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Abhishek Patil
Department of Computer Science and Engineering
Michigan State University
East Lansing, MI 48824

Jonathan Munson, David Wood, Alan Cole
IBM Research Division
Thomas J. Watson Research Center
P.O. Box 704
Yorktown Heights, NY 10598

Research Division
Almaden - Austin - Beijing - Haifa - India - T. J. Watson - Tokyo - Zurich

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Abhishek Patil[1], Jonathan Munson[2], David Wood[2] and Alan Cole[2]

[1] Dept of Computer Science and Engineering
Michigan State University
East Lansing, MI 48824

patilabh@cse.msu.edu

[2] IBM T. J. Watson Research Center
19 Skyline Drive
Hawthorne, NY 10532

{jpmunson, dawood, colea}@us.ibm.com

Abstract*: Asset tracking – knowing what you have and where it is located – is essential for the smooth operation of many enterprises. From manufacturers, distributors, and retailers of consumer goods, to government departments, enterprises of all kinds are gearing up to use RFID technology to increase the visibility of goods and assets within their supply chain and on their premises. However, RFID technology alone lacks the capability to track the location of items once they are moved within a facility. This paper presents a prototype automatic location sensing system that combines RFID technology and off-the-shelf Wi-Fi based continuous positioning technology for asset tracking in indoor environments. The system employs a robot, with an attached RFID reader, which periodically crawls the space, associating items it detects with its own location determined with the Wi-Fi positioning system. We propose three algorithms that combine the detected tag's reading with previous samples to compute its location. Our experiments have shown that our positioning algorithms can bring a two to three fold improvement on the raw accuracy provided by the positioning technology.*

1 Introduction

Consider a typical public library. Each book has its own place in a particular shelf. Usually, readers like to take several books (from different shelves) and browse through them until they find the right book. While some readers manage to return the unwanted books to the correct shelf, many of them either leave the books in some corner of the library or place them back in the wrong location. This latter situation is hard to detect and can become a librarian's nightmare. A similar situation exists in many retail stores where the customers can tryout several items before deciding which one to buy. In most cases, the customer never returns the tested item to its correct shelf. Some kind of automated tracking mechanism is required. The problem of asset tracking is not restricted to libraries or small retail stores. Many companies are realizing the importance of increasing the visibility within their supply chain. Asset tracking – knowing what you have and where it is located – is essential for the smooth operation of large manufacturing companies. It also helps big retailers (like Wal-Mart) isolate bottlenecks in their supply chain, reduce overstocking or locate spoiled cargo. Several government and military organizations are always on the lookout for cheaper (and more efficient) ways to track their assets and equipment.

Automatic location sensing is the key to enabling such tracking applications. One of the most well-know positioning systems is GPS [16], which relies on satellites to track location. However, due to its dependence on the satellites, GPS lacks the ability to accurately determine location inside buildings. In order to achieve location tracking inside buildings, researchers and industry have proposed several systems, which differ with respect to the technology used, accuracy, coverage, frequency of updates and the cost of installation and maintenance [22] [2] [25] [4] [14] [6] [20] [23]. Triangulation, scene analysis, and proximity are the three principal techniques for automatic location-sensing [18]. Steggles and Cadman [24] provide a good comparison of various RF-tag-based location sensing technologies. Many of the current location sensing systems are radio based (Wi-Fi - [14] [23] [26] [5] [1], Bluetooth - [3] [1]). By using base station visibility and signal strength or time of flight, it is possible to locate Wi-Fi devices with an accuracy of several meters.

In recent years, RFID technology has attracted considerable attention. RFID is emerging as an important technology that is reshaping supply chain management. RFID not only replaces the old barcode technology but also provides a greater degree of flexibility in terms of range and access mechanisms. For example, an RFID scanner can read the encoded information even if the tag is concealed (this might be for either aesthetic or security reasons). Several companies (like Wal-Mart, Gillette, CVS etc) are proposing to use RFID for identifying large lots of goods at pallet and carton level. Usually passive tags are preferred for tagging goods as they are much cheaper, long lived, lightweight and have a smaller foot print. However since passive tags work without a battery, they have a very small detection range. Current RFID systems are portal based where tagged items are scanned either when they enter or leave a facility. This scheme does not provide any information about the exact location of the item once it is moved away from the portal.

The prototype system described in this paper combines (passive) RFID technology and a Wi-Fi (802.11b) based continuous location positioning system to provide a periodic asset-locating sweep. Although, our system uses Wi-Fi based location positioning, it can work with any continuous positioning technology. The prototype system not only identifies but also provides location information of every RFID-tagged item in the sweep space. A portable system (e.g. laptop or PDA) running a Wi-Fi client and connected to an RF reader is mounted on a robot that moves autonomously through the space. As the robot moves, the RF reader periodically samples which tags are detectable. At each sample time, the robot's position is obtained from the positioning system. For each detected tag, given the estimate of the robot's current position, knowledge of the reader's physical detection range, and the robot's position estimates at previous detections, an algorithm computes an estimate of the tag's position. In summary, our experiments with the prototype system show that we are able to estimate positions of tagged entities to within 1.5m, given an accuracy of the raw positioning system of about 4m. We experimented with different position estimation algorithms and found that certain algorithms work better than others when the raw positioning system is capable of giving better accuracy.

The rest of the paper is structured as follows. In Section 2, we survey related work in the area of location tracking in indoor environments. Section 3 briefly describes RFID technology and its use in our project. Section 4 explains the Wi-Fi positioning system and our experience with its performance. In Section 5 we present results of experiments carried out using our prototype system (and our algorithms). Finally, Section 6 concludes the paper and presents directions for future research.

2 Related Work

Researchers and industry have proposed several location-sensing systems, which differ with respect to technology used, accuracy, coverage, frequency of updates and the cost of installation and maintenance. Some of these systems suffer from disadvantages that limit their use. For example, infrared systems [25] have line of sight restriction; ultrasonic systems [2] [4] are accurate but expensive. Recently, there has been an increase in the number of wireless companies that are seeking newer ways to track people and things in indoor environment. The rest of this section gives a brief description of several indoor location sensing technologies and various companies that make use of these technologies for asset tracking in indoor environment.

Some of the earlier attempts for location sensing used infrared (IR) technology. Active Badge, developed at Olivetti Research Laboratory (now AT&T Cambridge), used diffuse infrared technology [25] to realize indoor location positioning. The line-of-sight requirement and short-range signal transmission are two major limitations that suggest it to be less than effective in practice for indoor location sensing. More recently, the focus has moved to using radio frequency (RF) signals RF-IR combination or Ultrasonic. In case of RF, techniques such as Differential Time of Arrival or simple signal strength measurement at various sensors are employed. RADAR is an RF based system for locating and tracking users inside buildings [14], using a standard 802.11 network adapter to measure signal strengths at multiple base stations positioned to provide overlapping coverage in a given area. This system combines empirical measurements and signal propagation modeling in order to determine user location thereby enabling location-aware services and applications. WhereNet [13] on the other hand works by timing signals transmitted from tags to a network of receivers. It uses the same 2.4GHz band as the 802.11 and Bluetooth systems, but it uses a dedicated standard protocol (ANSI 371.1) optimized for low-power spread-spectrum location. AeroScout (formerly BlueSoft) uses 802.11-based time difference of arrival (TDOA) location solution. It requires the same radio signal to be received at three or more separate points, timed very accurately (to a few nanoseconds) and processed using the TDOA algorithm to determine the location. Ekahau [5] Wi-Fi positioning system computes the location of a client device by applying a probabilistic model to the signal strength measured at the Wi-Fi client device. Unlike AeroScout (and other TDOA based systems), the indoor environment has to be calibrated so that the positioning engine get a signal strength map of the room. Ekahau tags (or Wi-Fi devices running Ekahau client) constantly send their signal strength measure to the positioning engine which keeps track of each device's location.

Several other companies like Radianse [9] and Versus [12] use a combination of RF and IR signals to do location positioning. Their tags emit IF and RF signals containing a unique identifier for each person or asset being tracked. The use of RF allows coarse-grain positioning (e.g. floor) while the IR signals provide additional resolution (e.g. room). The Cricket Location Support System [4] and Active Bat location system [2] are two primary examples that use the ultrasonic technology. Normally, these systems use an ultrasound time-of-flight measurement technique to provide location information. Most of them share a significant advantage, which is the overall accuracy. Cricket for example can accurately delineate 4x4 square-feet regions within a room while Active Bat can locate Bats to within 9cm of their true position for 95 percent of the measurements. Ultra Wideband (or UWB♣) is a new technology that has entered the arena of indoor location sensing. Unlike conventional RF systems, UWB systems are much less affected by multipath distortion. The Ubisense [11] system uses UWB and is based on time of arrival rather than signal strength and claims to have an accuracy of 6 inches (15 cm) in 3D space at a confidence level of 95%. The system uses UWB tags (called UbiTags), which are fixed to the items being tracked.

Discussion

The asset tracking technologies mentioned above are mostly geared towards tracking items that individually have high value (e.g., emergency medical equipment or an important person – a surgeon). These items require continuous tracking and justify the use of expensive tracking equipment. However, in many tracking applications (e.g. the library scenario described earlier) the object being tracked is either too small or too low value to justify the use of a tracking system with high per-item cost. And in fact, many of these applications do not require continuous tracking. We believe there are many applications where it is valuable to know the precise location of an asset, yet it is permissible for an asset's location to

♣ An informative web site on UWB is provided by Multispectral Solutions, Inc [8] be updated on a periodic basis—nightly, for example. Our BlueBot system is targeted towards such applications.

We can characterize different tracking technologies by distinguishing between continuity in space and continuity in time, as illustrated in Table 1. A technology that provides space-continuous position estimates is able to provide a position estimate that falls anywhere in space (that may or may not be accurate). GPS is an example. A technology that provides time-continuous position estimates is able to provide position estimates at any point in time (intervals between estimates limited only by the performance of the system). Most positioning technologies are continuous in both space and time. An example that is continuous in time but not in space is "cell-ID," i.e., reporting the location of an entity as that of the wireless base station it is communicating with. The location is known to be somewhere in the coverage region of the base station but at no greater resolution than that. An example that is neither continuous in space nor in time is a typical RFID deployment, such as the EZ-Pass toll collection system, where the location of a tagged item is known only at the times that item passes near a reader.

We believe that the system discussed in this paper, BlueBot, represents a new point in this taxonomy, which provides position estimates continuous in space but not in time. As such, it points the way to tracking solutions that provide the precise location estimates needed by some applications, but, by sacrificing continuity in time, at a much lower cost.

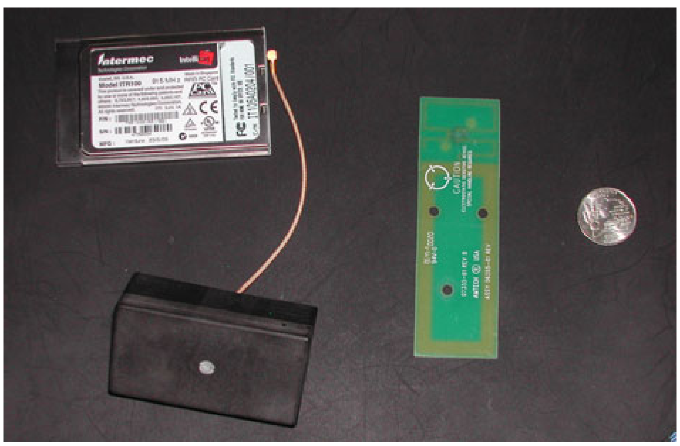
Table 1: Tracking Systems Taxonomy

		Continuous in Space	
		YES	NO
Continuous in Time	YES	GPS, TDOA, EOTD, Wi-Fi signal strength, etc.	Simple "presence" technologies (e.g., cellular system where cellID is reported as the cellphone's location)
	NO	**BlueBot**	Fixed Beacon (e.g., EZPass, Bluetooth)

3 RFID Technology

RFID (Radio Frequency IDentification) technology has attracted considerable attention in the recent past [15]. Government organizations, especially the military, and several companies (i.e., Wal-Mart, Gillette, CVS etc) have been investing heavily in RFID technology to increase the transparency of their supply chain and to provide asset tracking on their premises. There are several advantages of using RFID technology – no contact and non-line-of-sight, working under harsh environmental conditions, etc. RFID systems have a fast response time and in some cases tags can be read in less than a 100 milliseconds. The other advantages are their promising transmission range and cost-effectiveness. RFID tags can be concealed for either aesthetic or security reasons and yet be detected by an RFID reader.

RFID tags are categorized as either passive or active. Passive RFID tags usually operate without a battery and offer a virtually unlimited operational lifetime. They reflect the RF signal transmitted to them from a reader and add information by modulating the reflected signal. Passive tags are much lighter and less expensive than active tags. However, ranges of more than 1.5m are not easily achieved using passive tags. Active tags contain both a radio transceiver and a 2-5 year battery to power the transceiver. Since there is an onboard radio, active tags have more range than passive tags (30m or more). However, they are more expensive and have a larger physical footprint compared to passive tags.



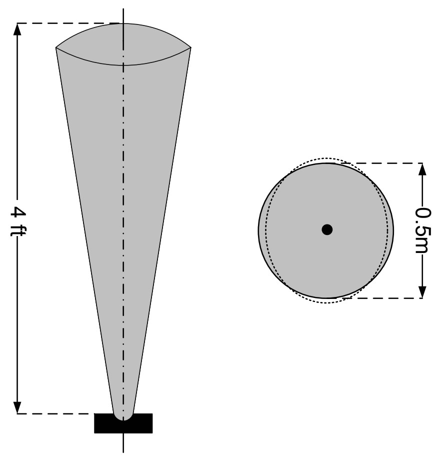


Figure 1: Intermec PCMCIA reader and passive tag. **Figure 2: RF characteristic of reader antenna.**

In our system, we use the Intermec [7] PCMCIA RFID reader (Figure 1), which operates at a frequency of 915MHz. The reader can be connected to any device that has a PCMCIA port. In our experiments, we had the reader connected to a laptop PC, but a smaller device, such as a PDA, or a custom-built PC, can be used as well for additional portability. The reader is attached to a directional antenna, which has a very short range (5 feet max). The reader's antenna is placed facing the ceiling such that its maximum gain is in the vertical direction. The RF characteristics of the reader would approximate a vertical cone with its vertex on the reader's antenna. We observed that tags at a height of 4 feet were detected with 90% (or higher) probability when the reader was (horizontally) within 0.5m of the tag (Figure 2). Due to the rectangular base of the reader's antenna, the RF characteristics had an elliptical shape (with the larger axis along the longer sides of the rectangle). However, we found that the eccentricity was close to 1. For all our experiments we have considered the reader's RF characteristics to be a circle.

4 Wi-Fi Positioning System

We use an off-the-shelf Wi-Fi (802.11b) positioning system to track our client system (consisting of the RFID reader, client machine and the robot - Figure 8). The positioning system computed the location by using signal strength information (as perceived by the client device being tracked). The positioning engine advertised an average accuracy of 1m (3.5 ft).

4.1 Calibration

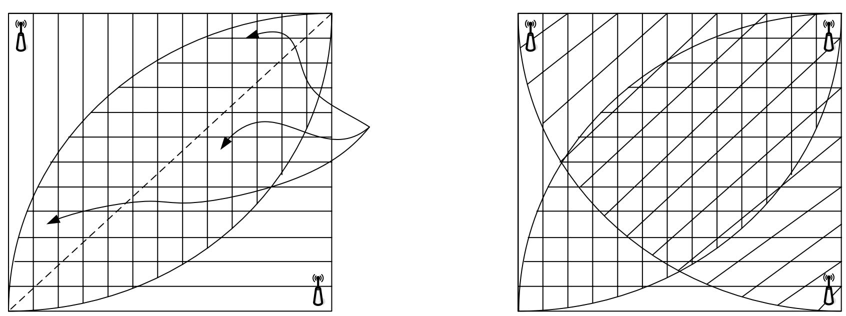


Figure 3: Asymmetric coverage improves positioning system's accuracy.

The positioning system we used needs to be calibrated before location scanning can begin. The calibration process establishes an RF-signal strength plot of the area into the positioning system's engine. The calibration process involves drawing a series of straight lines on the area map and recording *sample points* – signal strength at a given location along the line. While at a particular location, the recording device (client device e.g. laptop/PDA wirelessly connected to the positioning engine) is turned around 360° to record the signals from all directions. Several sample points are taken at 3-5m intervals along the lines. The calibration process is repeated until the entire area is covered. In general, a higher number of calibration points give better accuracy. Since the Wi-Fi system that we used was signal strength based, any major change in the environmental conditions in the room (e.g. moving of office partition, metal shelves/cupboards) required re-calibration to ensure maximum accuracy. The calibration process needs to be repeated if an access points are added, removed or moved from the calibrated area. There are some simple techniques to improve the overall accuracy of the system. One such technique is to avoid symmetric coverage within a room. For example, using two omnidirectional access points for coverage in an open room can cause a symmetric RF pattern. As a result, there would be two or more sample points that would record the same signal strength pattern from the two APs (Figure 3a). Using APs with directional antennas or having an asymmetric coverage by introducing a third access point (APs at 3 corners of the room - Figure 3b) can solve this problem.

4.2 Positioning Technology Accuracy Analysis

Because our tag-position estimation algorithms (described later) use characteristics of the positioning technology used to position the robot, we carried out two sets of experiments to examine the performance of our positioning system. The two sets differed in the density of calibration points and the size of the experiment area.

4.2.1 Case A

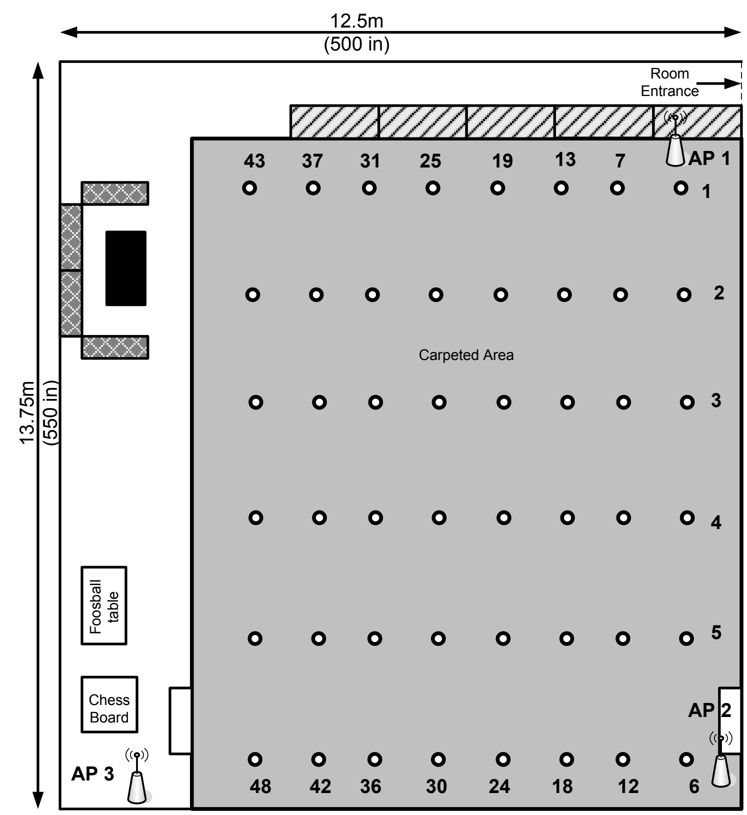


Figure 4: Experiment setup (case A)

The experiment area chosen was a large open 12.5m x 13.75m room (Figure 4). The positioning system was calibrated to work with only the three access points that were installed in the room (during the calibration process, the positioning engine was programmed to ignore any other access points installed in the building). The calibration points were spaced at a distance of approximately three meters. The three access points were powered down to run at 15mW. To improve accuracy of the system, we wanted to have the access point coverage such it gives the steepest signal strength gradient across the room. Our Cisco 340 access points had four power levels (100mW, 30mW, 15mW and 5mW). Using the positioning system's software, we found that 5mW power level didn't give complete coverage in the room which resulted in a higher error. We selected 15mW which seemed to give the best gradient.

After the calibration process, 48 points (refer Figure 4) were chosen as sample locations in an approximate area of 9m x 12m. An 801.11b client device was moved to each of the sample locations and positioning system was queried to report the position of the client. This process was repeated at four different times during the day with varying conditions in the room (e.g. people playing foosball or having a discussion on the couch, etc). The positioning system's API gave us the X, Y coordinates of the client and an error estimate *e* in meters. In general it can be observed that the error distance is more for points near the wall (e.g. sample points 1-6 and multiples of 6 – 6, 12, 18). There is no definite pattern for the error estimate values. Figure 5 gives the mean and variance of the error distance and error estimate for each of the sample points. Table 2 shows the mean (and variance) error distance (the positioning system's expected error) for this setup. Our experiments showed that the average positioning error (for the positioning system) was between 3.5-4 meters for this setup.

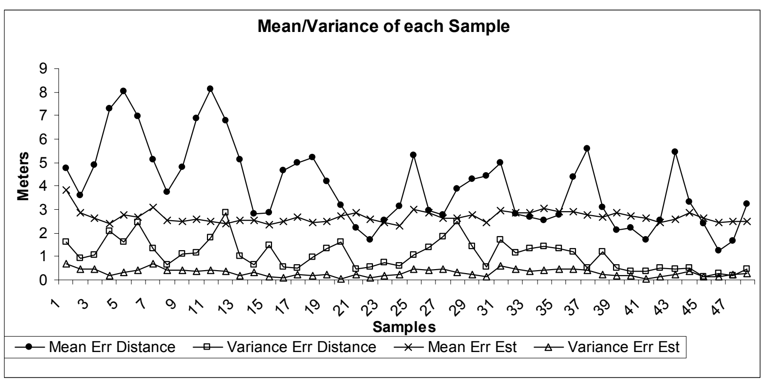


Figure 5: Mean/Variance Error Distance and Error Estimate for each sample point.

Table 2: Mean and Variance of Error Distance and Error Estimate for the entire set.

Mean error distance	Variance in error distance	Mean error estimate	Variance in error estimate
4.001	2.047	2.681	0.421

4.2.2 Case B

In our next set of tests, the positioning engine was calibrated for a smaller area (8.08m x 3.71m) within the room (see Figure 6). Unlike case A, the calibration points in this experiment were closely spaced (1m). The rest of the calibration setup (position of access points and their power level) was the same as case A. After the calibration process, 21 points (refer Figure 6) were chosen as sample points. We followed the same procedure as described in case A – the Wi-Fi client device was moved to each of the sample points and positioning engine was queried to report the location of the client (the process was repeated at four different times during the day with varying conditions in the room). The error distance and the error estimate values are much lower in this case (compared to case A) probably because the area is better calibrated (densely spaced calibration points). The error values are higher near the edges of the experiment area where there is uneven (and less dense) distribution of calibration points. Figure 7 gives the mean and variance of the error distance and error estimate for each of the sample points while Table 3 gives the mean and variance of the error distance and error estimate. The positioning accuracy has now improved to approximately 3m.

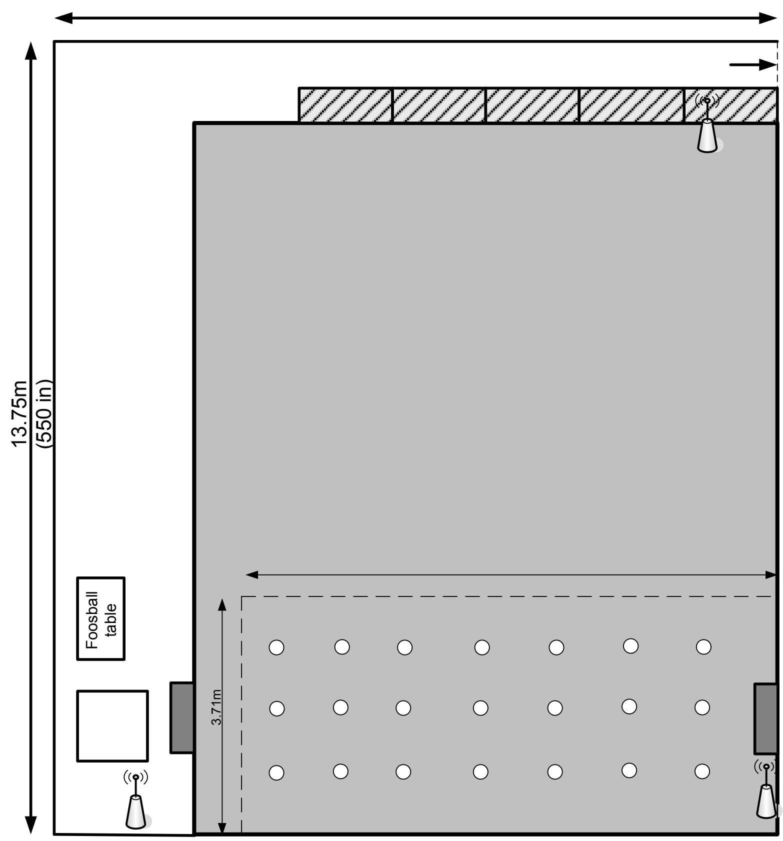


Figure 6: Experiment setup (case B).

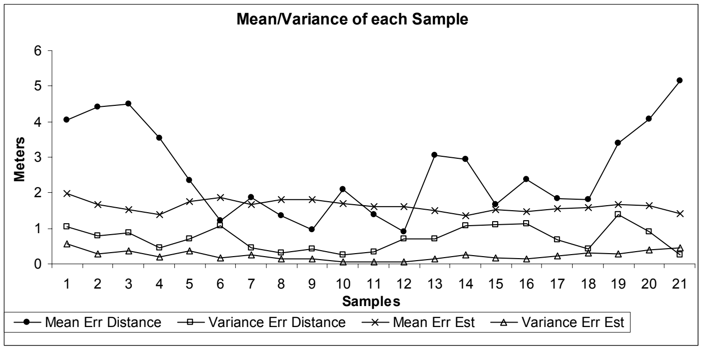


Figure 7: Mean/Variance Error Distance and Error Estimate for each sample point.

Table 3: Mean and Variance of Error Distance and Error Estimate for the entire set.

Mean error distance	Variance in error distance	Mean error estimate	Variance in error estimate
2.619	1.386	1.624	0.280

5 The BlueBot System

5.1 BlueBot Setup

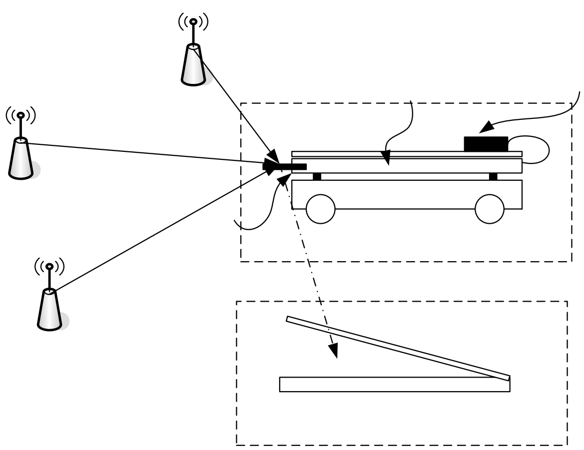


Figure 8: BlueBot Setup

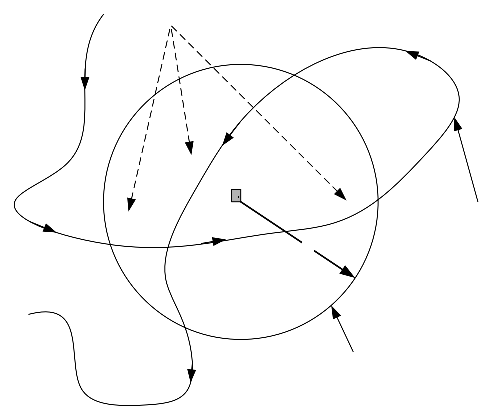


Figure 9: Samples for a particular tag during robot's random walk.

Our system uses the Roomba Robotic Floorvac [10] as the robot that moves autonomously in the sweep space. The Roomba uses intelligent navigation technology to automatically move around the room without any human direction. The Roomba expects to cover 90% of the room. A server machine running the positioning engine (PE) tracks our client device (laptop/PDA) that sits on the robot. Figure 8 depicts the BlueBot setup. The PE is calibrated to work with the access points placed in the corners of the experiment room (case B). The RFID reader is connected to the client device and records all the tags that it detects as the Roomba moves to different corners of the room. In our experiments, the tagged items were placed at a height of approximately 4ft from the ground. Whenever the reader detects a tag, the client machine sends a message containing the tag's id to the server. The server then notes the current position of the client and associates it with the detected tag. Our algorithms combine this sample with the previous samples to refine the position of the tagged item over time. As seen from Figure 9, a tag will be sampled only when the RF-reader enters its coverage area. Figure 10 gives a logical flow chart of the system. It should be noted that due to the random movement of the robot, consecutive samples for the same tag might not be equally spaced in time. Experimental results in later section confirm this.

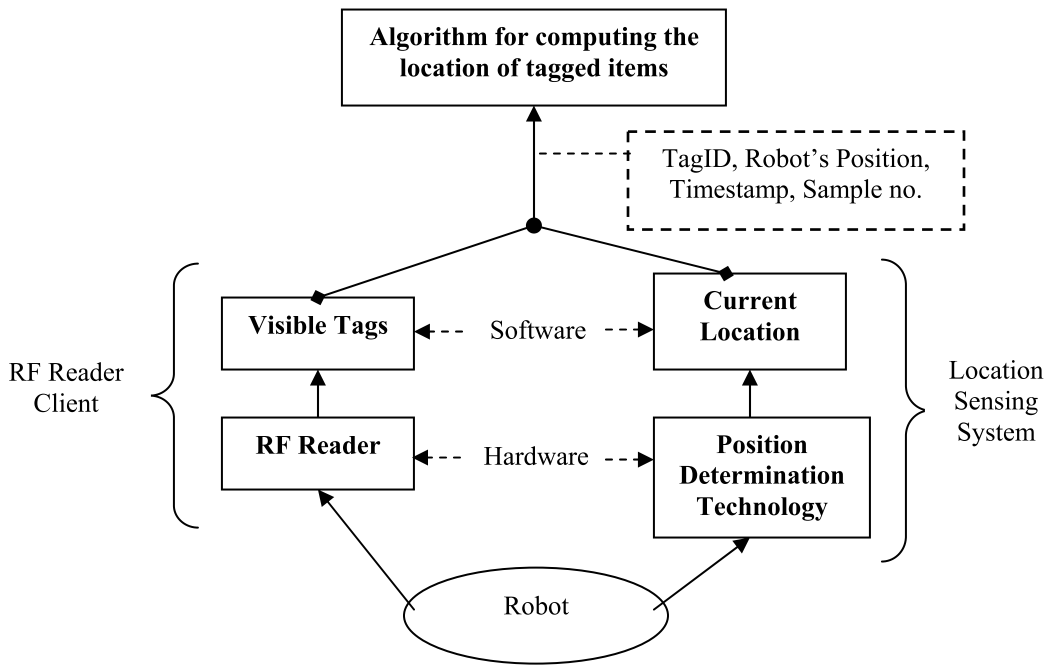


Figure 10: Logical flowchart of the robotic crawler system.

5.2 Algorithms

As mentioned before, the positioning system reported the X, Y coordinates and an error estimate *ee* in meters. We have seen before that the RF characteristics of the reader are in the form of a cone expanding outwards in the vertical direction. With the tags placed at 4ft from the ground, the reader's detection circle was determined to have a radius (r) close to 0.25m. A circle drawn with center at (X, Y) and radius (R) of $ee+r$ (Figure 11) will include the tag being tracked. We call this circle the *confidence circle*. We define the following:

t – represents the tag with id t

N_t – is the total number of samples for a given tag, t.

(X_{ti}, Y_{ti}) – is the location estimate for sample i of tag t

ee_{ti} – is the error estimate for the positioning report for sample *i* of tag *t*

r –is a constant representing the read radius of the RFID reader.

$R_{ti} = ee_{ti} + r$ - is the radius of the confidence circle for sample *i* for tag *t.*

$C[(X_{ti},Y_{ti}),R_{ti}]$ - is the confidence circle for sample *i* of tag *t.*

With these in mind, we provide three algorithms to compute the location.

Intersection Algorithm: Intersection of several confidence circles provides a finer estimate of a tag's position. We represent the tag's location as the centroid of the bounding box of this intersection area. As the number of samples increases, the intersection area decreases (Figure 12), thus improving the accuracy of the (tag's) calculated location. The estimate location then is:

$$(X_t,Y_t) = \text{Centroid}\ (\ \text{BoundingBox}\ (\ C[(X_{t1},Y_{t1}),R_1] \cap C[(X_{t2},Y_{t2}),R_{t2}] \cap \ldots . \cap\ C[(X_{Nt},Y_{Nt}),R_{Nt}]))$$

The precision of this algorithm is inversely proportional to the size of the intersection region. Smaller intersections imply higher probability distribution.

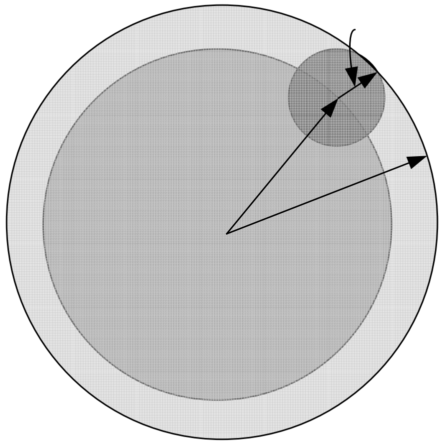


Figure 11: Total radius is the sum of the reader coverage and the uncertainty circle (error estimate circle).

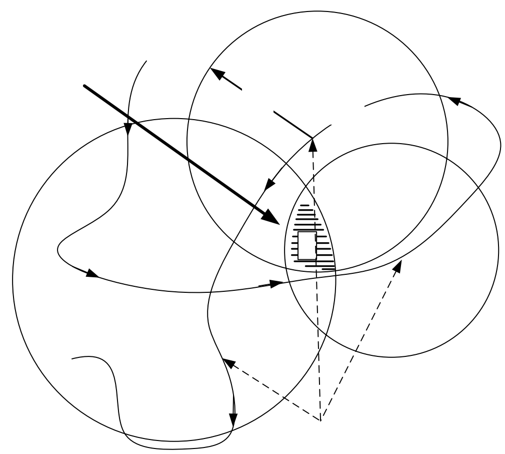


Figure 12: Intersection of the different 'sample' circles converges to the tag location (not all confidence circles are shown in the figure).

Weighted Averages: Here we create an algorithm that computes the location coordinates of the tagged entity as a weighted average of the reader's locations when it detected the entity. The weight of each location estimate is inversely proportional to the square of the error radius.

$$(X_t,Y_t) = [\ \textstyle\sum \{\ 1/ee_i^2 * (X_i,\ Y_i)\ \}\ ]/(\textstyle\sum 1/ee_i^2)$$

The positioning system's location estimates having a smaller error radius tend to be closer to the tag. Therefore, by using $1/R_i^2$, the algorithm is able to give higher weight to sample points that are closer to the tag. The accuracy of this algorithm depends more on the estimated position (X_i, Y_i) as reported by the positioning system and also to a large extent on the distribution of samples around the tagged entity. We assume that with enough samples, this will be averaged out.

Plain Averages: An algorithm that computes the location coordinates of the tagged entity as the statistical average of the reader's location when it detected the entity.

$$(X_t,Y_t) = [\ \sum (X_{ti}, Y_{ti})\ ] / N_t$$

The accuracy of this algorithm is similar to weighted average algorithm. However, since this algorithm does not take into account the error estimate of the positioning system, the errors in the estimated location this algorithm will be slightly higher compared to the estimated error for the weighted average.

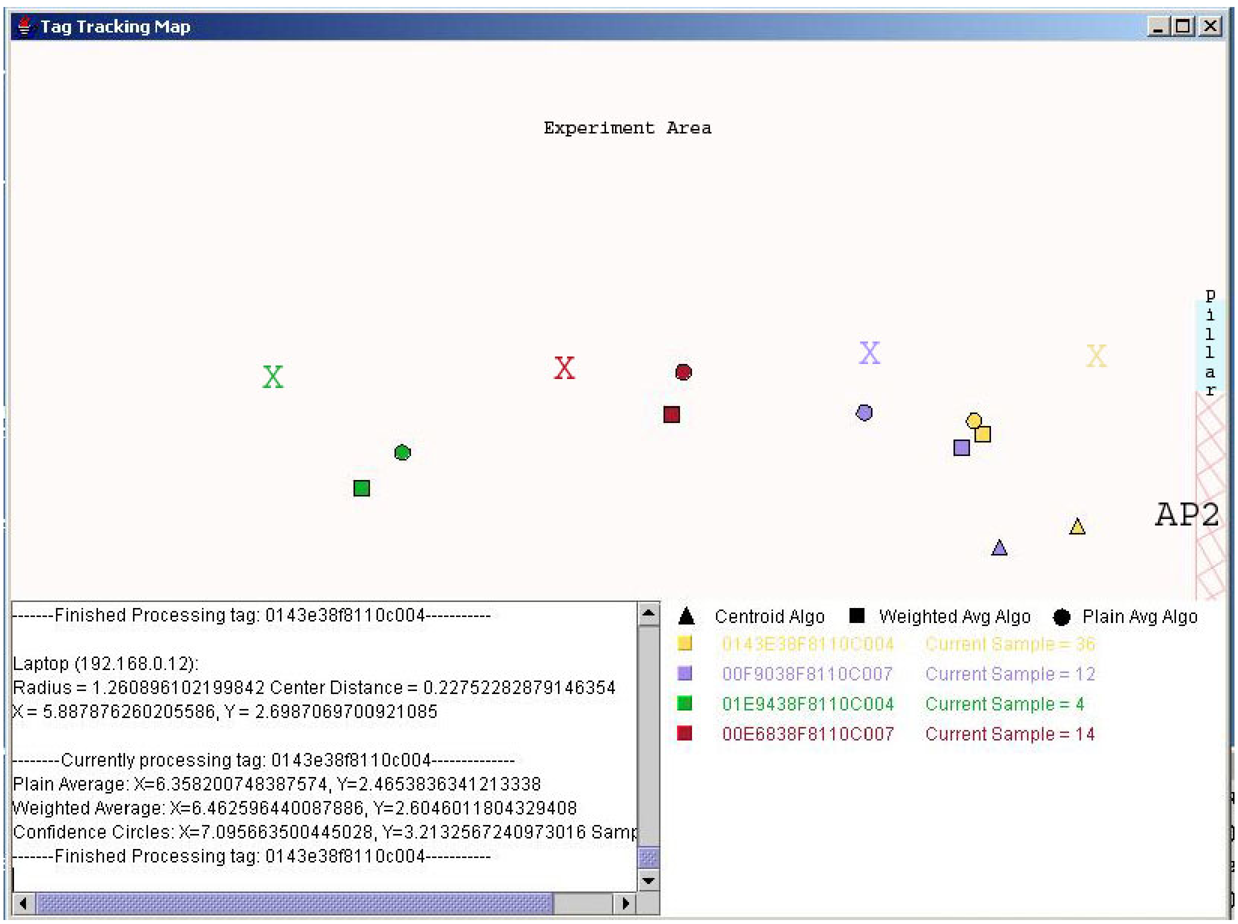


Figure 13: Screenshot of our Tag Tracker GUI before convergence ('X' marks the actual location of the tags).

Figure 13 shows our tag tracking GUI, which shows the computed positions of detected tags (by the three algorithms) on a map of the room.

5.3 BlueBot Performance

We used a large open 12.5m x 13.75m room (Figure 14) to carry out a series of experiments to examine the performance of our prototype system.

5.3.1 Experiment Set A

In the first round of experiments, the positioning engine was calibrated for the entire room as described in Section 4.2.1. For this setup (as seen in Table 2), the positioning system's accuracy was around 4m. The tag placement for this set of experiments is as shown in Figure 14. We recorded the performance of the three algorithms for this setup for four different runs of the experiment. Figure 15 shows the performance for one such run.

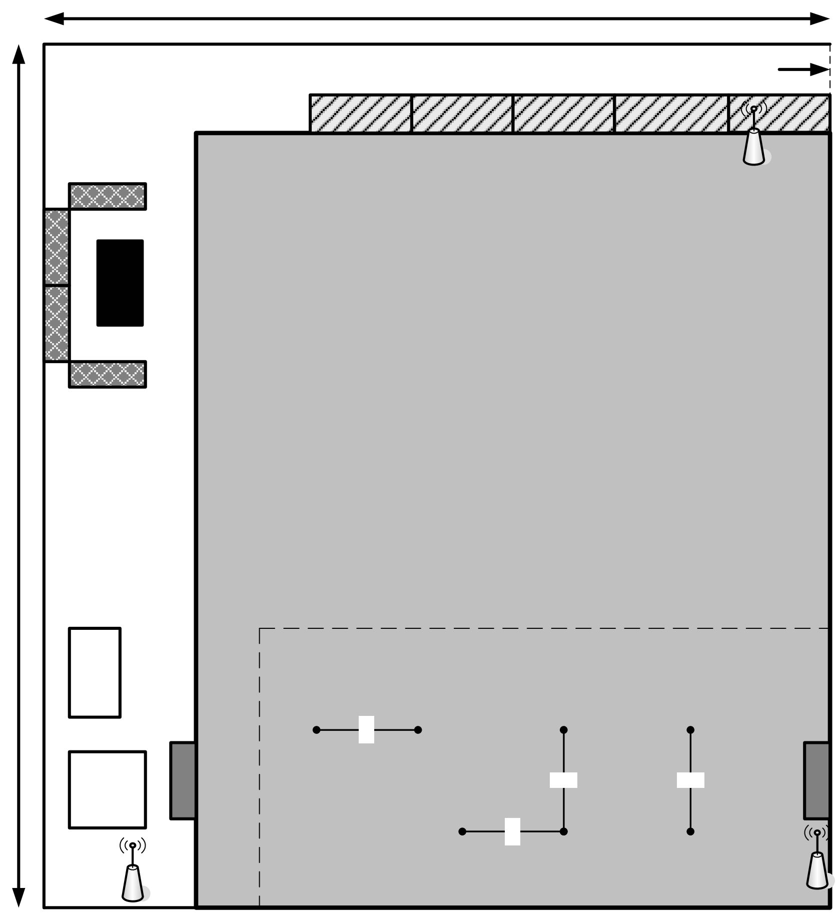
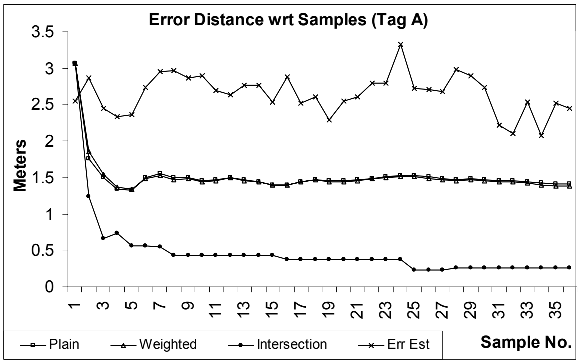
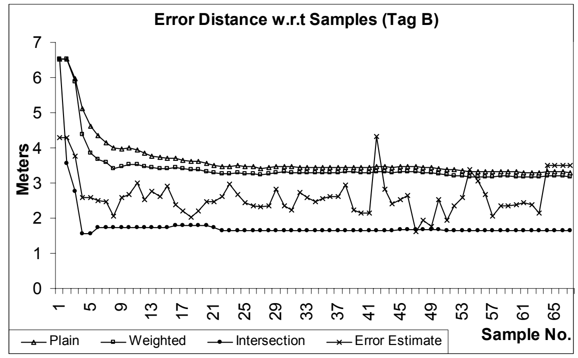


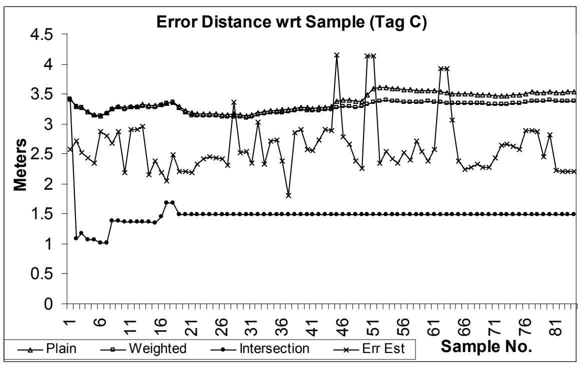
Figure 14: BlueBot setup with non-uniform placement of tags.



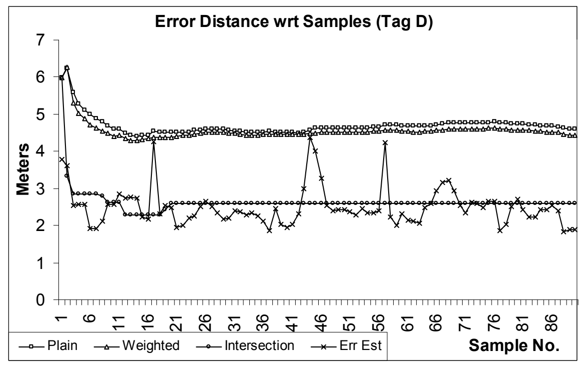
a)



b)



c)



d)

Figure 15: Error distance convergence w.r.t sample no. for each tag

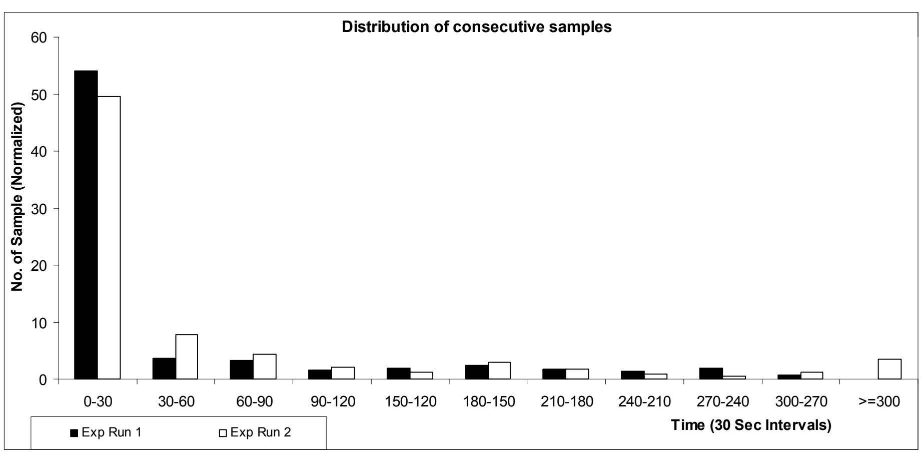


Figure 16: Sample distribution w.r.t time for two different experiment runs

It is easy to see that the positioning accuracy of the three algorithms greatly varies between tags. Part of the reason is due to the large variation in the number of detections for each tag. In our experiments we started the Roomba from the center of the experiment area. However, we noticed that since it moved in a random fashion, the number of 'detection' samples for each tag is not a uniform distribution. We expect that the averaging effect (from several runs of the experiment) to smooth out the large variation. Figure 16 shows the time distribution between consecutive detections. Since the number of samples per tag per run is different, the values (per run) have been normalized to be on the same scale.

We define the term *error distance* as the difference between the estimated location and the actual location of the tagged item. The three positioning algorithms start with a large error distance and as they get more samples, they slowly converge to the actual location of the tag. In order to quantify the performance of our system, we define a convergence point for each tag (in each run of the experiment). Convergence point can be thought of as the start of the steady state for a tag. Beyond this point, there is no significant change in the computed coordinates for that tag. For example, the convergence values for Figure 15 are shown in Table 4. We use convergence values to find the accuracy of our system. Table 5 shows the average time and the average number of samples at which the algorithms converged for each run of the experiment. Table 6 and Figure 17 show the mean and median at convergence for each of the three algorithms. As we can see from Figure 17, the Intersection algorithm was able to position the tags with accuracy close to 1.5m. This is almost a three-fold improvement in the accuracy provided by the positioning system. The two averaging algorithms (plain and weighted), however gave an average error close to 3.5m.

Table 4: Convergence values for Figure 15

Tag	Sample No.	Time (sec)	Plain (m)	Weighted (m)	Intersection (m)
A	25	1414	1.527	1.510	0.224
B	22	1380	3.478	3.267	1.642
C	19	2430	3.286	3.265	1.4868
D	20	1271	4.5123	4.386	2.583

Table 5: No. of samples and time (sec) at convergence

Run No.	No. of samples at Convergence			Time at Convergence (sec)		
	Mean	Median	Std Dev	Mean	Median	Std Dev
1	21.5	21	2.645	1623.75	1397	540.95
2	13.25	14	3.774	1178.25	1169.5	448.973
3	24.25	23	8.845	1706	1553.5	442.621
4	12.75	11.5	6.238	916.75	879	261.515
Average	17.9375	17.375	5.3755	1356.188	1249.75	423.514

Table 6: Error distance at convergence for each algorithm

Run No.	Plain Averages Algorithm			Weighted Averages Algorithm			Intersection Algorithm		
	Mean	Median	Std Dev	Mean	Median	Std Dev	Mean	Median	Std Dev
1	3.201	3.382	1.239	3.107	3.266	1.188	1.484	1.564	0.969
2	3.120	2.977	1.129	3.088	2.928	1.135	1.735	1.701	0.861
3	3.241	3.513	1.334	3.162	3.360	1.295	1.571	1.587	0.759
4	3.117	3.055	0.793	3.073	3.067	0.745	1.289	1.059	0.576
Average	3.170	3.232	1.124	3.108	3.155	1.091	1.520	1.478	0.791

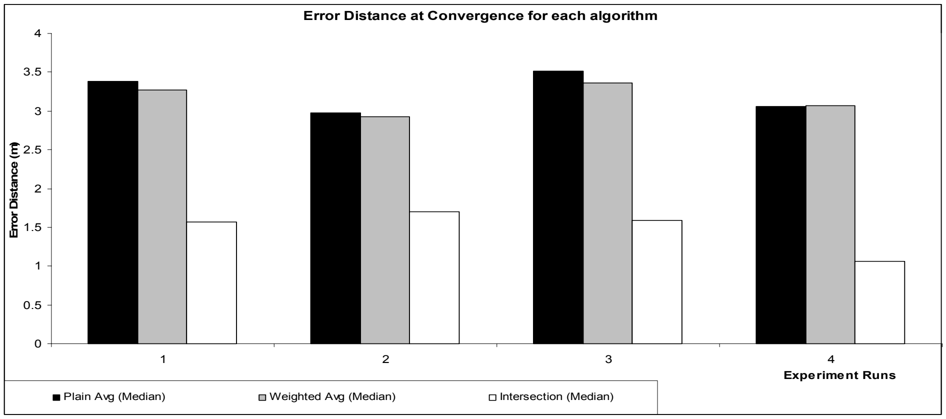
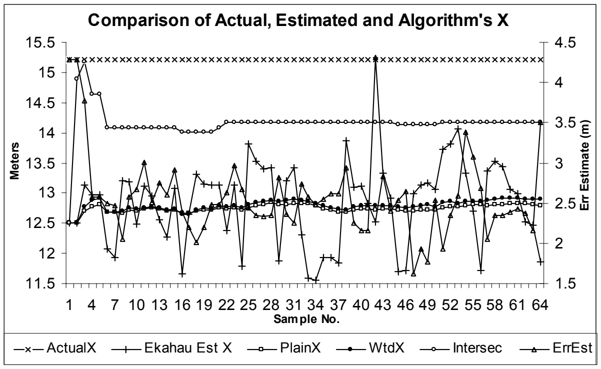


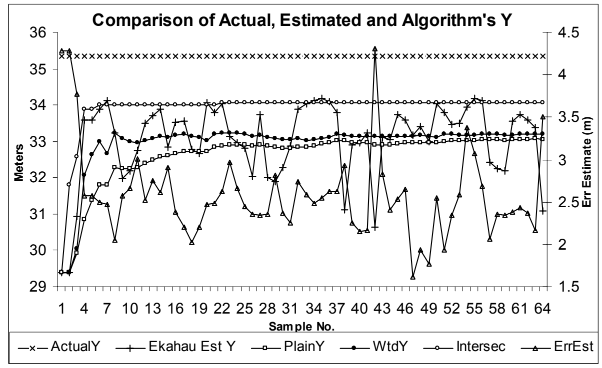
Figure 17: Error distance at convergence for each algorithm

We investigate the reason why the intersection and the averaging algorithm didn't converge to same error distance. As an example, we look at Figure 18 which shows the performance of the Wi-Fi positioning system and each of the three algorithms at every sample (for experiment set A tag B - Figure 15). The two averaging algorithms depend more on the positioning system's accuracy and hence, their performance is close to positioning system's accuracy (which as we saw in Section 4.2.1 was close to 4m). Referring to Figure 18a, one would expect a uniform distribution of the estimate (from positioning engine) around the actual 15.2m; however that was not the case. The positioning engine has an offset close to 3.5m in the estimated X (actual X=15.2m, Estimated X from positioning engine varies between 11.5m to 13m). For the averages algorithm to converge to the actual location, the offset from the positioning engines needs to be uniformly spread above and below the actual location. In this case, the offset was always below; hence the large error.

The intersection algorithm on the other hand is based on the intersection of several *confidence circles*. The intersection algorithm gives an area where the tracked entity is located. To better represent the result of the algorithm, the center of the bounding box around the intersection area is reported as the computed location. A close examination of the two graphs shows that the error estimate for the first few samples is high resulting in larger confidence circles. The intersection of these circles gives a large area, the centroid of which is reported as the calculated location. As the experiment proceeds, the error estimate (*ee*) decreases. Later on, more circles (with smaller radius) intersect and the intersection area slowly shrinks the centroid until a point where all the new circles overlap the intersection area or the intersection area is so small that there is not much change in its centroid. This is when the intersection algorithm converges.



a)



b)

Figure 18: Comparison of computed/estimated coordinates with the actual coordinates.

5.3.2 Experiment Set B

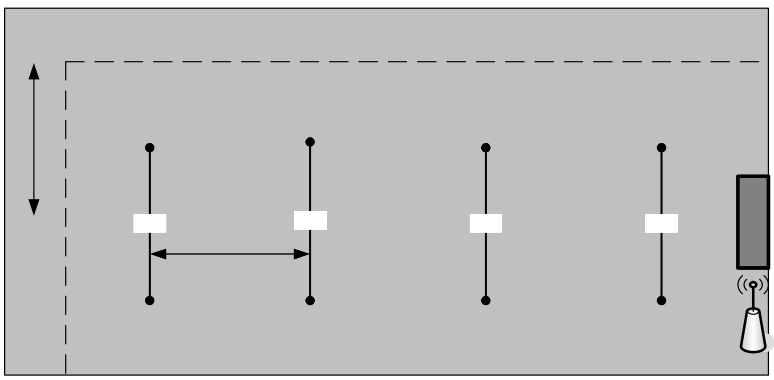


Figure 19: BlueBot setup with uniform placement of tags.

The calibration setup for our second round of experiments was that of Case B as described in Section 4.2.2. The positioning engine was calibrated to work with the smaller experiment area and the calibration points were closely spaced. As seen in Section 4.2.2, this setup gave accuracies close to 2.5m (Table 3). Figure 19 shows the placement of the tags. In this scenario, the positioning technology gave a better accuracy and had lesser variation in the error estimate. As a result, our averages algorithms performed better giving us accuracies close to 1m (Figure 23). In most cases, the averages algorithms surpassed the performance of intersection algorithm by at least 0.5m. Table 7 and Figure 21 shows the computed location of the tags at the end of an experiment run (same run shown in Figure 20).

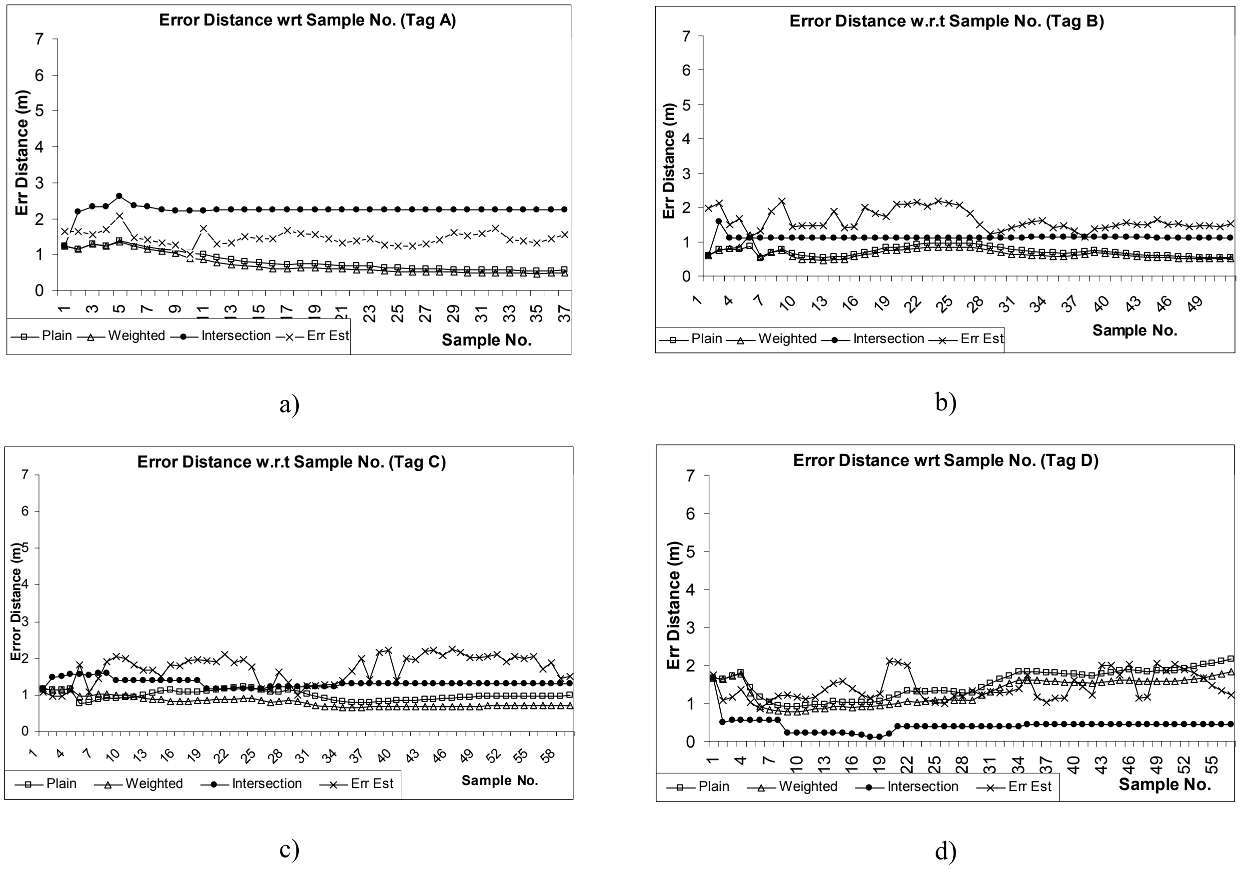


Figure 20: Error distance convergence w.r.t to sample no. for each tag

Table 7: Location coordinates of tags as computed by the three algorithms (for Figure 20)

Tag ID	Actual (X, Y)	Plain	Weighted	Intersection
A	(1,2)	(1.55, 1.86)	(1.43, 1.80)	(2.99, 3.02)
B	(3,2)	(2.94, 1.45)	(2.86, 1.50)	(4.01, 2.47)
C	(5,2)	(4.35, 1.29)	(4.80, 1.33)	(6.24, 2.35)
D	(7,2)	(4.99, 1.31)	(5.32, 1.41)	(6.62, 2.22)

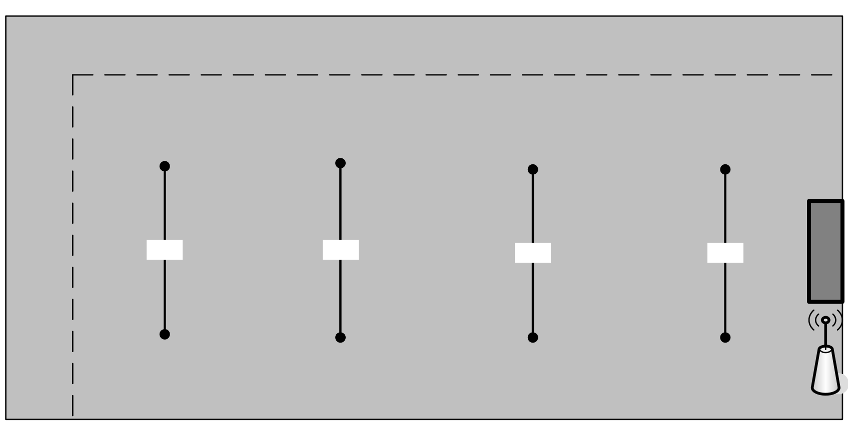


Figure 21: Position of tags as computed by the three algorithms (for Figure 20)

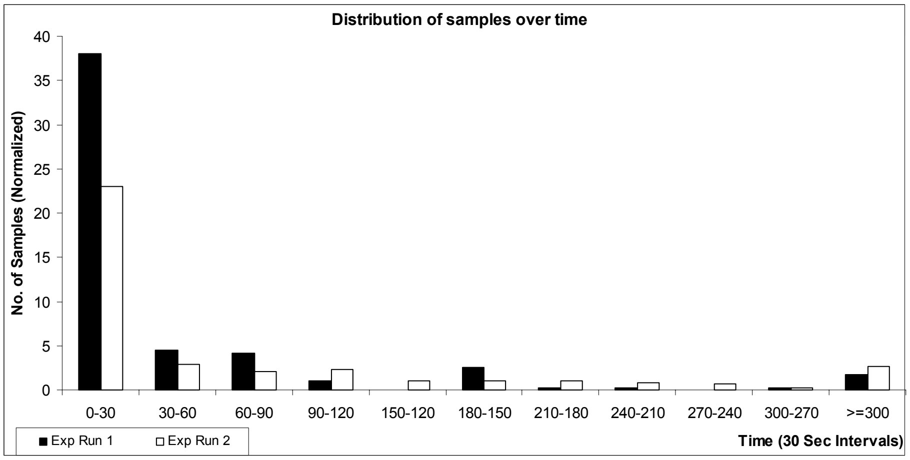


Figure 22: Sample distribution w.r.t time for two different experiment runs

Table 8: No. of samples and time (sec) at convergence

Run No.	No. of samples at Convergence			Time at Convergence (sec)		
	Mean	Median	Std Dev	Mean	Median	Std Dev
1	12.25	12.5	2.753	678.5	580	285.487
2	8.25	8.5	2.5	716	715.5	134.806
3	29.75	31.5	6.184	1335.75	1358.5	679.237
4	21.5	21	3.415	1538.25	1651.5	498.893
Average	17.938	18.375	3.713	1067.125	1076.375	399.606

Table 9: Error distance at convergence for each algorithm

Run No.	Plain Averages Algorithm			Weighted Averages Algorithm			Intersection Algorithm		
	Mean	Median	Std Dev	Mean	Median	Std Dev	Mean	Median	Std Dev
1	1.250	1.230	0.532	1.650	1.696	0.915	3.057	2.682	1.937
2	0.955	0.822	0.521	1.085	1.028	0.479	2.009	2.031	0.659
3	0.829	0.758	0.286	0.684	0.621	0.219	1.252	1.187	0.759
4	1.468	1.031	1.377	1.587	1.048	1.500	2.476	2.140	1.294
Average	1.126	0.960	0.679	1.252	1.098	0.778	2.199	2.010	1.162

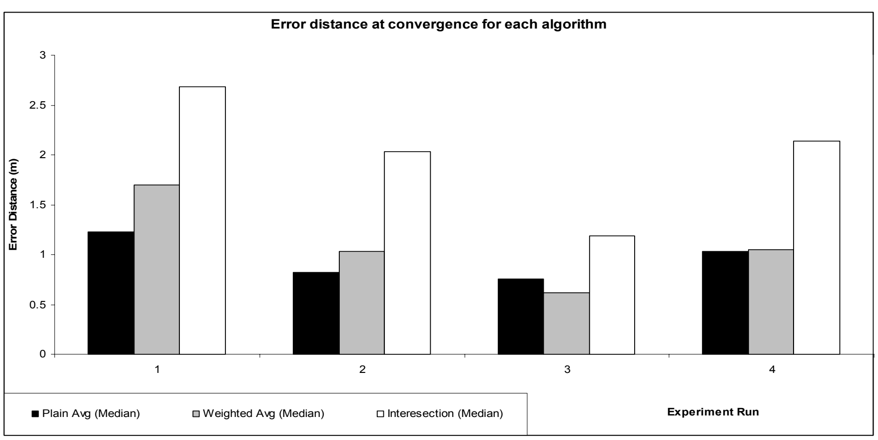


Figure 23: Error distance at convergence for each algorithm

A special note about run 1 in this set: during this run, access point 1 was blocked by a folded ping-pong table placed in front of it. This change in the environment altered the signal strength map of the room and hence affected the positioning system's accuracy. As a result, the three algorithms have a relatively higher error distance. This illustrates the inability of the (signal strength-based) positioning system's to adapt to change in environmental conditions. Some tracking applications may require recalibration of the room to accommodate the change in the signal strength pattern.

6 Conclusion and Future Research

In this paper, we have presented an inexpensive automated indoor asset tracking system called BlueBot. This prototype system works by making use of any off-the-shelf location positioning system and passive RFID technology. Beyond simply providing a novel mechanism to track tagged items, our experiments have shown that our positioning algorithms can bring a three-fold improvement on the raw accuracy provided by the positioning technology. We also found that the intersection algorithm worked better than the two averages algorithm when the positioning system was not very accurate. In the case where the positioning system had high accuracy, the averages algorithm out-performed the intersection algorithm. We are look at new algorithms that can average out the offset in the raw location reported by the positioning system.

In our current system, there is a high variation in the amount of time and number of samples required to converge to a certain level of accuracy. In the future, we are planning to reduce this variation by using a robot that can be controlled to move in a directed pattern. We have considered employing a feedback system; so that the direction of the robot is controlled by the RF system. A dual-variable gain antenna system can be used such that the high gain antenna controls the movement of the robot until its low gain partner sees the tag being hunted. We noticed that signal strength based Wi-Fi systems are easily affected by changes in the surroundings. In the future we plan to make use of systems that are immune to environmental changes (perhaps TDOA based positioning systems) and analyze the performance of our BlueBot system. Another approach would be to continue to use Wi-Fi signal strength, but add reference RFID tags through the environment that could be used to remove any positional offsets that might be present relative to the original calibration. We are also looking at various ways to make 3D positioning possible.

7 Acknowledgments

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