A Comparison between Vector Algorithm and CRSS Algorithms for Indoor Localization using Received Signal Strength

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Abstract **─** A comparison is presented between two indoor localization algorithms using received signal strength, namely the vector algorithm and the Comparative Received Signal Strength (CRSS) algorithm. Signal values were obtained using ray tracing software and processed with MATLAB to ascertain the effects on localization accuracy of radio map resolution, number of access points and operating frequency. The vector algorithm outperforms the CRSS algorithm, which suffers from ambiguity, although that can be reduced by using more access points and a higher operating frequency. Ambiguity is worsened by the addition of more reference points. The vector algorithm performance is enhanced by adding more access points and reference points while it degrades with increasing frequency provided that the statistical mean of error increased to about 60 cm for most studied cases.

Index Terms **─** CRSS, indoor localization, ray tracing, RSS.

I. INTRODUCTION

Indoor localization is the process of locating an object within a building, ideally with high accuracy and low computational effort [1]. Localization using Received Signal Strength (RSS) aims to establish a one-to-one relationship between the target location and the measured data [2]: as the distance between the target node and the receiver increases, the signal generally becomes weaker. Knowledge of the radio attenuation helps to establish the relationship between distance and RSS, a process known as radio mapping [2].

RSS-based localization techniques offer low cost, and low sensitivity to the bandwidth and undetected paths [3, 4]. On the other hand, they are sensitive to shadowing, low SNR, and non-line-of-sight propagation, with errors increasing with resulting rapid power attenuation [5].

It is noteworthy that actual distance does not always scale linearly with the RSS value, especially in indoor environments, where obstacles may reduce the strength of the signal, thus giving a false indication that the target is far away from the transmitter [6-8]. Deployment of AP, taking into account environmental features, enhances the localization accuracy [9]. The variability of RSS measurements is due to many factors [10, 11]:

- the orientation of the receiver;
- temporal factors - readings differ throughout the day because of the people movements;
- human factors since 50% of the human body is water;
- interference factors due to having devices operating in the same channel, although by using different channels the correlation becomes trivial.

Using wireless sensor networks for localization purposes brings the advantages of continuous monitoring, low cost, and a capability to work unattended, even for years [12]. However, some problems can arise as those devices operate at 2.4 GHz, and may experience interference with devices such as microwave ovens and Bluetooth devices, with a resulting increase in error probability [6].

There are many different RSS–based algorithms used for indoor localization, including radio frequency (RF) fingerprinting, one of the best-known algorithms [12-14]. This has two phases. In the off-line or training phase, predetermined points are chosen. At each location, the system collects RSS values from the access points, either experimentally which will consume effort, time and cost, or using ray-tracing software, whereby the system builds a database of RSS with locations. This database is called a radio map [15]. The software takes account only of approximate building information, and

Submitted On: February 25, 2015
Accepted On: January 9, 2016

details are ignored. This introduces more error in comparison with measurement data.

In the on-line phase, RSS measurements are collected from unknown locations, and then values are compared with the existing radio map. The closest match to the database is taken as the best estimate of the target location [15].

The present research work compares two indoor localization algorithms based on RF-fingerprinting, the vector algorithm and the Comparative Received Signal Strength (CRSS) algorithm. It extends previous work [16, 17]: here, we have adopted lower operating frequencies. Section II offers a brief explanation of the methodology, and then Section III sets out the environment and specifications of the study. Finally, Section IV presents a discussion of the results.

II. VECTOR AND CRSS ALGORITHMS

In our investigation, the relative benefits and drawbacks of two localization algorithms were investigated. The first algorithm, the vector algorithm, uses a vector of received signal strength readings measured at the reference point from the different access points within the facility. The readings are arranged according to the access point order.

Vectors from the reference points are stored in the database, and the test node vector is compared with the database, by calculating the Euclidean distance between the test vector and the database vectors. The smallest Euclidean distance represents the closest reference point to the test node.

The second algorithm is the CRSS algorithm. We extend the work done by authors in [18], whereby the vectors of the previous approach are converted into constraint matrices, which comprise the database of the radio map. Test node readings also are converted into a matrix, and then the Euclidean distance between this test node matrix and the database matrices is calculated, where again the smallest distance indicates the closest reference location to the test node.

In the initial off-line phase, $R_i(x, y)$ is the RSS from the transmitter or access point i at tag location (x, y). The elements of this matrix depend on RSS values, as shown:

$$M_\alpha(x,y) = \left[\mathrm{c_{ij}}(x,y)\right]. \quad i,j = 1,2,\ldots,\alpha, \tag{1}$$

$$\mathrm{c_{ij}}(x,y) = \begin{vmatrix} +1 & \mathrm{R_i}(x,y) > \mathrm{R_j}(x,y) \\ -1 & \mathrm{R_i}(x,y) < \mathrm{R_j}(x,y), \\ 0 & \mathrm{R_i}(x,y) = \mathrm{R_j}(x,y) \end{vmatrix} \tag{2}$$

$$\mathrm{c_{ij}}(x,y) = 0 \ \ for\ all\ i = j, \tag{3}$$

where $M_a(x, y)$ is the constructed matrix, and $c_{ij}(x, y)$ compares the RSS access point for access point i with that for access point j. (x, y) is the location for the mobile which is considered to be known. The following example illustrates the method: assuming there are three APs, the RSS values received at the RP located at (x, y) are [-20 dBm, -12 dBm, -14 dBm]. The first row compares the power received from the first AP with the other AP readings as explained in Equation (2), the second row compares the power received from the second AP with the RSS values from the other APs, etc. The resultant matrix is:

$$M_3(x,y) = \begin{bmatrix} 0 & -1 & -1 \\ 1 & 0 & 1 \\ 1 & -1 & 0 \end{bmatrix}. \tag{4}$$

In the on-line phase, the radio map is constructed just as in the off-line phase, except that the location of the test devices is estimated by comparing the constraint matrix of a tag with those in the radio map. The closest matrix is the one with the smallest Euclidean distance, thus the corresponding location for the closest matrix is taken to be the closest location to the tag.

The inherent redundancy that exists in each constraint matrix (i.e., insensitivity to the absolute RSS values) gives rise to an acceptable performance for the positioning algorithm and makes the system more robust.

In this work, we assume that the tags operate a protocol that avoids collision, so that in the case of multiple tags there will be no cross talk.

This study is based on a simple scenario without clutter, in order to clarify the relative merits of the proposed algorithms. We initially investigate a single room without clutter; further studies will examine the multipath fading arising from clutter.

III. SIMULATION AND RESULTS

A. The CRSS algorithm

A severe drawback of the CRSS algorithm was exposed during the analysis of the results obtained in the project, termed “the ambiguity problem”.

While generating the CRSS radio map, it was noted that some RPs have identical same constraint matrices, in that although each RP is likely to have unique power readings, the relative power readings are found frequently to coincide.

The generated matrix does not depend on the absolute RSS readings only, but also on the descending order of the received power readings of the APs. Thus, a test area may divide into regions in which all the RPs located in that region can be represented by identical matrices.

Consider a test area with three APs with RSS values: [x dBm, y dBm, z dBm]: we sort them according to these values, giving 13 possible arrangements as shown in the Table 1.

This means that if this test area has 20 RPs, then in the best case the area can be represented by 13 matrices, or even fewer. As shown above, this algorithm is dependent on the number of RPs and APs.

In the localization process, a test point will create a matrix based on its RSS readings, using which the Euclidean distance is calculated. Because we are interested in the elements with the same matrix indices the Euclidean distance is estimated as in following:

$$e = \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N}(c_{ij} - t_{ij})^2}, \tag{5}$$

where c_{ij} represents the elements in a radio map matrix c in row i and column j, and t_{ij} represents the corresponding element in the on-line matrix t.

Some RPs have identical matrices, and consequently, more than one RP will appear as closest to the test point. This problem is termed *ambiguity*. Figure 1 illustrates an example; four RPs appear equally closest to the test point, as their corresponding matrices have the same Euclidean distance to the test point matrix.

The effect of the ambiguity problem becomes worse if closest matrix is the same matrix for more than one RP. This can arise when RPs have similar propagation environments as shown in Tables 2, 3, 4 and 5: when more than one RP has the same matrix, the phenomenon is called similarity.

Table 1: Possible arrangements for RRS data from three APs

1	$x > y > z$	7	$y > x > z$
2	$x > z > y$	8	$y > z > x$
3	$x > y = z$	9	$y > x = z$
4	$x = y > z$	10	$y = z > x$
5	$x = z > y$	11	$z > x > y$
6	$x = y = z$	12	$z > y > x$
13	$z > x = y$		

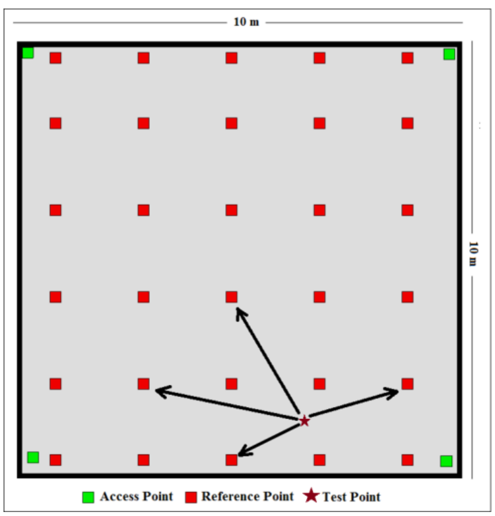

Fig. 1. Ambiguity example for a test area.

Table 2: Similarity in CRSS matrices for three APs at 200 MHz

No. of RPs	4	9	20	30
Unique Matrices	4	3	0	0
Matrix for 2 RPs	0	0	2	0
Matrix for 3 RPs	0	2	2	0
Matrix for 4 RPs	0	0	0	1
Matrix for 5 RPs	0	0	2	4
Matrix for 6 RPs	0	0	0	1

Table 3: Similarity in CRSS matrices for four APs at 200 MHz

No. of RPs	4	9	20	30
Unique Matrices	4	7	11	8
Matrix for 2 RPs	0	1	3	5
Matrix for 3 RPs	0	0	1	4

Table 4: Similarity in the CRSS matrices for three APs at 400 MHz

No. of RPs	4	9	20	30
Unique Matrices	4	4	0	0
Matrix for 2 RPs	0	1	2	1
for 3 RPs	0	1	1	0
for 4 RPs	0	0	2	1
for 5 RPs	0	0	1	2
for 6 RPs	0	0	0	1
for 7 RPs	0	0	0	0
for 8 RPs	0	0	0	1

Table 5: Similarity in the CRSS matrices for four APs at 400 MHz

No. of RPs	4	9	20	30
Unique Matrices	4	7	10	15
Matrix for 2 RPs	0	1	5	7
Matrix for 3 RPs	0	0	0	1

The example in Fig. 2 helps more clearly to explain these tables. Consider the similarity in the CRSS matrices for twenty RPs, four APs and 200 MHz as in Table 3: among the RPs, 11 of them have distinct matrices, while in 3 pairs of RPs each shares the same matrix. Finally, another 3 RPs generate the same matrix.

Inspection of the identical matrices shows them to be in adjacent location in groups of 2, 3, 4… etc. as also shown in the other tables.

Increasing the number of RPs tends to worsen the effect of ambiguity, with more RPs having the same constraint matrix. Table 3 shows the effect of increasing RPs in a test area with four APs and an operating frequency of 200 MHz. With only four RPs, all four generated matrices are unique, but with nine RPs two RPs share the same matrix while the other seven have unique matrices. With twenty RPs, three pairs of RPs share the same matrix, with a further triplet of three RPs having one matrix in common. The thirty RP case is even worse, with ten RPs sharing five matrices in pairs and twelve RPs sharing four matrices, i.e., four sets of triplet RPs with a matrix in common.

Similarity in CRSS matrices is affected by the number of APs used in the system, as the matrix size will correspondingly increase. Table 3 shows the similarity in the generated matrices using four APs for the same test area and the same operating frequency.

The difference between the cases of four APs and three APs is obvious; adding more APs reduces the similarity in the generated matrices. From the previous tables, it can be seen that adding more APs will reduce similarity, while adding more RPs will increase similarity.

Results obtained when changing the frequency from 200 MHz to 400 MHz are shown in Tables 4 and 5, which show that the similarity is reduced as the frequency increased.

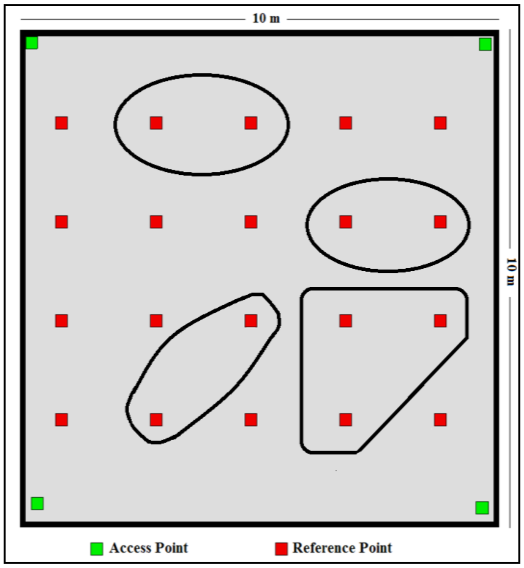

Fig. 2. Example of similarity.

Ambiguity need not always have negative consequences, namely if the estimated locations surrounded the test point. Rather than identifying the test point as close to a certain RP, it would be located within a specific area.

However, throughout all the experiments such a thing rarely happened. It is true that with increasing frequency, the similarity in the generated matrices will be less, but this does not mean that localization performance is thereby improved: a test point considered to be close to fewer RPs using 400 MHz does not mean that these RPs are closer than those estimated at 200 MHz, as shown in Fig. 3.

The localization process includes the calculation of the Euclidean distance between all the matrices in the database and choosing the one representing the least error. As a result, more matrices may have the same Euclidean distance, therefore, more RPs will be considered as the closest RP. There have been sincere efforts to characterize the effect of the ambiguity analytically, however, the results show randomness in the number of the linked RPs to the test point as Fig. 4 shows. Based on results obtained from one experiment, this shows the number of the closest RPs using different radio map resolution. The similarity in the twenty RPs is less relatively when compared to the system with thirty RPs, but still this does not necessarily mean that the ambiguity effect will be less. Moreover, even if the number of the estimated "closest locations" is less, this does mean that an estimated location lies closest to the test point, as depicted previously in Fig. 3.

The ambiguity problem is a severe drawback of the CRSS algorithm, which jeopardizes the system's credibility, despite claims that it outperforms the vector algorithm due to the redundancy in the information embedded within the matrix [2]. A similar analysis was conducted for a more elaborate scenario including a number of rooms adjoining a corridor on a single floor of the author's recent work [19] as shown in Fig. 5, and similar conclusions have been drawn.

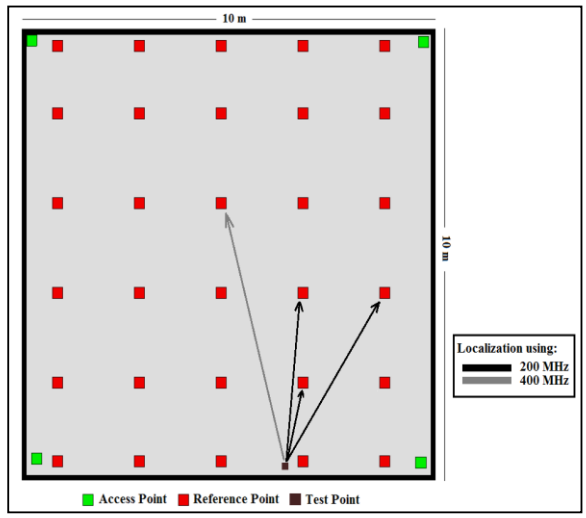

Fig. 3. Less ambiguity does not imply better localization.

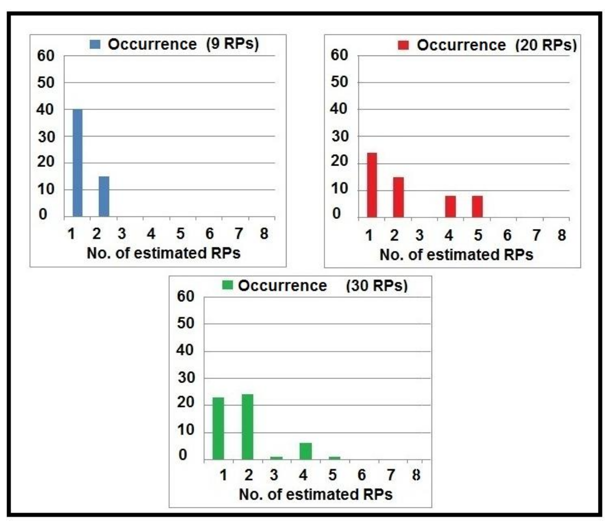

Fig. 4. The number of estimated RPs in the CRSS using different sets of radio maps.

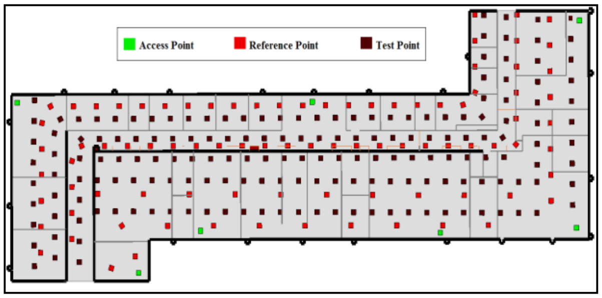

Fig. 5. The 3rd floor of the Chesham Building, University of Bradford.

As the present work shows that the CRSS algorithm is unreliable, in the following we consider the vector algorithm only.

B. The vector algorithm

This algorithm is deemed successful as long as the estimated location is the closest to the actual location of the mobile terminal. When the estimated RP is not closest to the actual location of the mobile terminal, then the algorithm is said to have failed. The percentage of correctly estimated locations gives the *success rate*.

Figure 6 shows the localization performance for the vector algorithm using three APs and different radio map resolutions. The performance is enhanced as the number of the RPs increases; e.g., P(Error $\leq$ 2 m) was about 0.26 for the four RP system, and increased gradually up to 0.8 for the thirty RP system.

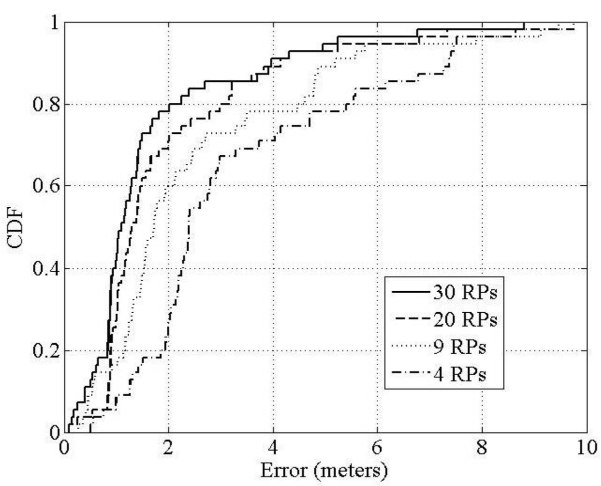

Fig. 6. Localization error for the vector algorithm using three APs, at 200 MHz.

The statistical mean of error was also reduced as shown in Fig. 7. Moreover, the performance shows more stability as the number of RPs increases; error deviation was reduced and the high error estimates were less common. For thirty, twenty, nine and four RPs the error for 85% of locations was less than (2.7, 3.2, 4.8, 6.15) m respectively. Thus, increasing the number of RPs improves localization and enhances stability.

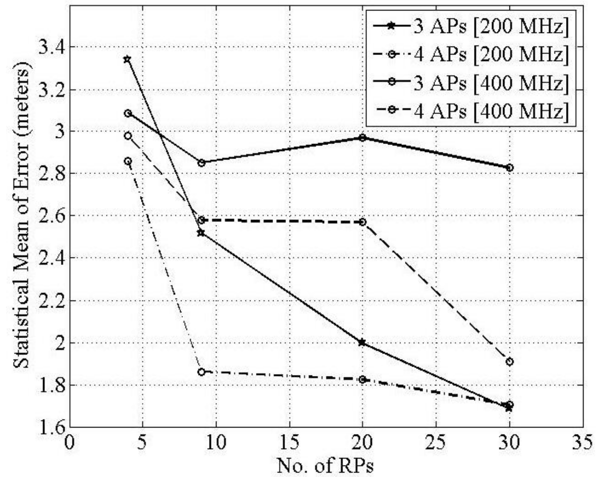

Fig. 7. Statistical mean error for the vector algorithm.

Figure 7 shows the statistical mean error for the vector algorithm using three and four APs at different frequencies. The figure shows that the overall performance of the algorithm is poor for low-resolution radio maps. It improves gradually as the number of APs and RPs in the system increases. The system performance at 200 MHz improves steadily until it reaches a maximum level of accuracy. As shown in the metrics in Table 6, the algorithm performance does not give satisfactory accuracy at 400 MHz except for the system that used thirty RPs and four APs. In general, the performance at 200 MHz is significantly better than at 400 MHz, however high-resolution radio maps and adequate numbers of APs will improve the algorithm's performance to acceptable levels.

Table 6: Success rates for different sets of RPs, APs and frequencies

No. of APs	No. of RPs	200 MHz	400 MHz
3 APs	4 RPs	65%	67%
	9 RPs	58%	47%
	20 RPs	49%	32%
	30 RPs	49%	32.7%
4 APs	4 RPs	78%	72%
	9 RPs	72%	58%
	20 RPs	58%	54%
	30 RPs	52%	61%

It can be noted that the success rate decreases as the number of RPs increases, as shown in Table 6, although the localization error improved. This can be justified thus: the algorithm is considered successful when the estimated location is the closest RP to the test point.

When the number of RPs in the radio map is limited, the RPs will be large distances away, and it is expected that they will be exposed to different fading parameters, so it will be easier for the algorithm to estimate the closest RP. However, as the number of RPs increases, they become closer to each other, and they will have more similar propagation environments, and thus comparable RSS readings. It will be more difficult for the algorithm to estimate the closest RP, and therefore the error will be enhanced.

Figure 8 shows the localization performance using four APs for different numbers of RPs, showing the outstanding performance of the algorithm especially with a high-resolution radio map, and they underline the importance of the number of APs in determining the overall system performance. They also suggest that even low-resolution systems could provide a system with good accuracy as long as there were an adequate number of APs in the system. If we exclude the 4 RPs system, the algorithm shows stability and robustness, with deviations constant for the other systems. The most interesting result obtained is the performance of the localization using nine RPs, which is almost the same as for those using twenty and thirty RPs in the 0-2 m window, and outperforms them slightly in the 2-4 m window. For thirty, twenty, nine and four RPs the error for 85% of locations was less than (3.37, 3.2, 2.28, 5.385) m respectively. This may be considered as the optimum system, which has good performance metrics with only a few RPs used.

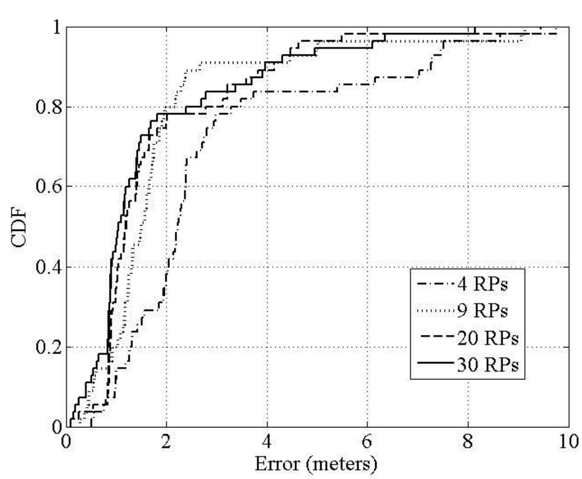

Fig. 8. Localization error for the vector algorithm using four APs, at 200 MHz.

Figure 9 shows a localization error comparison between the three AP and four AP systems. The four AP system shows better performance, with a success rate enhanced from 58% to 74%. The statistical mean of error was improved from 2.52 m to 1.86 m. Standard deviation was reduced from 2.12 m to 1.7 m. The error performances of the two systems are almost the same in the 0-1 m window, but they do vary in the 1-2 m window.

P(Error ≤ 2 m) for three RPs was about 0.6 whereas it was around 0.8 for the four RP system. This accuracy is satisfactory for many applications. The effect of adding an extra AP to the system is obvious as all the metrics reflect enhancement in performance.

Figure 10 shows the localization performance for the vector algorithm using three and four APs with a radio map resolution of thirty RPs. The success rate was enhanced from 49% to 52%, and the mean error has changed slightly from 1.68 m to 1.7 m. Standard deviation remained the same at 1.68 m. The performance of the two systems is effectively identical. It is clear that increasing the number of RP points will make the need for more APs less. In addition, increasing the number of RPs will enhance the performance of localization but the enhancement obtained may become insignificant, as the accuracy will saturate at a certain level.

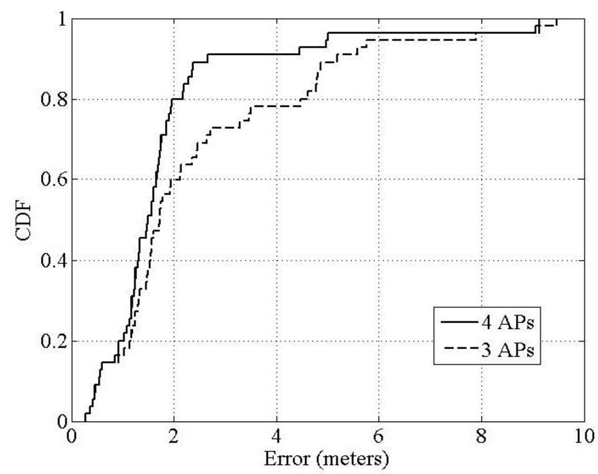

Fig. 9. Localization error for the vector algorithm using nine RPs.

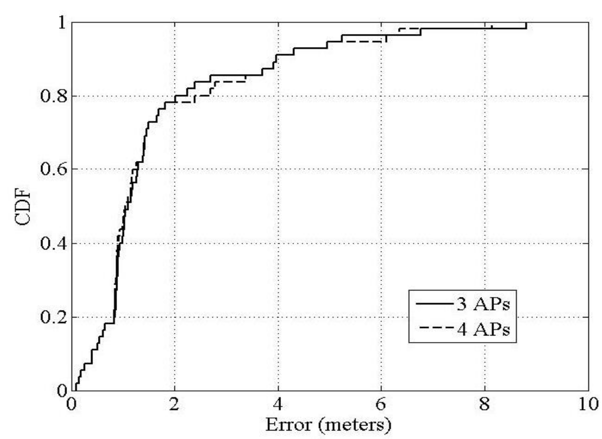

Fig. 10. Localization error for the vector algorithm using twenty RPs, at 200 MHz.

As mentioned above, two operating frequencies, 200 MHz and 400 MHz, were used to conduct the experiments. In general, the localization performance with 200 MHz is better. A justification for such results can be found in propagation theory. When a signal travels in space over a surface, as well as the direct wave there is also a ground wave traveling with it. Due to the different paths that the signals take, a phase shift of 180 degrees occurs every $\lambda/2$, leading to destructive interference and thus reduced power at those points. For example, at 400 MHz, this happens every 0.375 m, so test points at such locations will be completely irrelevant to the RP measurements. As the power readings in the area around the RP will change significantly, mapping the received power vector with the location will result in weaknesses in RSS-based algorithms. At 200 MHz, cancellation occurs every 0.75 m and so the fluctuation in power readings is slower than with 400 MHz.

Figure 11 shows the performance of the vector algorithm for two different operating frequencies and a radio map resolution of twenty RPs. The algorithm performance with 200 MHz is clearly better than with 400 MHz. The error for 85% of locations was less than 3.2 m (three and four APs at 200 MHz), 6.3m (three APs at 400 MHz) and 6.6m (four APs at 400 MHz). Moreover, Table 7 shows that the algorithm performance at 200 MHz with the use of three APs only is better than its performance with the use of four APs at 400 MHz provided that the statistical mean of error increased to about 60 cm for most studied cases. These results emphasize the importance of the operating frequency in determining the algorithm performance.

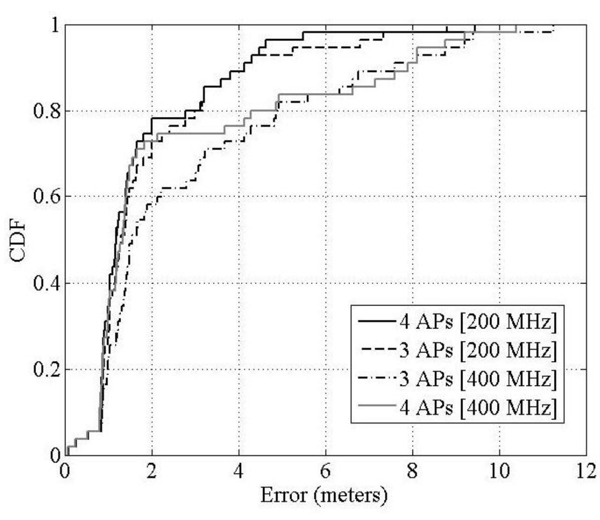

Fig. 11. Localization error at 200 MHz and 400 MHz, for twenty RPs.

Table 7: Performance metrics of the vector algorithm for 200 MHz and 400 MHz

No. of APs	Metric	200 MHz	400 MHz
3 APs	Success rate	49%	32.7%
	Mean	2 m	2.97 m
	Standard deviation	1.75 m	2.27 m
4 APs	Success rate	58%	54%
	Mean	1.82 m	2.57 m
	Standard deviation	1.61 m	2.75 m

IV. CONCLUSIONS

The paper compares two indoor localization algorithms using received signal strength, the vector algorithm, and the CRSS algorithm. The experiment was carried out at 200 MHz and 400 MHz, and the localization performance was tested for different numbers of access points (AP), and for different numbers of reference points (RP). In the vector algorithm, increasing the number of RPs enhances the localization process up to a certain limit, while increasing the number of APs will also result in better performance. Experiments show that increasing the number of RPs will compensate for a reduction in the number of APs, which seems to be attractive commercially. The CRSS algorithm suffers from ambiguity since more than one RP may have the same matrix, and increasing the number of RPs will only make the ambiguity worse. Reducing the number of the APs will increase the algorithm's ambiguity.

It is noted that a lower frequency is better for localization than a higher one. Based on the experimental results the vector algorithm is better in terms of accuracy, cost, and effort.

ACKNOWLEDGMENT

The authors would like to acknowledge support from the TSB-KTP project grant No. 008734 with the Seven Technologies Group, Leeds, United Kingdom.

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