SIB: Noise Reduction in Fingerprint-based Indoor Localisation using Multiple Transmission Powers

Paul Crane
Computer Science
University of Otago
Dunedin
New Zealand
pcrane@cs.otago.ac.nz

Zhiyi Huang
Computer Science
University of Otago
Dunedin
New Zealand
hzy@cs.otago.ac.nz

Haibo Zhang
Computer Science
University of Otago
Dunedin
New Zealand
haibo@cs.otago.ac.nz

ABSTRACT

Research efforts into indoor localisation have focused on improving the accuracy of location estimates. In this paper, we propose a novel approach called SIB that uses RSSI values from low-power transmissions to exclude the noisy measurements from usual high-power RSSI measurements. SIB can effectively reduce the effect of noise in fingerprint-based localisation according to our analysis on the function of power loss ratio to transmission distance. Our results, based on evaluation in a real-world environment with noisy data, show a decrease in the geometric error of 85% in our indoor localisation.

Categories and Subject Descriptors

C.2.m [**Computer-Communication Networks**]: Miscellaneous

General Terms

Design, Experimentation, Measurement, Performance

Keywords

RSSI fingerprint, indoor localisation, noise reduction, wireless, transmission power

1 Introduction

In recent years research efforts into indoor localisation have focused on improving the accuracy of location estimates. They are motivated by applications such as autonomous robotics [11], advertising (and other consumer related behaviour) [6], and indoor navigation [10], which require high accuracy of location estimates. However, many such approaches require extra hardware such as ultrasound [16] to improve accuracy and are not very practical for commodity mobile devices such as smart phones. Received Signal Strength Indicator (RSSI) measurements are readily available but are notoriously noisy and so it is difficult achieve high accuracy.

However, our proposed approach Shorter is Better (SIB) can remove excessively noisy RSSI data to improve accuracy during indoor localisation using multiple transmission powers. When we query the database we exclude the fingerprints based on the visibility of the minimum transmission power, thus excluding excessively noisy anchor nodes and improving the accuracy of the location estimates. As far as we know, this work is the first time multiple transmission powers have been used in this manner.

The main contributions of this work are firstly, we propose a novel noise reduction approach SIB using multiple transmission powers. Secondly, based on the noise reduction, we propose a new fingerprinting algorithm based on SIB with multiple transmission powers. Thirdly, we conduct comprehensive experiments to show that SIB can achieve better accuracy than many existing fingerprinting methods.

We first discuss related work below, then in Section 3 we present our approach to noise reduction and our fingerprinting algorithm based on SIB. Our test environment is described in Section 4 where we also present the results. Our conclusions appear in Section 5.

2 Related Work

Typically there are two broad classes of indoor localisation methods: range-free (relying on a distance-per-hop metric [17], and are inaccurate) and ranged-based. Range-based methods estimate more accurately the distance between the mobile node and the anchor node. This family of techniques includes Time of Arrival (TOA), Time Difference of Arrival (TDOA), Angle of Arrival (AOA), and RSSI. For a more thorough discussion refer to [14]. Apart from RSSI these methods require specialised hardware not typically found on commodity devices.

There are two techniques that apply to RSSI, trilateration [9], where we estimate the distance to multiple anchor nodes and calculate the position of the mobile node; and fingerprinting [4, 24], where the estimated location is found by matching between the observed signal patterns and the previously collected signal patterns. The main problem with trilateration is that the distance calculation is very sensitive to noise. Conversely, fingerprinting methods are well known for their high accuracy relative to trilateration.

To increase the accuracy of the fingerprinting approach we can either use advances in hardware, such as Multiple-in and Multiple-out (MIMO) and channel responses, to give us more fine-grained fingerprints [19, 20] (and increasing the cost of the hardware), or we can investigate different algorithmic approaches to processing the RSSI data. Some previous work consists of techniques such as hardware calibra-

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tion, (which necessitates fitting a model to data and expensive testing hardware) [1, 22]; smoothing measurements, for example, complex noise removal [8], Kalman filtering [2], and regression models [7] — all of these increasing the complexity of calculations; particle filtering [18]; using a combination of sensor data (requiring that those sensors are available for use) [3, 12]; and finally, changing the underlying model of how to compute the distance [15]. All of these have improved the accuracy in their respective environments, either in simulation [7, 12, 18] or in the real-world [2, 8, 15, 22].

The use of multiple transmission powers has been used in other work. Some fit models to the different transmission power levels [23] and use a trilateration method, or combining multiple transmission power information to increase the accuracy [13] (but due to limitations in their storage they only achieve an accuracy of 2m), or use multiple transmission powers to provide a bound to their range-free method [5]. As discussed above, trilateration and range-free methods are not accurate.

In summary, these techniques are usually expensive in computation and may not be suitable for real-world localisation. The accuracies for different fingerprinting approaches from real-world experiments range from 1.3m to 4.69m [2, 4, 8, 15, 19, 20, 22, 24].

3 Shorter Is Better (SIB)

Traditional fingerprinting methods, like Radar [4], divide an area into a grid. At each of the grid point RSSI samples are collected from anchor nodes. For each node, the samples are averaged to give a single RSSI value. The location information is used to group the anchor node IDs and their associated RSSI values into a tuple – called a fingerprint. Note that it is possible that some anchor nodes are out of range of the point in which cases the RSSI values are set as *nil*. During localisation, RSSI values are collected from the anchor nodes at an unknown location and are put into a query tuple. Then the Euclidean Distance between the query and each of the fingerprints in the database is calculated. Finally the tuple in the fingerprint database with the minimum distance is chosen and its associated location is decided to be the estimated location.

The noisy RSSI problem is more serious when the distance between the query location and an anchor node is very large. The problem can be explained by the well-known log distance path loss model, $\mathrm{P_{tx}} - \mathrm{P_{rx}} = \mathrm{P_{ref}} + 10\gamma \log \frac{d}{d_{\mathrm{ref}}}$, shown graphically in Figure 1 (the low transmission power is the dashed curve, high power is the solid curve). When the distance between a location and an anchor node is large, the power loss ratio to distance becomes smaller according to the solid curve in Figure 1. The technical specifications of the TelosB sensor motes used in our study describe a ±6dB level of noise associated with the RSSI measurements [21]. Given this level of noise in the measurements and the shape of the curve there is a large range where we can observe the same RSSI value, especially at a large distance from the transmitter.

In Figure 1 the dotted lines indicate a measurement with an error at two different transmission power levels. The closer we are to the transmitter the less effect this measurement error has on the distance range, conversely, the further from the transmitter, the larger the distance. For example, we receive a high power RSSI measurement of between -75dB and -81dB we could between 15.0m and 18.5m away from the transmitter. Therefore, we should use RSSI values collected at shorter distances from anchor nodes to reduce the effect of measurement noise (for example, a measured RSSI between -19dB and -25dB results in a position between 2.0m and 2.5m).

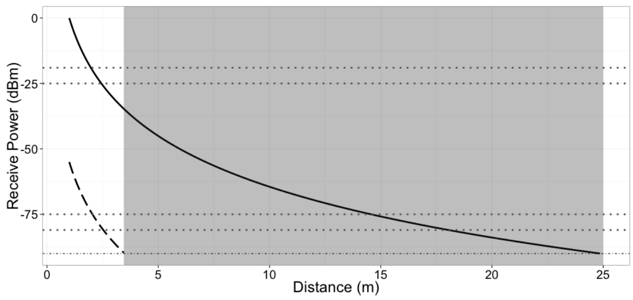


Figure 1: Signal strength as a function of distance for two transmission power levels (0dBm and -55dBm)

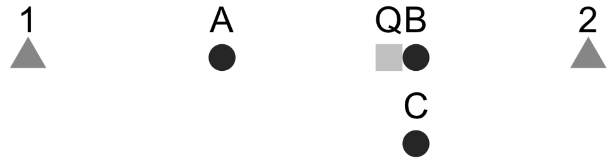


Figure 2: The example situation

A simple solution is to use a distance threshold (where the distance between the sample point and anchor node is, say, less than 10m) but this is not satisfactory as different anchor nodes may have vastly different thresholds dependant on the environmental factors. The low transmission power provides a natural cut-off. Because the devices cannot receive a signal below a threshold defined in the hardware (in our devices the limit is -90dB) we can use the visibility of the minimum transmit power as a measure of proximity to the transmitter.

We collect both high-power and low-power RSSI values from each anchor node in the query and fingerprint tuples. For each anchor node, if the low-power RSSI value is not available we ignore the anchor node in the subsequent distance calculation. Because we do not observe the low transmission power, we must be far from the transmitter, or in the shaded portion of Figure 1.

3.1 Example

Though fingerprinting has good localisation accuracy compared to other RSSI-based methods, its accuracy is susceptible to noise as discussed previously. In our typical example, we have three grid points (A, B and C) and two anchor nodes (n1 and n2), illustrated in Figure 2. At each grid point we record the signal strengths from the two anchor nodes and construct the fingerprint database. These values are presented in the second and third columns of Table 1.

Suppose we collect a query tuple $Q = (-70, -70)$ at a location close to grid point B. Though the query tuple is

Point	$n1$	$n2$	Distance from $Q = (-70, -70)$
A	-69	-72	$\sqrt{\frac{1^2+2^2}{2}} = 1.6$
B	-73	-69	$\sqrt{\frac{3^2+1^2}{2}} = 2.2$
C	-73	-70	$\sqrt{\frac{3^2+0^2}{2}} = 2.1$

Table 1: A worked example of fingerprinting.

Point	n1 (low,high)	n2 (low,high)	Distance from Q $(nil, -70), (-87, -70)$
A	(-88, -69)	(nil, -72)	nil
B	(nil, -73)	(-86, -69)	$\sqrt{\frac{1^2+1^2}{2}} = 1.0$
C	(nil, -73)	(-89, -70)	$\sqrt{\frac{2^2+0^2}{2}} = 1.4$

Table 2: Continued worked example with multiple powers.

collected at a location close to B, its RSSI value from anchor node *n1* differs from that of B due to the noise in the RSSI measurements, which is very common in real RSSI measurements.

In the example outlined in Table 1, the estimated location is A as it is the one that has the smallest distance. However, we know that our result as the location should be B. This is due to noise in the samples being collected. We also note that even C is closer than A.

Since we collect both high-power and low-power RSSI values, our query is now $Q = ((nil, -70), (-87, -70))$, where the RSSI values are collected at a location closer to grid point B. Since Q is far from anchor node *n1*, it cannot receive the low-power RSSI value from *n1*, so its value is *nil*. Likewise, in Table 2, since point A is far from anchor node *n2*, the low-power RSSI value from *n2* is set *nil*. Similarly *nil* is set for low-power RSSI value of *n1* in the fingerprint tuple at points B and C.

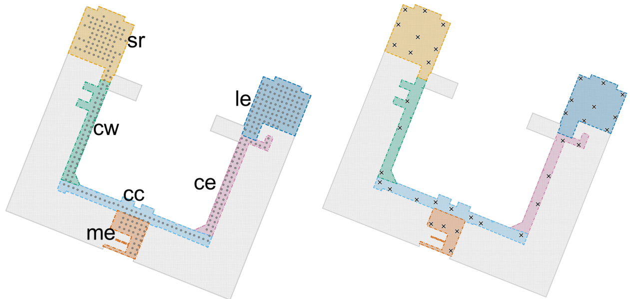
Given we ignore every high-power RSSI value where the corresponding low-power RSSI value is *nil* in the distance calculation, the noise from high-power RSSI values of long distance are excluded. In our example in Table 2, we exclude point A from consideration as all its high-power RSSI values are excluded by *nil* low-power RSSI values from either the query tuple or the fingerprint tuple of A. Since A is excluded, our candidate points are now C and B, both are closer to Q than A. Because B's distance is smallest we present this as our estimated location which is much closer to the ground truth than our previous estimate. Even if C were selected due to noise in low-power RSSI values, the error is much smaller than that if A were selected, because the power loss ratio is larger in shorter distances as explained previously and shown in Figure 1. It is worth noting that C is not selected because its low-power RSSI value sets it apart from the query tuple, though C is a close competitor of B.

3.2 SIB-based Fingerprinting Algorithm

When we receive a query we iterate over the fingerprint database and for each point, we find a set of anchor nodes common to the query and the fingerprint, which means the common nodes are *visible* to both the query location and the location associated with the fingerprint. If this set is empty, we move onto the next point, otherwise we then find a set of common power levels per node. If the common power levels set is not empty, we then calculate the difference between the stored value and the query and add the square of the value to the cumulated distance, keeping a count of the number of the items included. In the SIB approach we add an additional condition here: that the set of common power levels must contain the minimum transmission power. Once we have finished processing all the nodes and power levels we divide the cumulated distance by the count, and take the square root. If the final value is smaller than the

Data: q as query, fp as fingerprint database
Result: estimated location
begin
    smallest point = nil
    smallest distance = ∞
    for *p in the fingerprint database* **:**
        cumulated distance = 0
        cumulated count = 0
        ν = calculate the common node set
        for n *in* ν **:**
            ϱ = calculate the common power levels set
            if *the minimum transmit power is not in* ϱ **:**
                continue
            for l *in* ϱ **:**
                cumulated dist += (q[n][l] - fp[p][n][l])^2
                cumulated count += 1
        dist = $\sqrt{\text{(cumulated dist / cumulated count)}}$
        if *dist* < *smallest distance* **:**
            smallest distance = dist
            smallest point = p
    return *smallest point*

Algorithm 1: SIB-based Fingerprinting Algorithm



(a) Each coloured area is a different region in the building, annotated with the area.

(b) Each cross is the location of one of the 37 anchor nodes deployed.

Figure 3: The Owheo building anchor node and sample point layouts, orientated so north is at the top of the images.

current minimum, then we update the estimated location to the point we have been evaluating. Algorithm 1 shows this process in detail. Our fingerprint database is indexed first by position, then node ID, then power levels.

4 Results

The data set for our experiments comes from the first floor of the Owheo Building, on the corner of Union and Forth streets in Dunedin, New Zealand. The building covers an area of 2842.71m^2 (51.9m by 48.1m). We divide the building into six non-overlapping regions to make the data collection more manageable. In Figure 3a each colour represents a different region, with the grey areas indicating private offices (giving us a sample area of 339m^2. We collected data from a grid with a distance between each point of 1m. This produces the grid points for sampling RSSI fingerprints as shown in Figure 3a. Once we have recorded the relative position of the mobile node we broadcast 50 requests from the mobile node at the maximum transmission power. When this message is received by an anchor node, it measures the signal strength and sends it back the 29 available power levels. The query tuple is derived from a Gaussian distribution based on the parameters in the fingerprint database (each

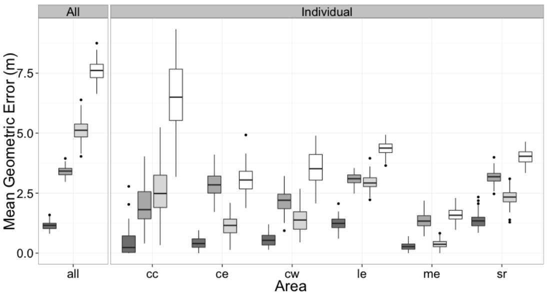


Figure 4: The comparison of the methods across the different regions.

anchor node has multiple transmission power levels, each of these has a μ and σ). This is repeated 100 times for each of the sample points.

We include four localisation algorithms for evaluation which perform in a similar manner to Algorithm 1 except the selection of RSSI values of different power levels in the calculation of distance. The first algorithm, Radar, uses only a single maximum transmission power. MinRadar is where we use only the minimum transmission power. AllRadar is where we use all the transmission powers that we observe. Finally, SIB is our algorithm where we exclude anchor nodes when we cannot observe their minimum transmission power.

The left hand panel of Figure 4 shows the mean errors of the four localisation algorithms from a database of points across the entire floor. From the figure we can see that SIB has the lowest mean error at 1.15m. We can see that there is a lower error when we increase the number of transmission power levels available. Comparing Radar (7.6m) with AllRadar (5.13m), or SIB (1.15m) with MinRadar (3.42m). SIB performs 66% better than MinRadar, 78% better than AllRadar, and 85% better than pure Radar, and is 12% better in comparison with previous work.

The right hand panel of Figure 4 shows the performance in the different regions of the building. In the figure, we can see that in all areas SIB has the smallest error of all the algorithms. We attribute the performance difference between **le**/**sr** and **ce**/**cw** is due to the shape of the areas. The ce and cw areas are long (21m) narrow (approx 2m) corridors, compared with the almost square rooms (roughly 10m by 11m), thus the potential for large errors is also reduced.

5 Conclusions

We have proposed a novel approach SIB that uses RSSI values from low-power transmissions to exclude the noisy measurements from usual high-power RSSI measurements. We believe that this is the first time that this novel technique has been used in RSSI-based fingerprinting systems.

We conducted comprehensive experiments in a real-world situation. Experimental results have shown SIB can reduce the geometric error by 85% and achieves an accuracy of 1.15m. This improvement is across all the sampled areas, and is better than most other RSSI-based fingerprint systems. We have also shown that making use of all the transmission powers received decreases the error significantly. To the best of our knowledge, we are the first to use this idea to increase the accuracy of RSSI fingerprinting systems.

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