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Indoor Positioning Using Fingerprinting With Locata Signals

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ABSTRACT

This research studies indoor positioning using power-level-fingerprinting with a time-synchronised Locata network. We compare our results to another fingerprinting-based positioning method using WiFi access points. With an accuracy of 1.2 - 1.5 metres, our technique can be a powerful fall-back option when regular Locata positioning fails due to difficult signal conditions. Moreover, our results serve as a benchmark for future research on indoor positioning with Locata.

KEYWORDS: Locata, Pseudolites, Fingerprinting.

1. INTRODUCTION

The location of a mobile node in a wireless network is very powerful information. It allows the development of Location Based Services - applications that deliver context aware functionality based on the user's location. Navigational tools that provide visual map-based instructions such as the GPS Navigators for vehicles are examples of LBSs.

GPS (The Global Positioning System) is a fully functional Global Navigation Satellite System (GNSS). It uses a constellation of 24 satellites in medium Earth orbits which transmit precise signals in the L band. Despite its widespread usage and increasing popularity, it has its limitations. The satellite signals are very susceptible to shadowing effects and are easily absorbed and reflected by buildings, walls and mountains thus making it imperative to have direct line of sight between the receiver and satellites. Hence GPS does not work well indoors, inside tunnels, and in urban canyons.

Indoor positioning is especially useful for several commercial and security applications. Many dedicated systems exist for this purpose [9], for example: Active Badge [2], Cricket [3], and The Bat [4] - to name a few. These systems typically require the installation of a dense system of *beacons* which incurs considerable establishment overheads. There have been attempts to perform indoor localisation using existing infrastructure like WiFi access points [1][5], mobile phone networks [10][18] and television signals [11]. For example, [1], [17], [19] and [5] explore the fingerprinting approach for estimating locations using wireless access points within a building. Ekahau [6], Pango [7], and Skyhook [8] are some commercially available wireless positioning products based on fingerprinting.

Fingerprinting requires the construction of a *reference* database of *fingerprints* in the area where location information is required. A fingerprint F at a particular location is defined as a vector $F = \{f_1, f_2, \dots, f_N\}$ where f_i is the signal strength received from transmitter i and N is the total number of transmitters used to construct the database. A *reference database* consists of fingerprints at points with known locations. Once this set of reference points has been collected, it can be used to estimate locations of new points by measuring a fingerprint at the required location and then comparing it with the reference database. [1] studies different algorithms for this purpose - ranging from a simple nearest neighbour to more complicated statistical approaches.

This paper extends the concept of fingerprinting to an indoor Locata Network for the first time.

Locata (developed by Locata Corporation [12]) is a terrestrial GPS-like positioning technology [13][14][15][16] which has given promising results with several positioning applications like construction environments and military, reaching upto centimetre level accuracy in some scenarios like structural deformation studies [20]. It deploys a network (*LocataNet)* of terrestrially-based transceivers (*LocataLites* – see Figure 1(a)) which transmit precise ranging signals. A *LocataNet* achieves a high level of time-synchronisation using the *TimeLoc* procedure developed by Locata. Thus, it can potentially perform single point positioning with centimetre-level accuracy without differential corrections and data links requirements. Currently, Locata operates in the 2.4 GHz ISM frequency band and uses its own proprietary signal structure for positioning. A *Locata Rover* (Figure 1(c)) is a stand-alone GPS-like receiver that tracks the signals from the LocataNet.

The LocataLites read their configuration parameters from a flash memory card. For the TimeLoc algorithm to work correctly, each LocataLite should be configured with the coordinates of its 2 transmitting antennae (Figure 2) as well as those of the master's. We surveyed the positions of all antennae with a total station to obtain accurate coordinates for this purpose.

In this paper, we study the fingerprinting approach of positioning in a LocataNet as opposed to using the original Locata technique. The reasons we examine fingerprinting are two fold: first, it is useful to have fingerprinting accuracy to indicate a 'lower bound' of the accuracy that is acceptable from an indoor Locata network. Second, if the indoor conditions are so challenging that normal Locata positioning is not possible, fingerprinting offers a 'fallback' method. We also compare our results with those of [1] which studies a similar fingerprinting positioning method using Wifi access points. In areas where WiFi access points are available, [1] offers another option to obtain location information.

(a)

(b)

(c)

Figure 1: (a) A LocataLite box; (b) Omnidirectional antenna used by the rover; (c) A Locata Rover

It is important to note that the equipment used for our experiments was optimized for outdoor use and an 'indoor' version of Locata is under development[1]. Using this indoor technology in the past, Locata has demonstrated cm-level positioning accuracy in a severe multipath environment using line-of-sight signals [21], and sub-metre level accurate positioning in an office block with non-line of sight signals [15].

Even though we are interested only in the 'power levels'[2] received from different LocataLites, we still require them to be time-synchronised (using Locata's TimeLoc technology). There are two main reasons for this: firstly, when the LocataLites are synchronised to each other, we can use the TDMA (or 'pulsing') technique and have each LocataLite transmit its signal on an exclusive time slot. This solves the 'Near-Far Problem' where if the rover is closer to one of the LocataLites, the power level from the latter will be much stronger and will mask out the signals from any other LocataLite which is transmitting at the same time thus making it impossible to record a complete fingerprint. Secondly, if all LocataLites are not synchronised, their codes will drift at different rates. Hence, when they transmit simultaneously, there will be a time-varying cross-correlation at the rover which will make it very difficult to obtain fingerprint data. However, when synchronised, this cross-correlation is a constant value which becomes an inert part of the fingerprint.

Clearly, due to the multipath indoors, the synchronization between LocataLites will not be as accurate as when a direct line-of-sight exists. We need synchronization only to make sure that reliable fingerprints can be collected. Thus, the precision of positioning from our technique is

[1]This does not affect our experiment because we do not perform positioning using Locata's original technique.
[2]The output of the rover is not actually the true received power level but an indication of power after software scaling and possible variable AGC (Automatic Gain Control). We will use the term 'power level' for these indicators henceforth.

independent of the accuracy of synchronization.

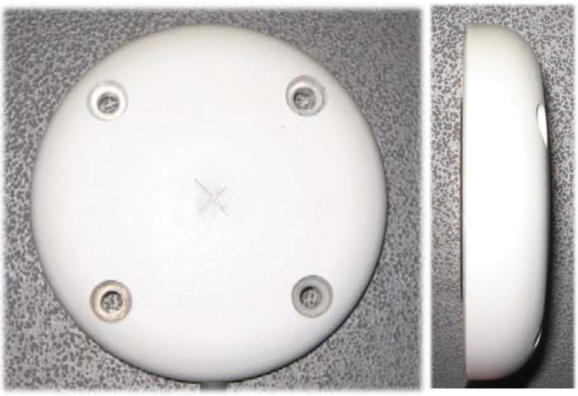

Figure 2: The patch antenna used by LocataLites for transmitting and receiving signals

A Locata receiver is similar to a GPS receiver. It uses an omnidirectional antenna (Figure 1(b)) to receive ranging signals from the LocataLites and calculates its position using pseudorange measurements (much like a GPS receiver – except that Locata works in the unlicensed ISM frequency band and gives a 2D position estimate). The rover reads configuration parameters from a flash memory card. There are two methods for positioning – the Code Solution and Carrier Phase solution; the latter being more accurate. The carrier-phase solution can give a very high level of accuracy (sub-centimetre level in appropriate conditions) but at present the rover requires a priori information on the initial location of its receiving antenna to resolve ambiguities. On the other hand, the code solution gives metre-level accuracy. These accuracies are similar to the code and carrier solutions in GPS.

2. Experiment

2.1 Setup

We setup a small indoor LocataNet in the School of Surveying and Spatial Information Systems at the University of New South Wales.

Figure 3 shows the floor plan of the experiment location and the positions and orientations of the 5 LocataLites used. These were placed in approximately similar positions to the wireless access points in [1] so as to make the comparisons of our results with those of [1] more meaningful.

Each LocataLite has 2 transmitting antennae which emit ranging signals allowing rovers to calculate their positions. These are similar to the way a GPS receiver calculates its position by using the signals transmitted by the satellites. Since a LocataNet is time-synchronised, one of the LocataLites is designated as the *master* to which all other *slave* LocataLites synchronise their clocks. Hence, all *slaves* have an additional receiving antenna for this purpose.

LocataLites use patch antennae with 70° beam width (Fig. 2) for transmitting signals. In order to have maximum signal coverage in the testing arena, the 10 antennae (2 per LocataLite) were oriented in such a way that their principal beam directions were well distributed over all directions (e.g. both antennae of L-1 point to the right, while both antennae of L-3 point to the left). Similarly, the transmitting antennae of L-2, L-4, and L-5 are also distributed in different directions. Figure 3 shows the direction of the principal beam of each transmitter.

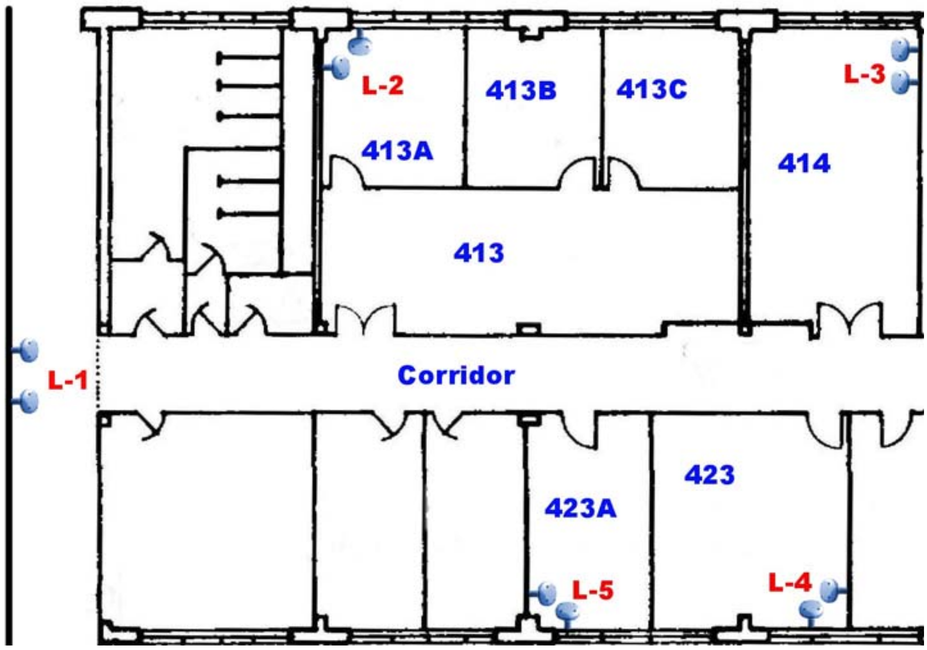

Figure 3. Floor Map of the School of Surveying and Spatial Information Systems, UNSW. The location of all 5 LocataLites are marked as L-1, L-2, ..., L-5

It was initially decided to have a single master LocataLite (marked L-1 in Figure 3) and have all other LocataLites synchronise to it. For this purpose, we configured all receiving antennae (on L-2, L-3, L-4, and L-5) to point towards L-1. Since many of the slave LocataLites were separated by several walls, we configured L-1 to transmit at full power. Although there was initial scepticism about LocataLites actually synchronizing with the master, it turned out to be satisfactorily stable despite the severe multipath due to walls and furniture. There were, however, a few problems with L-3, the farthest LocataLite, which was unable to sustain its TimeLoc with L-1. Upon investigating the cause, we realized that the power levels from both antennae of L-1 were severely attenuated (due to walls and furniture). Hence, L-3 was configured to synchronise with L-4 which was relatively closer. Thus, in Fig. 3, L-4 is a secondary master for L-3 as well as a slave to L-1.

Figure 4 shows the positions of the points in the database of reference fingerprints. Taking into account static obstacles like cabinets and other furniture, we tried to maintain a uniform density of points over the entire test area. The distance between consecutive reference points is always kept between 0.8 and 1.5 metres and constant in a single room.

The rover uses an omnidirectional antenna for receiving signals from the LocataLites. The rover connects to a laptop computer through a serial port and power levels were automatically collected from the rover. More about the computational tools used for this purpose is discussed in section 2.2. Throughout the experiment, we tried to measure all fingerprints at a constant height by keeping the rover on a stool. Figure 5 shows the equipment used in the experiment.

2.2 Computational Aids

We created several tools to assist in the experimentation process. Figure 6 shows a screenshot of the main tool used to collect the fingerprinting data.

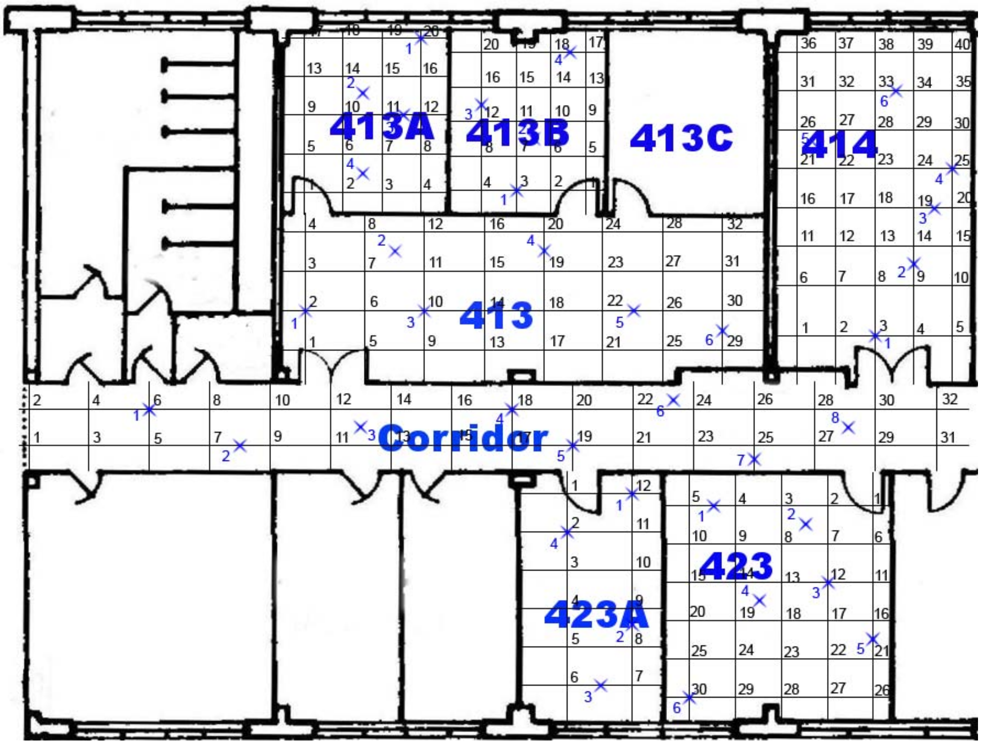

Figure 4: The numbered points on the grid represent the set of 186 reference point. The points marked with crosses are test points

This tool collects the output of the rover (referred to as the power levels from now on) at a frequency of 2Hz and displays them on the screen. It maintains a running average of the last 10 samples for each transmitting antenna. If each measurement is within a reasonable threshold from the average, the software decides to start logging the measurements of the fingerprint.

The image of the floor plan on the left hand side is a geo-referenced image. Clicking on a reference point stores its coordinates automatically along with the fingerprint data. Local coordinates are used for the purpose of this experiment.

It was also observed that the rover output drops down extremely low every now and then. Since these are obvious outliers that are not representative of the real power levels, we configured the software to ignore these sudden drops when recording data. These drops may be due to software or hardware problems and are ignored while collecting test points for positioning as well. Further investigation of these drops may occur later.

2.3 Measurements

Preliminary measurements were initially made during office hours and the received power levels fluctuated significantly with people walking around in the corridors. Therefore, all subsequent measurements were made in the relatively sterile environment of late nights. This has the obvious problem of not matching a real positioning scenario, but is appropriate for comparison with [1].

For each reference point, sixty measurements of the power levels were recorded. For any measurement which had too many points outside a certain threshold of the running average (which could be due to varying multipath from moving people or closing doors for example) the measurements were performed again in order to ensure that the reference database is free from any outliers – as far as possible. Any devices that could interfere with our signals in the ISM band were also turned off (mainly computers using WiFi).

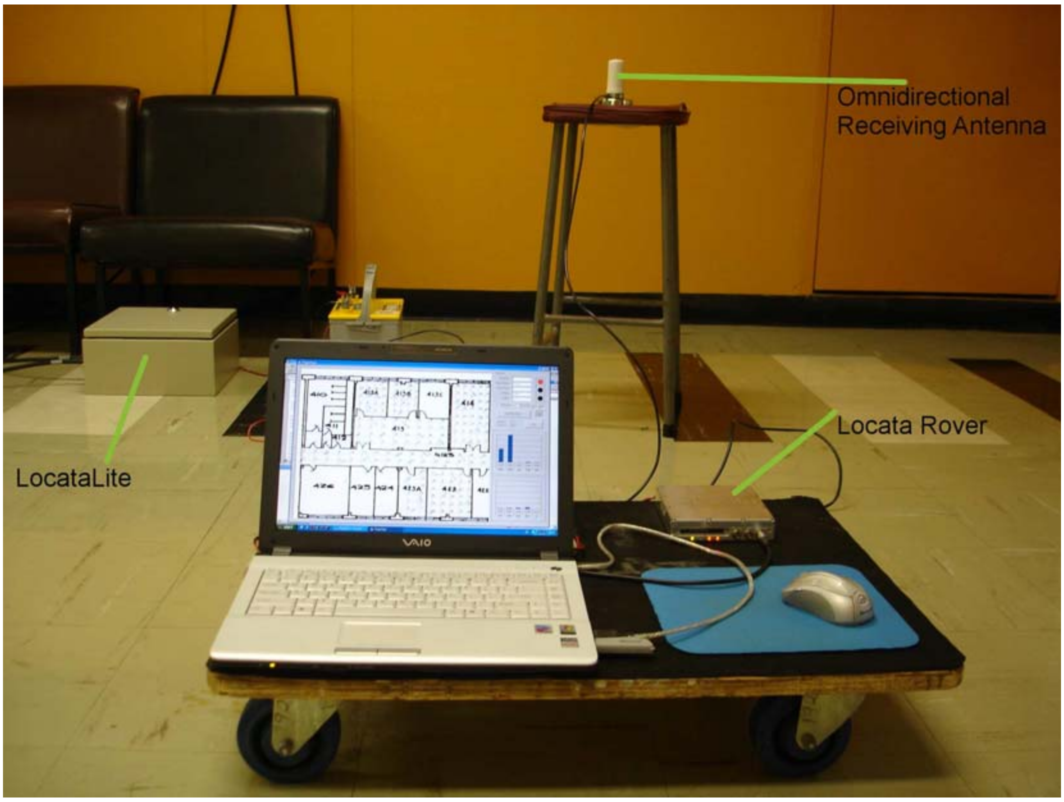

Figure 5: The equipment used in the experiment

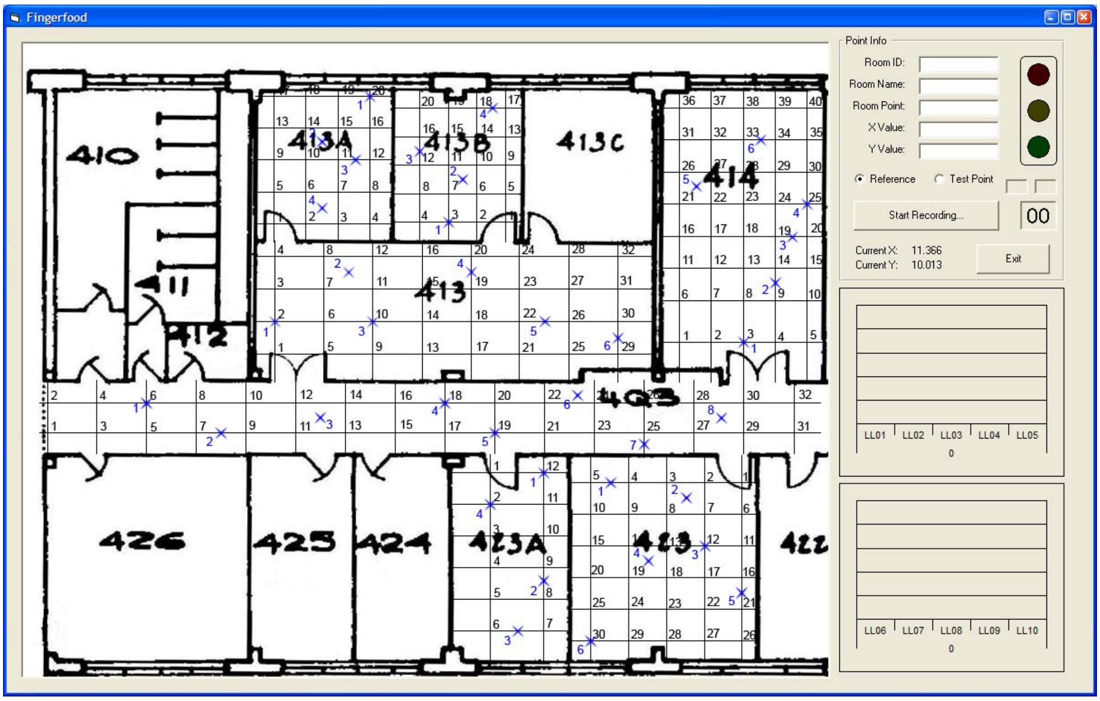

Figure 6: The software used to record data

To get an idea of the effect of multipath in the severe indoor environment, changes in power levels on a smaller distance scale were recorded. It was observed that the power levels fluctuate greatly even with a 10cm shift in the position of the antenna. Even in an empty corridor, the power levels of some LocataLites as much as doubled with only a 10cm shift in position. However since the measure for fingerprinting used is not a true power level, this variation might not be due to multipath.

3. RESULTS

3.1 Distance Functions

A fingerprint F is defined as: $F = \{f_1, f_2, \dots, f_N\}$ where f_1 is the power level received from transmitting antenna 1 of LocataLite L-1; f_2 is the power level received from transmitting antenna 2 of LocataLite L-1; f_3 is the power level received from transmitting antenna 1 of LocataLite L-2; and so on.

The analysis of the results from our experiments are based on the basic assumption that the distance between 2 fingerprints F_1 and F_2 in the 10-dimensional space defined above corresponds meaningfully to the physical distance between the points at which the fingerprints F_1 and F_2 were collected.

Let $D(F_1, F_2)$ be the distance between 2 fingerprints. Here, $D: R^{10} \times R^{10} \to R$. We will discuss the nature of the function *D* later.
Let $P(F_1)$ denote the actual point at which fingerprint F_1 was taken.
In the following analysis we assume that if $D(F_1, F_2) < D(F_1, F_3)$ then $P(F_1)$ is closer to $P(F_2)$ than to $P(F_3)$.

This assumption may be flawed in that the measurements from the rover are the result of possible software scaling and AGC, but these effects are not known. However, later results (section 3.2) indicate that the assumption is useful.

Definition 1: (Ratio Distance)
Let $A = \{a_1, a_2, \dots, a_{10}\}$ and $B = \{b_1, b_2, \dots, b_{10}\}$ be 2 fingerprints. Then, the *ratio distance* between A and B is defined as:

$$D_R = \frac{\max(a_1, b_1)}{\min(a_1, b_1)} \times \frac{\max(a_2, b_2)}{\min(a_2, b_2)} \times \dots \times \frac{\max(a_{10}, b_{10})}{\min(a_{10}, b_{10})}$$

It was anticipated that this distance function may cancel out some scaling issues with the 'unknown' measurements. The use of this distance function is backed up by the results.

Definition 2: (Logged Manhattan Distance)
Let $A = \{a_1, a_2, \dots, a_{10}\}$ and $B = \{b_1, b_2, \dots, b_{10}\}$ be 2 fingerprints. Then, the *logged Manhattan distance* between A and B is defined as $D_M = \sum_{i=1}^{10} \left|\log(a_i) - \log(b_i)\right|$

Lemma 1:
Let $A = \{a_1, a_2, \dots, a_{10}\}$ and $B = \{b_1, b_2, \dots, b_{10}\}$ be 2 fingerprints. Then, $D_M(A, B) = \log(D_R(A, B))$.

Proof:

$$D_M = \sum_{i=1}^{10} \left|\log(a_i) - \log(b_i)\right|$$

$$\Rightarrow D_M = \sum_{i=1}^{10} \left|\log\left(\frac{a_i}{b_i}\right)\right|$$

Since log(x) > 0 when x > 1; and log(x) < 0 when x < 1,

$$\left|\log\left(\frac{a}{b}\right)\right| = \begin{cases} \log\left(\frac{a}{b}\right), & b < a \\ \log\left(\frac{b}{a}\right), & b \geq a \end{cases}$$

Hence,

$$D_M = \sum_{i=1}^{10} \log\left(\frac{\max(a_i, b_i)}{\min(a_i, b_i)}\right)$$

$$\Rightarrow D_M = \log\left(\frac{\max(a_1, b_1)}{\min(a_1, b_1)} \times \frac{\max(a_2, b_2)}{\min(a_2, b_2)} \times \ldots \times \frac{\max(a_{10}, b_{10})}{\min(a_{10}, b_{10})}\right)$$

$$\Rightarrow D_M = \log(D_R)$$

□

Definition 3: (Logged Euclidean Distance)
Let $A = \{a_1, a_2, \ldots, a_{10}\}$ and $B = \{b_1, b_2, \ldots, b_{10}\}$ be 2 fingerprints. Then, the *logged Euclidean distance* between A and B is defined as

$$D_E = \sqrt{(\log a_1 - \log b_1)^2 + (\log a_2 - \log b_2)^2 + \ldots + (\log a_{10} - \log b_{10})^2}$$

One major difference between Manhattan Distance and Euclidean Distance is that the latter penalizes large distances disproportionately more than smaller distances. For example, consider 2 points in 2-dimensional Euclidean space with coordinates (0,1) and (1,0). Then, the Manhattan distance between them is 2 and the Euclidean distance is $\sqrt{2}$. Now consider 2 points with coordinates (0,0) and (2,0). Again the Manhattan distance between them is 2. But this time the Euclidean distance is also 2. More generally, when for 2 points there is a large difference between the value of only one coordinate, Euclidean distance returns a larger value than if the same difference is distributed over several coordinates.

It is for this reason that Euclidean distance is more appropriate for this experiment than Manhattan Distance. Since analogue versions of power levels are collected, their values at the same point will differ from time to time, albeit within a small range when compared with values at points separated by some distance. Hence, typically for points that are far apart, there will be a large difference in certain *coordinates*[3] as compared to the same coordinates

[3]For a fingerprint $F = \{f_1, f_2, \ldots, f_N\}$, each of the f_i are referred to as the coordinates of the fingerprint.

for physically closer points. Thus, we want a distance function that takes this into account and returns a larger 'distance' for fingerprints where certain coordinates differ by a large amount. Also, the Logged Euclidean Distance is used to negate the software and hardware normalization effects.

In section 3.2, we discuss the results using Euclidean distance. Due to lack of space, we do not show the results obtained using Manhattan Distance (which, on an average, had 20cm worse accuracy than Euclidean distance).

3.2 Results

Table 1 shows the results of positioning accuracy with fingerprinting. After collecting the reference database of fingerprints, test points were collected in each room. Figure 4 shows the positions of these test points. The estimated position of these test points was then determined using fingerprinting and compared to the actual position. This accuracy is reported in the following tables.

AvgNN denotes the average distance to the nearest neighbouring reference point that was obtained through fingerprinting. Avg2NN denotes the average of the distances between each test point and the centroid of its 2 nearest neighbours (as derived from fingerprinting). More generally, Avg*i*NN denotes the average of the distances between each test point and the centroid of its *i* nearest neighbouring reference points.

In the test points database, there are 3 types of test points. Type-1 points were taken on exactly the same position as a reference point. Type-2 points lie on the centre of a line (a line parallel to a wall of the room) joining 2 neighbouring reference points. Type-3 test points lie on the centre of a square formed by 4 reference points (figure 7).

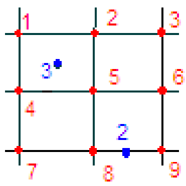

Figure 7: The points in red represent the reference points. The blue labels denote the type of test points

It was found that Type-1 points typically have the best accuracy when only 1 nearest neighbour is considered. In fact, in 70% of the cases, the fingerprinting method identifies the exact reference point on whose position the test point was taken. There are 13 Type-1 points, 15 Type-2 points and 10 Type-3 points in the test fingerprint database. Type-2 points show a better accuracy when more than 1 nearest neighbour is considered[4]. Type-3 test points have the worst accuracies when only 1 nearest neighbour is considered (see Table 1). However, as more nearest neighbours are taken into account, the accuracy improves significantly (for example, with 6 nearest neighbours, type-3 test points give an accuracy of 1.422 metres).

These results can be explained as follows. Consider test point 3 in Figure 7. The first nearest neighbour would be (say) reference point 1 (labelled in red). The next nearest neighbour would be (say) 2. The centroid of reference points 1 and 2 is closer to 3 than either of the

[4] Note that this trend is not reflected in Table 1 due to a single outlier test-point (413/6) that dramatically deviate the averages. When the outlier is excluded from the calculations, the average results for Type-2 points are: 1.914, 1.714, 1.740, 1.669, 1.696 and 1.820 (AvgNN to Avg6NN respectively).

reference points themselves. The next 2 nearest neighbours would be 4 and 5 (say). The centroid of reference points 1, 2, 4, and 5 is exactly point 3. Thus, the accuracy of positioning improves if we consider more nearest neighbours. The case for test points of type 2 is similar. For type-1 test points, it is the opposite case. As we keep taking more nearest reference points, their centroid is likely to move further away from the actual position of the test point. This is especially the case when the test point is near a wall because 'nearby' test points in space are not necessarily nearby in the fingerprint space.

Table 1: Accuracy of positioning using Euclidean distance function for fingerprints. All values are in metres.

	AvgNN	**Avg2NN**	**Avg3NN**	**Avg4NN**	**Avg5NN**	**Avg6NN**
All Test Pts.	1.551	1.817	2.079	2.041	1.974	1.929
Type-1 Pts.	0.998	1.816	2.231	2.426	2.317	2.418
Type-2 Pts.	1.820	1.991	2.122	1.958	1.907	2.077
Type-3 Pts.	1.865	1.578	1.816	1.664	1.629	1.422

Table 2: Positioning accuracies for all test points. All values are in metres.

Type	**Test-Pt.**	**1NN**	**2NN**	**3NN**	**4NN**	**5NN**	**6NN**
1	Cor/1	0	1.554	2.000	1.871	1.531	1.036
2	Cor/2	0.735	0.467	1.405	1.940	2.879	3.268
3	Cor/3	0.863	1.509	1.267	2.257	1.960	2.007
1	Cor/4	0	0.467	1.044	1.567	1.597	0.973
1	Cor/5	0	0.748	1.496	1.884	2.422	2.292
3	Cor/6	0.884	0.346	0.883	2.020	1.855	0.862
2	Cor/7	4.525	3.832	2.578	2.381	1.485	1.369
3	Cor/8	0.900	0.019	0.748	0.734	0.153	0.272
1	413A/1	0	2.079	3.008	3.787	3.712	3.505
3	413A/2	0.666	0.699	2.317	2.700	2.670	2.084
2	413A/3	0.435	0.041	0.844	1.120	1.495	1.411
3	413A/4	2.911	3.653	3.713	2.093	2.636	2.916
1	413B/1	0	2.799	2.141	1.406	1.438	1.275
3	413B/2	1.372	0.960	1.232	1.253	0.718	0.623
2	413B/3	2.464	1.983	2.863	2.497	2.553	2.461
2	413B/4	4.638	4.149	4.632	4.408	4.458	3.665
1	413/1	0	1.018	2.471	2.955	3.005	3.452
3	413/2	3.759	4.853	4.383	2.625	2.545	2.152
1	413/3	1.495	1.248	2.013	2.605	2.625	2.040
2	413/4	2.950	2.065	2.235	2.437	2.094	1.624
2	413/5	2.401	2.853	2.396	2.119	2.474	2.941
2	413/6	0.509	5.873	7.469	6.010	4.861	5.690
1	414/1	5.647	5.505	5.146	5.158	4.126	3.412

2	414/2	1.838	1.825	1.085	0.319	0.970	1.550
2	414/3	2.060	2.518	0.593	0.967	0.311	0.523
1	414/4	3.513	3.585	2.452	2.514	2.753	2.954
3	414/5	2.496	1.008	1.166	1.600	1.333	1.007
2	414/6	1.119	1.514	1.685	1.044	1.016	1.520
2	423/1	1.143	1.591	1.989	1.512	1.318	1.288
3	423/2	2.526	1.578	1.486	0.785	1.475	1.522
1	423/3	0	0.990	1.319	1.134	0.503	0.199
3	423/4	2.276	1.155	0.968	0.571	0.948	0.774
2	423/5	1.214	0.558	1.222	0.970	1.437	1.389
1	423/6	2.286	1.143	1.660	1.867	1.706	2.066
1	423A/1	0	0.975	0.971	1.711	1.957	2.301
2	423A/2	0.425	0.565	0.095	0.673	0.425	0.915
2	423A/3	0.842	0.040	0.734	0.976	0.834	1.548
1	423A/4	0.029	1.499	3.276	3.084	2.748	2.416

Table 2 lists the positioning accuracies[5] for all the test points. It can be seen that certain points are particularly poor – for example point 414/1 (i.e. test point 1 in Room 414 – see Fig 4 for its position). Typically, each room has a 'signature' fingerprint. That is, the signals from some LocataLites (especially the one placed in that room) will always be stronger than the others. This makes sure that while calculating Euclidean distances of fingerprints in the 10-dimensional power-level space, at least the correct room is always identified (as was the case in [22]). However, points like 414/1 may be in a region handicapped by severe multipath, thus distorting its fingerprint beyond appropriate limits from the 'signature'-fingerprint of that room, and hence leading to degraded positioning accuracy with fingerprinting.

Accuracies for type-3 points improve further when additional nearest neighbours are considered. Table 3 shows these accuracies for 7, 8, 9, and 10 nearest neighbours. With about 1.2 m accuracy, these results are fairly promising.

Table 3: Positioning accuracies for type-3 test points with greater than 6 nearest neighbours.

Avg7NN	**Avg8NN**	**Avg9NN**	**Avg10NN**
1.186	1.199	1.161	1.176

3.2 Power Level Distributions

Figure 8 shows the power level distributions in Room 414 (the room which had the worst positioning accuracy). Although the signal levels from most LocataLites do not follow a theoretical quadratically decreasing value (which is due to the software scaling and AGC of outputs as well as severe multipath), we still get decent positioning accuracies because fingerprints at a particular position are near-constant and repeatable (i.e. if we record a

[5]Note that all positioning accuracies would have at least a ± 10cm error. There are several factors leading to this error. Firstly, to mark the coordinates of test points, a software was used to identify the position by clicking on the screen, which could have upto 5cm of error. Also, there can be a further error of 5cm while placing the rover antenna at a particular point. These error values have been identified by analysing the data shown in Table 2.

fingerprint at the same position at a different time, we will get similar values).

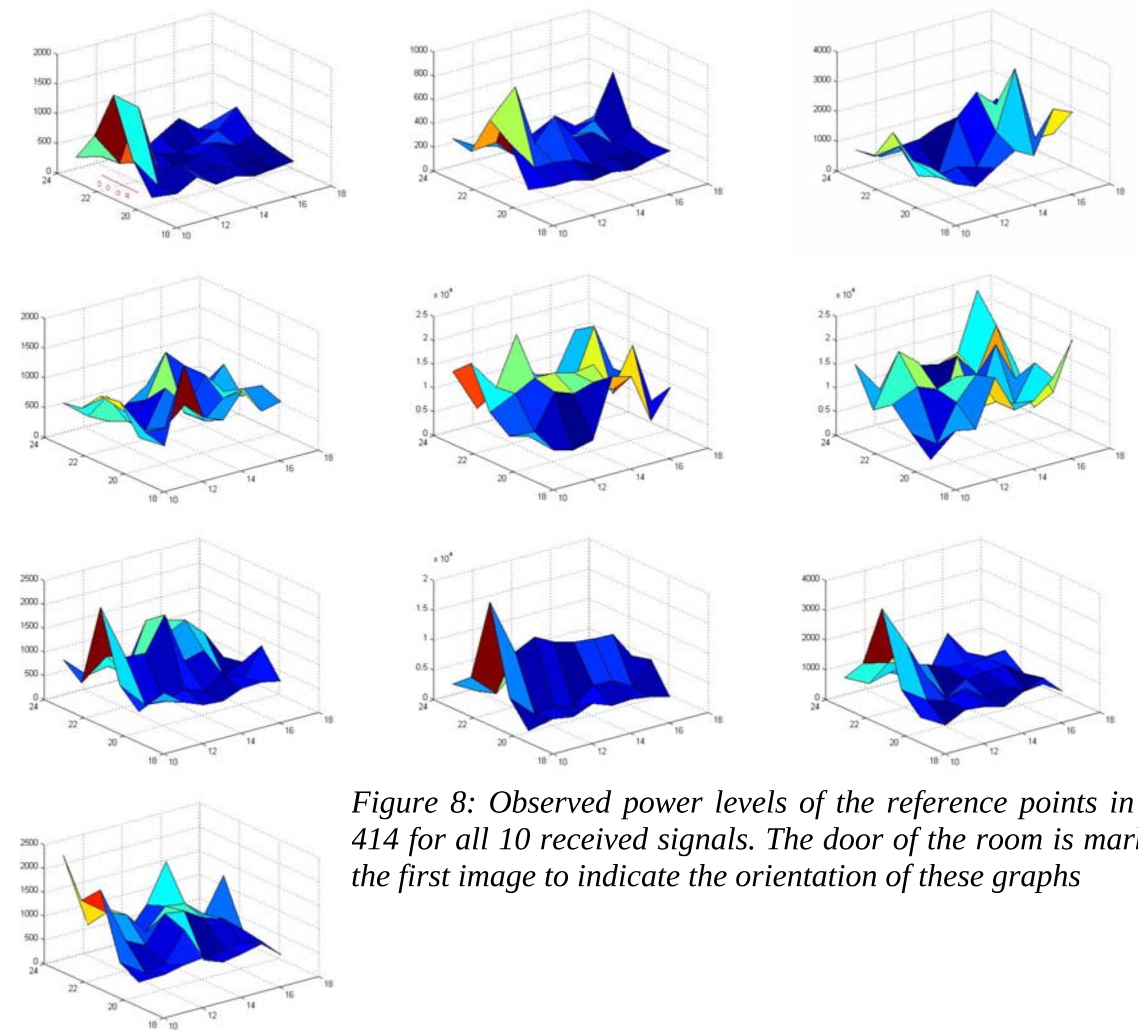

Figure 8: Observed power levels of the reference points in room 414 for all 10 received signals. The door of the room is marked in the first image to indicate the orientation of these graphs

4. FUTURE WORK

The concept of fingerprinting has a scope of refinements to improve its accuracy. Consider a test point near a wall. As more and more of its nearest neighbouring reference points are considered, their centroid will keep drifting away from the test point - in the opposite direction from the wall (see Figure 9). Such cases can be identified by observing the increasing *i*NN values with increasing *i*. Our experiments have revealed that points near walls have poorer positioning accuracies than points away from walls. This can be corrected by identifying points near walls (using the aforementioned technique) and considering only a few (1 or 2) nearest neighbours to determine the X-coordinate. However, several nearest neighbours can be considered to obtain a very accurate Y-coordinate.

Another interesting technique to study would be to first create a 'signature'-fingerprint for each room. Using this, test points can first be localized to one room (or a set of rooms). Subsequently, nearest neighbour algorithms can be run within this reduced reference database (similar work was done in [22]). It was observed that on many occasions, the average position estimate gets thrown off because fingerprints from different rooms are identified as closer to a test point. Such situations can be eliminated by this method.

Several other more complicated statistical approaches can be adopted as distance measures in the fingerprint space. A weighted average of nearest neighbours [1], which gives more weight to closer neighbours, can be experimented with.

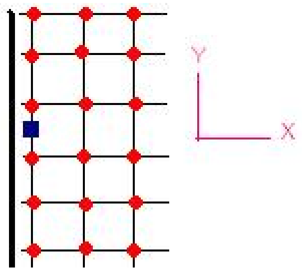

Figure 9:The thick black line on the left indicates the wall. The point marked in blue is a test point. The grid of red points are the reference points. The axes are labelled to the right

5. CONCLUSION

With an average positioning accuracy of approximately 1.5m, we feel that fingerprinting using Locata signals emerges as a cogent fallback option when regular Locata positioning is unable to provide satisfactory results. Moreover it serves as a competent benchmark for more complicated indoor positioning technologies (like Locata itself).

With accuracies in the range of 1.2 m – 1.5 m (which include extremely poor points like the ones in Room 414), Locata signals fingerprinting is comparable to WiFi fingerprinting as studied in [1]. The authors of [1] observed positioning accuracies in the range of 1.2m – 1.8m. These accuracies are under ideal conditions at night with minimal activity from people walking around and all 2.4 GHz devices such as WiFi turned off. In a more 'real-world' scenario, accuracies are likely to be worse.

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