 ] = b[ i ];
    // only using the frist column of bm. // nq - 1 is the number of rows.
  }

  // compute A-transpose times vector b and then put the results in atbm.
  // A'b.
  mult( t, bm, atbm,  2, 2, nq - 1 );
  printf( "content of atbm = A-transpose times b =\n" );
  print( atbm, 2, 1 ); // atbm matrix is 2 by 1.

  // mi matrix is 2 by 2.
  // compute M-inverse times ( A-transpose times b ( atbm ) ) and then put
  // the results in ans.
  mult( mi, atbm, ans, 2, 1, 2 );
  // ans matrix is 2 by 1; so only the first column is used.  ans is the
  // least square "solution" to the system of equations.

// ans[0][0] = x - x1,
// x,y is co-or the target; x1,y1 is the 1st tag in the system of equations
// ans[1][0] = y - y1.
// estx = ans[ 0 ][ 0 ] + tag 1's x co-or
// esty = ans[ 1 ][ 0 ] + tag 1's y co-or
// the first tag, i.e. tag 0 in C language indexing; see above.

  estx = ans[ 0 ][ 0 ] + tag1x ;
  esty = ans[ 1 ][ 0 ] + tag1y ;   // y co-or of the est loc of target.

  // diff in x's from the est to target; cx is the x co-or of target.
  dx = estx - cx;
  dy = esty - cy;
  ds = dx * dx + dy * dy; // ds = distance squared.

  A[ numAns ].error = sqrt( ds ) ; // save the answers for printout later.
  A[ numAns ].gap = gapr ;
  numAns++;
 }// end of outside for loop; gapr is the counter for this loop.
```

```
 printf( "gap, estimate error in meters\n" );
 for( i = numAns - 1 ; i >= 0 ;  i-- )
   printf( "%.1f, %f\n", A[ i ].gap, A[ i ].error );
 return 0;
} // End of main().
```

Sample output of executing the above C program (with the headings "gap" as the reference tag density and "error" being the distance from the estimated target location to the true target position):

```
gap, estimate error in meters
1.0, 0.679215
2.0, 0.743556
3.0, 0.732719
4.0, 1.163622
5.0, 0.579871
```

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