Bluetooth Indoor Positioning System using Fingerprinting

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Abstract. Indoor Positioning has been an active research area in the last decade, but so far, commercial Indoor Positioning Systems (IPSs) have been sparse. The main obstacle towards widely available IPSs has been the lack of appropriate, low cost technologies, that enable indoor positioning. While Wi-Fi infrastructures are ubiquitous, consumer-oriented Wi-Fi enabled mobile phones have been missing. Conversely, while Bluetooth technology is present in the vast majority of consumer mobile phones, Bluetooth infrastructures have been missing. Bluetooth infrastructures have typically been installed as part of complete hardware-/software IPSs that often incur a substantial hardware cost. Furthermore, Bluetooth has low power consumption compared to Wi-Fi devices, which promotes longer battery life-time on mobile phones. In this paper, we present a Bluetooth IPS based entirely on commodity-grade products. The positioning accuracy is evaluated by using the so-called location fingerprinting technique which is well-known from Wi-Fi positioning literature. The results show that 2 meters median accuracy is achievable - a result that compares favourably to results for Wi-Fi based systems.

Key words: indoor positioning, bluetooth, fingerprinting, radio map

1 Introduction

Since the turn of the century, Location-Based Services (LBSs) have been hailed as one of the next "killer apps". To provide such services, an underlying positioning system is required. One such system is the Global Positioning System (GPS), which has uncovered the potential of LBSs as witnessed by the proliferation of LBSs that work outdoors. Unfortunately, GPS radio waves are unable to penetrate most building structures, leaving large areas of indoor positioning potential untapped. Thus, an Indoor Positioning System (IPS) is needed to enable LBSs in indoor environments.

Wi-Fi is an appealing technological alternative in GPS-less environments due to the ubiquity of Wi-Fi infrastructures and has thus been the subject of much recent research [1, 2, 3, 4, 5, 6, 7, 8]. However, consumer-oriented Wi-Fi enabled mobile phones currently constitute only 18% of the total mobile phone market [9, 10]. Although, the market share is rising (e.g. Nokia provides Wi-Fi capabilities in 35% of their new models in the UK [11]), the vast majority of mobile phones have Bluetooth capabilities. It is estimated that 75% of all existing phones and 95% of all new phones on the Australian market have Bluetooth [12]. Thus, it can be expected, that for some time to come, Bluetooth will remain more common, especially since manufacturers only provide Wi-Fi capabilities in their high-end mobile phones. Although Bluetooth has been an integrated part of mobile phones for years, Bluetooth infrastructures have been rare. Typically, Bluetooth infrastructures have been set up as part of a complete hardware-/software Indoor Positioning System (IPS), e.g., as developed by companies like BLIP Systems [13]. The cost of a complete hardware-/software IPS may be too prohibitive for many, especially smaller companies, but recently, a cheaper alternative has emerged. It is now possible to set up a Bluetooth infrastructure at a very modest cost simply by extending modern commodity-grade Wi-Fi access points with Bluetooth dongles [14, 15]. This extension also provides the possibility of making a combined Wi-Fi/Bluetooth IPS based on the same infrastructure.

Another advantage of using Bluetooth is that it has a low power consumption. Specifically, it only uses 81-120mW compared to Wi-Fi which uses 890-1600mW under load [16]. Thus, Bluetooth is ideal for mobile phones where a desirable property is to increase battery life-time.

Positioning in an indoor environment is a non-trivial task. As signals propagate through an indoor environment, they are reflected, scattered, and subject to multipath fading. Moreover, signals are affected by transient effects such as changes in humidity level and human bodies absorbing the signals.

The most widely used technique for accurate indoor positioning is called *location fingerprinting* and is a technique that counters the adverse effects from environmental factors by relying on empirically measured signal strengths. The term *location fingerprinting* refers to the fact that the Received Signal Strength (RSS) values from nearby access points form spatio-temporally, approximately unique, RSS vectors.

The location fingerprinting technique is divided into two phases. In the *offline phase*, before an IPS becomes operational, a location fingerprint is created by empirically measuring the RSS values at a particular location for a period of time. At the end of the measurement period, the $\langle location, RSSvector \rangle$ pair is saved as an entry in a *radio map*. This measurement process is typically conducted for locations spaced 2-3 meters apart throughout the indoor environment. In the operational *online phase*, a location estimate is obtained by comparing the RSS values recorded by an end-user's device with the entries saved in the radio map. The location of the closest matching RSS vector is returned as location estimate.

Accuracy and precision are two common performance metrics of a positioning system whose definitions are described below and used in the following:

Accuracy describes the extent to which the estimated location deviates from the actual location. That is, accuracy denotes the euclidian distance between an estimated location and the actual location.

Precision refers to the percentage of measurements retaining a particular accuracy.

In this paper, we examine the positioning accuracy that can be obtained by a cheap dongle-based Bluetooth IPS using the location fingerprinting technique. Additionally, we investigate how different Bluetooth power-classes influence the performance, and evaluate the performance/cost tradeoff. Finally, we investigate the effect of different ways of constructing a radio map with respect to user orientation. Traditionally, a fingerprint is constructed by measuring RSS values in four orthogonal orientations and then averaging them [1, 2]. However, this may mask important RSS differences dependent on orientation as noted in [14, 15]. Thus we have compared three different radio map construction methods:

– Average Method
– Four Directions Method
– Single Direction Method

The *average method* refers to the traditional approach of constructing a fingerprint. The *four directions method* keeps all four fingerprints without averaging them. Finally, the *single direction method* is identical to the *four directions method* in the offline phase. However, when matching the fingerprints in the online phase, only a subset of fingerprints, corresponding to the user's current orientation, is searched. The intuition is that accuracy may be improved by disregarding fingerprints from other directions that may potentially yield erroneous results. The vision is that the system is able to deduce orientation of the user either by harnessing a compass, which is available in many smartphones today, or by using the history of previously estimated locations to deduce a path, which may provide a heuristic of user orientation.

The remainder of this paper is organised as follows: Section 2 describes related work on IPSs, Section 3 presents the challenges of using Bluetooth as an IPS technology, Section 4 describes the methodology of our research, followed by Section 5 where the results are evaluated, and finally, Section 6 concludes the paper.

2 Related Research

As mentioned, signals are vulnerable and influenced by several environmental factors such as reflection, changing humidity levels, presence of people, and multipath fading. The interplay of influencing factors means that traditional trilateration and signal propagation techniques are not equipped to deliver accurate position estimates [3, 4, 17].

Wi-Fi is a widely adopted as technology for indoor positioning. As Wi-Fi and Bluetooth operate on the same frequency band, they are both vulnerable to the same impacting environmental factors. One of the primary motivations for using Wi-Fi is that it is ubiquitous; many facilities such as educational institutions and companies include a Wi-Fi infrastructure for extending the Intranet for the mobile users. Hence, the deployment cost of a Wi-Fi based IPS is low.

The RADAR project [17], carried out at Microsoft Research, pioneered the field of IPSs by proposing the *location fingerprinting* technique to enable accurate indoor positioning in the face of a noisy Wi-Fi channel. The RADAR project used a deterministic Nearest Neighbour algorithm to match online fingerprints against the offline fingerprints saved in the radio map resulting in a median accuracy of 2.94 meters. Subsequent research efforts have tried to improve the obtainable positioning accuracy by different classification algorithms, including Support Vector Machines [5, 6], Neural Networks [7, 8], and Bayesian Inference [18, 19]. Moreover, motion models have been applied to counter adverse effects caused by increased signal strength fluctuations when users are moving [1, 20] (We refer to survey papers such as [21, 22] for an additional overview of existing algorithmic approaches). However, the obtainable accuracy can not be attributed exclusively to the use of a particular location determination algorithm, as it is also affected by factors such as the number and placement of access points, the number of samples used in the measurement process, the density of the radio map, the sensitivity of the antennas, orientation, and the environment [1, 3, 23]. In fact, the obtainable accuracy is inherently limited by the very nature of the Radio Frequency (RF) signals: Elnahrawy et al. [24] performed an extensive study that compared a wide range of different positioning algorithms. The study concluded that ten feet accuracy represents a feasible lower bound due to inherent limitations of differentiating RSS values at closer distances. Therefore, at roughly the ten feet mark, algorithms are only able to improve the precision, i.e., the percentage or confidence with which a given accuracy is obtained. However, ten feet accuracy is still more than enough to support a wide range of IPSs.

Commercial Bluetooth IPSs have typically used trilateration or discrete positioning to deliver context-aware information to end-users in certain information zones [13, 25]. Lower granularity position estimates are acceptable for pushing content to end-users whereas navigation scenarios impose higher demands on positioning accuracy.

3 Bluetooth Challenges

Using Bluetooth for indoor positioning introduces some challenges which we have not observed elsewhere in the Wi-Fi literature. The following describes the challenges we have encountered in our work and our solutions to these.

3.1 Received Signal Strength Indicator (RSSI) Values

The Bluetooth specification [26] dictates that a signal strength can be read in terms of an RSSI value, which, as the name implies, is a metric indicating the strength of the signal. However, the problem is that the Bluetooth specification does not prescribe a standardised mapping between the RSS values measured in dBm and the RSSI values. This means that individual Bluetooth vendors are responsible for implementing their own mapping. Typically, an interval of RSS values are mapped to one RSSI value, hence the distribution granularity is relatively coarse. However, the granularity may be sufficient if the RSSI values are distributed such that small changes in distance yield distinguishable RSSI values. To ensure that the Bluetooth implementation on the mobile phone exhibits this behaviour, we have made preliminary experiments where RSSI values are measured at different distances using a Class 2 Bluetooth device [14]. As shown in Figure 1, the RSSI values are distinguishable at the different distances and the Bluetooth implementation on the mobile phone is thus applicable for indoor positioning.

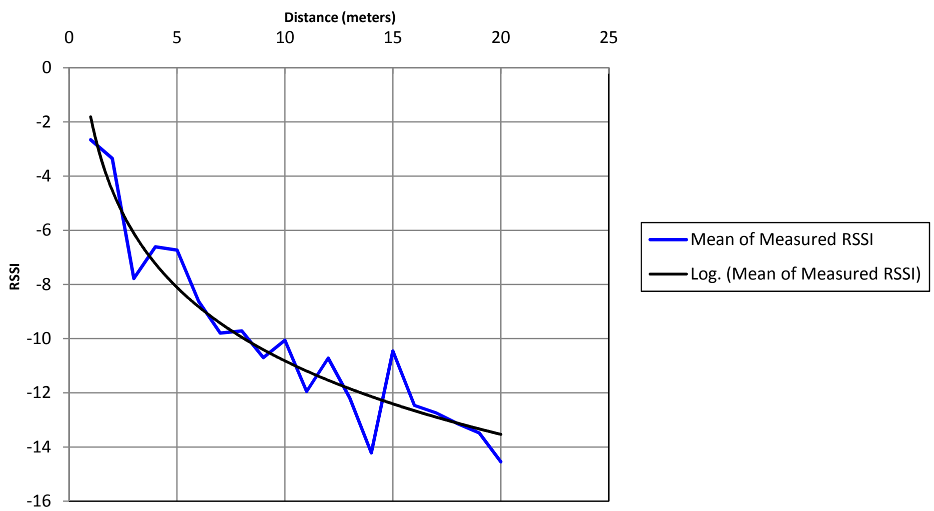

Fig. 1: Relationship between RSSI values as a function of distance.

Furthermore, it should be noted that they follow the radio propagation models describing the theoretical relationship between RSS and distance to be logarithmic [27] for distances up to 20 meters. This is a rather interesting result since the Bluetooth specification describes that Class 2 devices have an effective range of 10 meters and that useful RSSI values cannot be expected if this range is increased. However, as evidenced by the graph in Figure 1, the experiment yielded results that are in accordance with the radio propagation model. Hence, we can conclude, that our Class 2 devices do not exhibit unusual behavior at distances up to 20 meters thereby proving them amenable for comparison with Class 1 devices that theoretically, according to the Bluetooth specification, can yield useful RSSI values up to a range of 100 meters.

3.2 RSSI Cache

Through observations [15], we determined that the implementation of RSSI value measurement on our mobile phone updates an internal RSSI value cache whenever it receives a signal in the form of a packet from one of its peers, and it is this value which is returned when enquired. If multiple enquiries are made for the RSSI value in-between updates, the same value is returned multiple times. It is subject to further research whether this problem applies to all Bluetooth hardware, or only for particular models. However, it indicates that the problem requires some attention when developing indoor position systems. A simple solution is to force the cache to be updated whenever RSSI values are enquired, by setting up a small communication which ensures that the internal RSSI cache is updated.

3.3 Measuring RSSI Values

An important characteristic of Bluetooth is its usage of frequency hopping in order to reduce the impact of interference from other wireless communication using the same frequency [26]. Specifically, Bluetooth hops every 625 microseconds between 78 frequencies with 1 MHz intervals above 2.4 GHz. This impacts the time required for discovering visible devices and connecting to devices since the frequencies must be searched to synchronise. As a consequence, a search that with high probability detects all discoverable Bluetooth devices takes up to 10 seconds [28], hence doing this will only allow position estimates to be made with this interval. However, [29] have shown that the search time can be optimised by manually decreasing the search time to 5 seconds since this does not decrease the quality of the search. That is, Bluetooth position estimates can be made with 5 seconds intervals.

In a deployment, we suggest to reduce the search time to 5 seconds, and, if supported by the hardware, make a discovery search return the RSSI values for the discovered devices. However, in our research, we want to test in a controlled environment, and therefore, we make manual connections to the access points.

4 Method

Currently, Bluetooth devices are classified into three power-classes denoting the power of the transmitted signals and thereby the effective range of these. Class 1, 2, and 3 have theoretical ranges of 100, 10, and 1 meters, respectively. Class 1 devices, given their communication range, offer the lowest installation cost of a Bluetooth-based IPS, but Class 2 devices theoretically have the potential to perform better due to RSSI values being distributed in a lower range which produces higher diversity in fingerprints on smaller distances [15]. Class 3 devices are not considered applicable for an IPS due to the short communication range and thereby high cost.

The applicability of Class 1 and 2 Bluetooth location fingerprinting IPSs has been evaluated by performing experiments in three different environments. As part of the evaluation, it has been examined how the *average method*, *four directions*, and *single direction* approaches influence the results.

4.1 Hardware

The experiments were conducted using three types of hardware: A mobile phone, access points, and Bluetooth adapters for the access points. Table 1 specifies the hardware used and the corresponding price.

Mobile Phone	
Device	HTC Touch Diamond
Operating System	Windows Mobile 6.1
Access point	
Device	Asus WL-500gP V2
Firmware	OpenWRT Kamikaze 8.09.1
Price	93.96 Eur
Bluetooth Class 1 Adapter	
Device	Belkin Bluetooth USB
Price	10.00 Eur
Bluetooth Class 1 Adapter	
Device	Deltaco BT-108 USB
Price	14.63 Eur
Bluetooth Class 2 Adapter	
Device	Kensington BT Micro USB
Price	29.99 Eur

Table 1: Specification and price of used hardware in the experiments.

4.2 Test Bed and Setup

The experiments are conducted in three different environments (denoted Cluster 1 to 3) at the Department of Computer Science at Aalborg University. The floor plans of the clusters are shown in Figure 2 and 3. Note that the floor plans of Cluster 1 and 2 are equal.

Following is a description of each of the clusters:

Cluster 1. Is primarily a corridor environment containing many offices that leads to a common room. The experiments were conducted in the summer period, and this cluster remained empty from people and Wi-Fi activity was at a minimum. This environment was chosen to provide a picture of how Bluetooth applies under nearly optimal conditions.

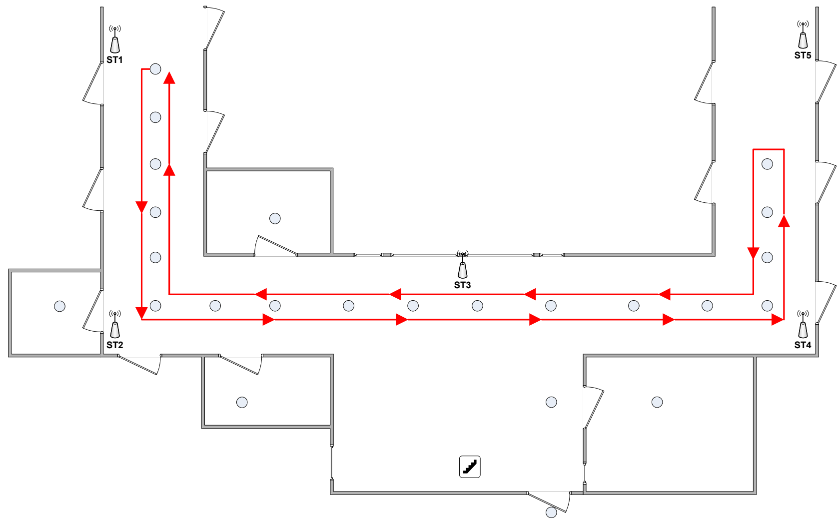

Fig. 2: Floor plan of Cluster 1 and Cluster 2. Circles represent fingerprinted locations. The marked line indicates the walked route during the online phase.

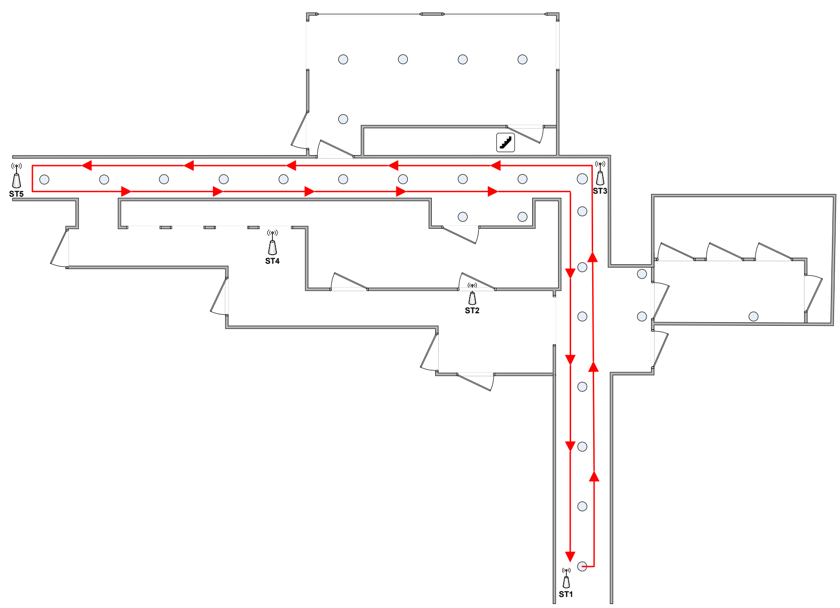

Fig. 3: Floor plan of Cluster 3.

Cluster 2. The floor plan of this environment is equivalent to Cluster 1. However, the significant difference is that many negatively impacting factors were present. These include people in the majority of the offices, high Wi-Fi activity, and other temporal differences in the environment caused by the presence of people. This cluster was chosen to provide evidence for whether or not Bluetooth is sufficiently robust to sustain many temporal differences in the environment.

Cluster 3. This environment is not equivalent to the two aforementioned. It resembles medium Wi-Fi activity and people density and is generally a more open environment containing a wide range of different surface materials and obstacles. The environment was primarily chosen to determine how well Bluetooth performs in a different environment than the others.

Fingerprints in the offline phase were collected according to the *four directions method*, since data collected using this method can be used to derive radio maps for the remaining two methods. For each fingerprint, 20 RSSI values for each detectable access point were collected in a round-robin fashion 10 times. This gives a total of 200 RSSI values per access point collected over a period of time, reducing the impact of the natural fluctuation of RSSI values [15].

This approach is consistent with the fact that the values are normally distributed. We have demonstrated this distribution experimentally by sampling RSSI values at a constant distance. The distribution of these is shown in Figure 4. Hence a certain amount of values can be averaged to indicate which RSSI value is most likely to be obtained on the specific position from a specific access point.

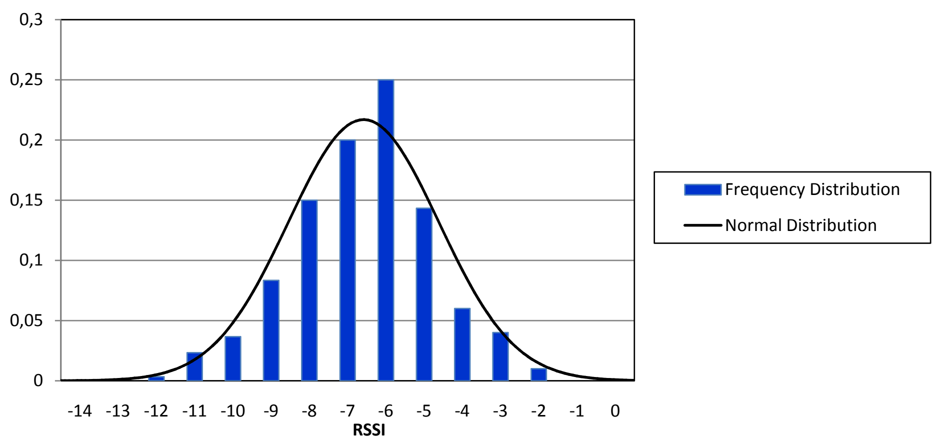

Fig. 4: Histogram showing the frequency of each measured RSSI value at a 4 meters distance.

Fingerprinted locations were spaced three meters apart, and access points were placed such that three access points were detectable at each fingerprinted location.

In the online phase, a path covering the majority of the given cluster was walked in both directions. Online fingerprints were collected by measuring RSSI values when moving between two adjacent positions along the path. When the latter position was reached, the measurements were stored. During all measurements, the mobile phone was positioned in the hand of the user to resemble normal usage and the walking speed was approximately $1m/s$.

A benchmarking tool was developed which calculates the cumulated accuracy of a walked path in the online phase given a radio map and online fingerprints [15]. The tool uses K-Nearest Neighbour (KNN) and the Manhattan distance to match online fingerprints against the radio map. In our case, we have chosen $K = 3$. The results from the *average method* were obtained by comparing the online fingerprints against the averaged values in the radio map. The results from the *four directions method* were obtained by comparing online fingerprints against the radio map entries in all directions. Finally, the *single direction* results were obtained by comparing online fingerprints against the subset of fingerprints that matches the user's orientation.

5 Results

This section summarises the results of the Class 1 and 2 Bluetooth experiments in the three different environments using the three different radio map construction methods. Figures 5 and 6 show the results of the construction methods with Class 1 and 2 devices, respectively.

Figure 5 shows the results of using the three different methods together with Class 1 devices. As can be seen, Class 1 differences are negligible with different construction methods. In contrast, Class 2 devices indicate greater variations (see Figure 6). Here, the *single direction method* tends to be better up until the 6 meter accuracy mark. This behaviour is likely attributed to the fact the Class 2 devices use a lower power output which means that larger fluctuations occur if a person breaks the line of sight between a sender and receiver.

Comparing the overall performance of Class 1 and 2 devices from the graphs, it can be seen that they have a similar median accuracy (around 2 meters) with the single direction method. The performance remains similar up until the 85% precision mark (at ca. 6 meters). After that, the accuracy curve of the Class 2 devices grows more steeply, and 8 meters accuracy is achieved with 95% precision compared to ca. 11 meters for Class 1 devices. Of course, the question for a given deployment is whether the final performance boost of Class 2 devices warrants the increased hardware cost. To cover very large areas, approximately ten times more Class 2 devices are needed due to the shorter communication ranges. Motion models, such as the weighted graph model suggested in [1] may prove to even out the differences at no extra hardware cost.

5.1 Class 1 and 2 Performance in Different Environments

Figure 7 illustrates the differences caused by environmental factors. The results indicate that the best accuracy is observed in Cluster 1 - the office environment where relatively few people were present at the time of the experiment.

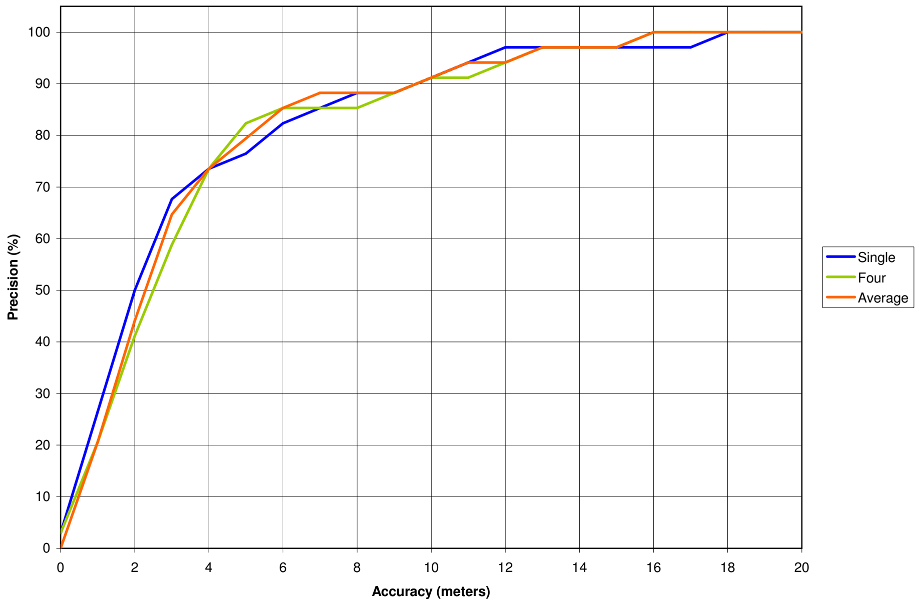

Fig. 5: Accuracy for the different map construction methods using Class 1.

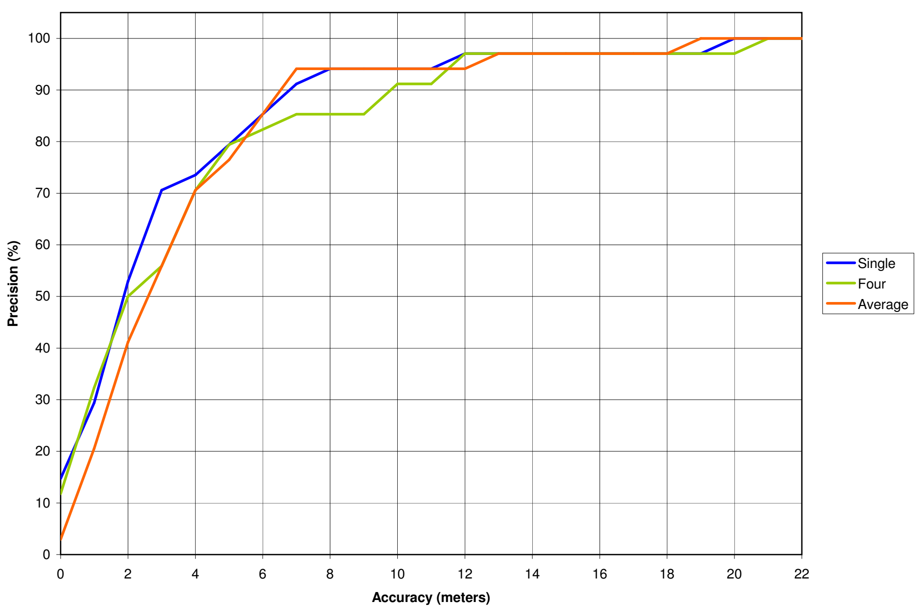

Fig. 6: Accuracy for the different map construction methods using Class 2.

In comparison, Cluster 2 - the same office plan but with more people present - illustrates the effect on positioning accuracy in a more dynamic environment. The main difference between Cluster 2 and Cluster 3 is that Cluster 3 contains a significantly more open environment with a diverse set of obstacles such as continuous pillars in each side of the corridor; factors that are known to impact the Bluetooth signals [4]. However, the median accuracy in Cluster 3 with Class 1 devices is still below three meters, thus, demonstrating the applicability of Bluetooth location fingerprinting with low-cost equipment.

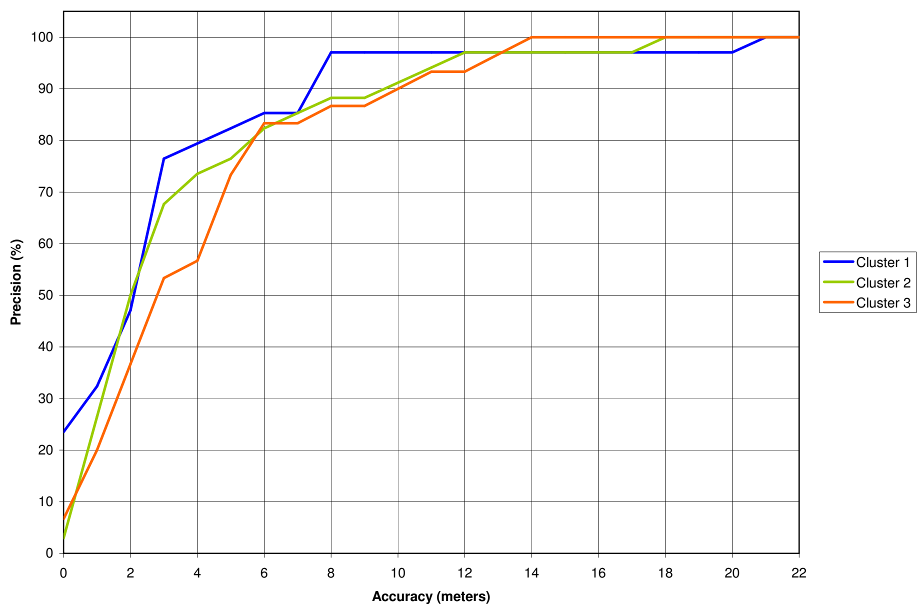

Fig. 7: Class 1 accuracy in the different environments using the *single direction method*.

5.2 Summary

To better distinguish the different configurations, Table 2 summarises the accuracy for different configurations at certain percentiles interpreted from the graphs.

As shown, the accuracy is 2-3 meters at the 50th percentile for all the configurations. A similar constant accuracy is observed at the 80th percentile where the accuracy is 5-6 meters. Finally, at the 90th percentile the accuracy ranges from 7 to 10 meters. From table 2 it is clear that Class 2 devices give better accuracy, especially at the higher percentiles.

Percentile	Class 1			Class 2		
	Single	Four	Average	Single	Four	Average
50	$2m$	$3m$	$3m$	$2m$	$2m$	$3m$
80	$6m$	$5m$	$6m$	$6m$	$6m$	$6m$
90	$10m$	$10m$	$10m$	$7m$	$10m$	$7m$

Table 2: The achievable accuracy at given percentiles using Class 1 and 2 devices. Furthermore, whether the accuracy is for the *single direction*, *four directions* or *average direction* construction method is denoted as Single, Four, and Average, respectively.

6 Conclusion

In this paper, we have examined the positioning accuracy of Class 1 and 2 Bluetooth IPSs using the location fingerprinting technique and low-cost Bluetooth dongles that function as Bluetooth infrastructure. The impact of orientation was examined by comparing three different radio map construction methods. The *single direction method*, where a user's current orientation is used as a parameter in location determination, indicates to have a positive effect on the achievable positioning accuracy with Class 2 devices. Overall, the experiments showed that both Class 1 and 2 devices are able to achieve 2 meters median accuracy. These results, coupled with the fact that the signal strength measurement process can be conducted simultaneously for Bluetooth and Wi-Fi, means that accurate IPSs that target the maximum number of end-users can be developed easily and cheaply. Furthermore, using Bluetooth in isolation in IPSs can potentially reduce the power consumption of the mobile phones.

Using Bluetooth as foundation for an IPS, we observed some challenges which must be accounted for. Initially, one must be aware of the usage of RSSI values and how they are affected by increasing the distance from transmitter and receiver. Through an analysis, we showed that the equipment used in our experiments, distributes the RSSI values sufficiently over increasing distances, hence allowing for fingerprints with fine granularity.

7 Acknowledgements

This work was partly supported by the SmartCampusAAU project funded by the North Jutland Region - Vækstforum/Den Europæiske Fond for Regionaludvikling (European Regional Development Fund).

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