Fast and Accurate Wi-Fi Localization in Large-Scale Indoor Venues

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Abstract. An interest and development of indoor localization has grown along with the scope of applications. In a large and crowded indoor venue, the population density of access points (APs) is typically much higher than that in small places. This may cause a client device such as a smartphone to capture an *imperfect* Wifi fingerprints (FPs), which is essential piece of data for indoor localization. This is due to the limited access time allocated per channel and collisions of responses from APs. It results in an extended delay for localization and a massive unnecessary traffic in addition to a high estimation error. This paper proposes a fast and accurate indoor localization method for large-scale indoor venues using a small subset of APs, called *representative APs* (rAPs). According to our experimental study in a large venue with 1,734 APs, the proposed method achieves the estimation error of 1.8∼2.1 m, which can be considered a very competitive performance even in small-scale places with a few hundreds of APs.

Keywords: WiFi fingerprints · Indoor localization · Probe response

1 Introduction

Location-based services (LBS) are becoming a huge market with the proliferation of mobile devices such as smartphones and tablets. To make it ubiquitous, localization and navigation indoors within urban structures is critically important. This is evident by recent news including the foundation of In-Location Alliance (Broadcom, Nokia, Sony Mobile, Samsung, Qualcomm, etc.), Qualcomm's IZat chipset, Google's Indoor Maps, and Apple's acquisition of WiFiSLAM. WLAN (IEEE 802.11)-based Positioning System (WPS) attracts a lot of attention for this purpose because GPS signal is not reachable but existing WiFi infrastructure is abundant. A set of *received signal strength* (RSS) values from reachable WiFi *access points* (APs), called *fingerprint* (FP), is used to estimate the location in WPS [2,24]. A WPS typically consists of offline and online phases.

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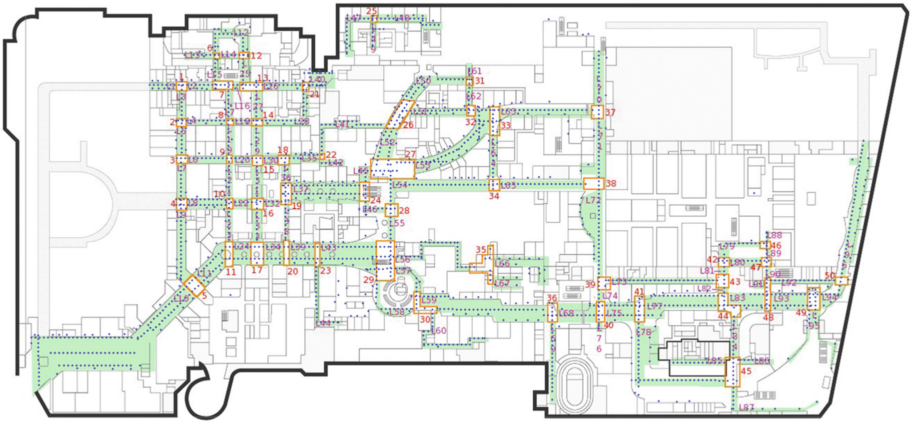


Fig. 1. A map of underground mall of Coex of $505 \times 237\,\mathrm{m}^2$ or $119,685\,\mathrm{m}^2$ in downtown Seoul, South Korea. (Small dots denote 2,028 locations where FPs are collected. Shaded areas and numbers represent 96 line segments and 50 intersections, respectively, which will be explained later in this paper.)

In the offline phase, FPs are collected at several locations in the venue, creating a *WiFi radiomap*, where each FP is annotated with the corresponding location information. In the online phase, the location of a client device is estimated by searching the radiomap to find the FP(s) that is(are) closest to the measured FP by the client device.

In this paper, we show that FPs are *imperfect* in large-scale indoor venues due to the *probe response explosion problem*. This has not been studied in the literature mainly because most of previous work have been tested in small places We, then, propose to use a predetermined subset of APs called *representative APs* (rAP) instead of an exhaustive set of all APs in the neighborhood, which leads to indoor localization at a higher accuracy with a fraction of time during the online phase. Note that rAP can be considered as a landmark [16] or an anchor [22] in the context of localization in sensor networks and robot navigation. According to our experiments with real-life radiomap of a large-scale indoor venue with 1,734 APs, the proposed method achieves an estimation error as small as 1.8 m while conventional Wifi FP-based method cannot make it lower than 5.2 m. To our knowledge, this can be considered one of the best performance reported in the literature. Estimation delay is an order smaller than conventional methods as it uses less APs.

The rest of this paper is organized as follows: Sect. 2 explains characteristics of a large-scale indoor venue contrasting with a typical academic building. It also overviews Wifi FP-based indoor localization methods. Section 3 presents a notable phenomenon exhibited in a large, AP-crowded place. Section 5 proposes the idea of rAP and how it can help improve the localization accuracy and reduce the estimation delay, which is followed by performance study in Sect. 5. Finally, we will conclude this paper in Sect. 6.

2 Background and Related Work

2.1 Characteristics of a Large Indoor Venue

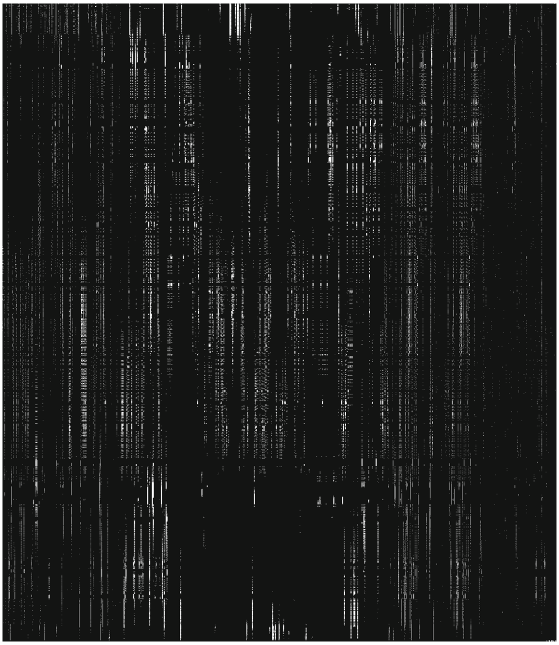
The main subject we are dealing with in this paper is a very large indoor site. As an example venue, we surveyed underground mall of Coex, which is a building of business and shopping complex. It is about $120,000\,\text{m}^2$ of total floor space ($505 \times 237\,\text{m}^2$) with 1,734 APs as shown in Fig. 1. It is obvious that any single AP cannot cover the entire area. FPs are collected at 2,028 locations in the venue (marked as blue crosses in the figure) but as a matter of fact, we measured FPs 20 times at every measurement location to deal with noise and signal fluctuation as discussed in [2].

Figure 2a visualizes the radiomap matrix of Coex mall, where rows and columns represent FPs (locations) and APs, respectively. In the matrix, RSS of APs at every location is marked by a white point whenever the corresponding AP is detected and its beacon message is received successfully. As shown in the figure, the radiomap is sparse, i.e., only 2.8 % of the 3,516,552 cells have meaningful values. In order to compare the scale of Coex mall with typical indoor venues studied elsewhere, an academic building at the Hong Kong University of Science and Technology (HKUST) has been used in this paper [23]. It has a dimensions of $145.5\,\text{m} \times 37.5\,\text{m}$ with 101 APs and 247 FPs measured. Figure 2b shows the radiomap matrix of HKUST with the sparsity of 8.7 %. One important observation is that each FP (location) has almost an order of magnitude greater number of features (APs) in Coex than in HKUST. One can observe 52 APs at a location on the average in Coex but this number reduces to 9 APs in HKUST. For more detailed comparison between Coex and HKUST, please refer to [1].

2.2 Related Work on WPS

WLAN-based positioning system (WPS) is an attractive indoor localization technique because of the wide deployments of Wifi infrastructures. It is based on location fingerprinting, or known as scene analysis as discussed in Introduction. RADAR [2] is the first of this kind that determines user location using *k*NN (*k*-nearest neighbor) for matching. In other words, it finds '*k*' closest locations (FPs) in terms of Euclidean distance in RSS space and estimates the location of a client device as the centroid of those '*k*' locations. Other methods such as probabilistic methods [24] and neural network [3] can be used instead of *k*NN.

Due to the large amount of radiomap data, there has been an active research in reducing the computational cost for WPS localization [7, 14, 15, 24, 25]. Previous work either reduces $|FP|$ or $|AP|$ (subsetting either FPs or APs) to decrease the search space. Note that most of previous work focused on the former because small-scale environments like academic buildings, where most of previous studies experimented, have a small $|AP|$ and $|FP| \gg |AP|$. A widely used approach is to divide FPs into a number of clusters based on, for example, the commonality of strongest APs (APs with the highest RSS values). This reduces the computational time because the search space is reduced to a particular cluster rather than the entire radiomap [14, 24].



(a) Coex

(b) HKUST

Fig. 2. Radiomap matrices (The horizontal and the vertical axis represent APs and locations, respectively, and the size of the two matrices are $2,028 \times 1,734$ and 247×101. In Fig. (a), $|FP| \approx |AP|$ while, in Fig. (b), $|FP| \gg |AP|$.)

However, with a large number of APs observed at each location (or FP) in Coex mall, the difference in RSS values of two subsequent APs may be very small when they are ordered according to the RSS values. Slight variations in RSS measurement would result in a different set of the strongest APs as well as a different cluster. Some clustering algorithms group FPs based on the commonality of the existence of a few APs. However, with a large-scale dataset collected from Coex, this would produce a huge number of clusters, rendering the online phase of the localization an overwhelming process. Some other cluster FPs based on their physical locations [8], which seems not feasible due to the continuous nature of the huge indoor space such as Coex mall.

Although not very popular, it is also possible to use a subset of APs for the purpose of reducing the computational cost [7,15,25]. However, this idea of subsetting APs or choosing more "discriminative" APs may not be trivial in a large-scale environment due to the large number of APs. Moreover, it may not be effective because every AP could be important to localize a place or a store where the AP is installed. This is due to the fact that a majority of APs are observed at less than ten locations at Coex, which is in turn caused by the greater path loss in urban structures with lots of obstacles and people movement [1]. Elimination of some APs in the radiomap may need to trade a significant performance degradation in exchange of less complexity.

Alternately, there are approaches that do not rely on Wifi FPs [6,21]. Even they represent meaningful improvements, mostly they require additional hardwares including image sensors and bluetooth devices [6], or need to modify lower layer implementation [21].

3 Explosion of Probe Responses and Missing APs

3.1 WiFi FP and Scanning

A more serious problem in large-scale indoor venues is *probe response explosion problem* introduced earlier. WPS-based localization requires WiFi FPs, which is essentially the scanning of APs in the proximity. It has been an active area of research for at least two decades because it is an important part of handoff procedure [5,19,20]. *Passive scanning* depends on periodic beacon messages from APs. Although it does not incur any additional traffic in the network, it causes a non-negligible delay as the beacon interval is typically 100 ms.

On the other hand, *active scanning* uses *probe request* and *probe response* management frames. A client device sends a probe request frame with the destination of broadcast address and receives probe responses from nearby APs as well as their RSS to constitute a FP. Since there are multiple channels in 802.11, the client device switches from one channel to the next to scan all available channels. It stays at one channel during a predefined time period, called *MinChannelTime*. However, it does not stay more than another predefined time, called *MaxChannelTime*, in a channel. 802.11 standards do not specify the values but they are typically 1 and 30 ms, respectively [20].

3.2 Missing APs

The standard scanning process mentioned above does not pose a challenge in small venues, which are typically used in most of previous work on indoor localization. However, it poses a serious problem in large indoor venues. For example, in Coex mall, there are about 52 APs within the communication range at a certain random location. If a majority of them use one of three non-overlapping channels (1, 6 and 11), each channel is crowded with more than 15 APs, probe responses from which cannot be accommodated within the given *MaxChannelTime*. FPs will be *imperfect* as the client device cannot receive all probe responses. Moreover, it is possible that a stronger probe response captures weaker ones in case two or more APs send simultaneously.

Imperfect FP: Missing some APs could affect the accuracy of WPS in a significant manner because it results in incorrect Euclidean distances and thus offers a wrong set of closest FPs. However, investigation of the radiomap of Coex mall shows that a single scan misses a large number of APs. In other words, the AP population detected at a location is much less than what can be observed as

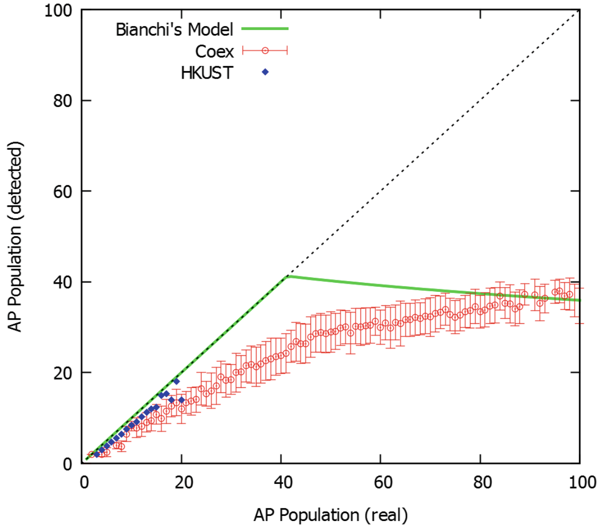


Fig. 3. AP population: real versus detected per scan. (Real and detected almost coincide at HKUST but they diverge in Coex mall when real exceeds 40. Parameters for Bianchi model are: Data rate 11 Mbps, Slot time 20 µs, SIFS 10 µs, DIFS 50 µs, MaxChannelTime 30 ms, Packet header 100 bytes, Payload 300 bytes, ACK 14 bytes.)

clearly shown in Fig. 3. Note that the real AP population is obtained because we surveyed 20 times at each of 2,028 locations in Coex mall. With a such reception ratio shown in Fig. 3, an intact FP cannot be composed. And the imperfect FP will cause miscalculation of a vector distance leading to an incorrect location estimation. In typical Wifi FP-based localization methods, missing values in a FP is replaced by the smallest possible value (i.e., −95 dBm) assuming that they are not detected because their signals are too weak. It is evident that this could cause a high estimation error in large places with many APs.

It is important to note that the phenomenon of missing APs is no surprise considering the analysis results in Fig. 3. It is based on Bianchi's model [4], in which throughput of the IEEE 802.11 DCF is analyzed according to the number of competing devices. We have simplified the problem to count the number of successful probe request and response pairs during the *MaxChannelTime* with parameters defined in the figure assuming that each of 11 channels has a similar number of devices (APs). According to the result, the AP population detected gets saturated when the real AP population goes beyond 40. The analysis shows a bit more number of APs in the figure because it does not take into consideration other packets in the network.

Another important observation is that, in a crowded place with many APs, there is a probability that probe response packets can collide with each other. A weaker response is missing but a stronger response signal is affected as well due to the phenomenon called *signal capture*. While this is not a concern in general communication, it is the case in indoor localization because signal's RSS values are as important as the signal's contents.

Estimation Delay for Localization: With a large number of AP in the area, a client device would experience an intolerable delay to estimate its location. This is because it observes APs in every channel and thus waits for MaxChannelTime at every channel, which is compounded by the high computational complexity searching for the matching FP(s) in the radiomap.

On the other hand, it is desirable to increase MaxChannelTime to collect all responses, which in fact pushes the estimation delay even further. A longer time allocated per scan means less time and a higher delay for normal data traffic. Nonetheless, it was suggested that at least 50 ms is needed per channel in the network with many APs [19]. A simple calculation is that 50 ms for each of 11 channels gives 550 ms. If it is combined with the scanning frequency, for example every 600 ms [13], network performance could be significantly degraded. In the context of localization, this could be overwhelming when fast localization is needed for quick navigation of the venue.

4 Representative Access Points (rAPs)

Conventional Wifi FP-based localization algorithms have a serious problem in terms of accuracy and delay in large-scale venues as discussed in the previous section. The main cause of the problem is the scanning process and the corresponding probe response traffic. In the context of handoff studies, [10] suggested to use passive scanning as it does not cause any additional traffic. Reference [5] suggested unicast probe request in case the destination APs are known in advance. The proposed method in this paper adopts the latter approach where a subset of APs are identified during the offline stage. They are called *representative APs* (rAPs) and help address the probe response explosion problem by directing probe requests to rAPs only during the online stage. Assuming that localization is a continuous operation, i.e., each client device has a rough idea of its whereabout in terms of line segments, the localization problem is restricted to a certain hallway with reference to a few rAPs specific to that area.

Offline Phase to Identify Line Segments and rAPs: The proposed rAP-based method divides the entire map of a venue into small areas of hallways (line segments) and corners (intersections) and identifies a few rAPs for each of those line segments and intersections. Observe 96 line segments and 50 intersections in Coex mall as shown in Fig. 1. For your reference, HKUST has 6 line segments and 3 intersections.

To choose rAPs in each line segment, the following criteria are used: (i) rAPs should be observed over the entire range of the line segment. For that matter, we divide a line segment into several if it is too long. (ii) rAPs should exhibit high RSS values because weak APs typically are prone to signal fluctuations and thus, impact the estimation accuracy. (iii) rAPs should be distinctive with each other, which can be translated as rAPs positioned as far as possible among themselves. On other hand, at about an endpoint of a line segment or an intersection, rAPs are chosen in a way to identify which line segment or direction the client is heading. Note that the process of choosing rAPs and discarding the rest represents the elimination of redundant information in the radiomap as some nearby APs would offer no additional information in terms of localization.

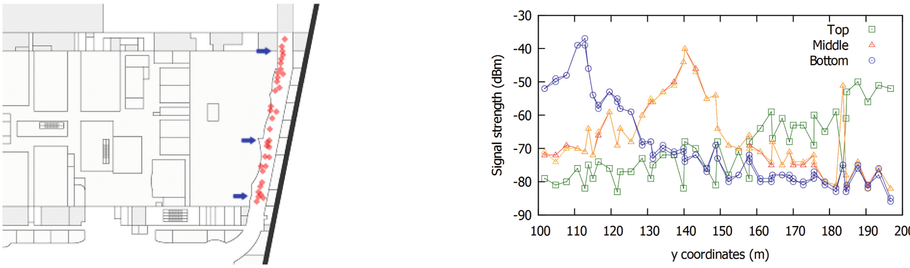
Online Phase to Estimate Location via Probing Representative APs: During the online phase, a few rAPs chosen for the particular line segment will be probed individually (unicast) rather than probing all nearby APs (broadcast). If a client device is at about an intersection, then rAPs along with multiple line segments connected to a corresponding intersection will be probed in a similar fashion.

The measured RSS values from rAPs can be used to find the closest matching FPs (locations) in the radiomap. Since we're using a fraction of features (APs), the computational complexity is greatly reduced. On the other hand, the estimation accuracy could be impacted because the proposed method does not utilize all observable APs. Alternatively, it is possible to utilize propagation model to improve the localization accuracy. A series of RSS values from a certain rAP along a line segment can be analyzed during the offline stage to derive the propagation parameters (path loss exponent and wall attenuation factor) for the particular rAP. This can be used during the online stage to estimate the position of a client device. For that matter, we use the propagation model developed in [2,17], which takes the path loss along the distance and across walls. Path loss at distance d is measured as

$$PL(d) = PL(d_0) + 10\, n\, \log\left(\frac{d}{d_0}\right) + p \times SAF + q \times CAF,$$

where d_0 is the reference distance, n is the path loss exponent, p and q are the number of soft walls and concrete walls, and SAF and CAF are the attenuation factor of a soft wall and a concrete wall, respectively. Please refer to [2,17] for details about the propagation model.

Example Line Segment in Coex: In the below, we show an example line segment identified along a vertical hallway in the rightmost part of the Coex mall as shown in Fig. 4a. It is 96 m long and observes 93 APs marked as small diamonds in the figure. However, a single probe detects 40 APs on the average. Note that we have estimated the locations of each of those 96 APs by averaging all of coordinates that observes a particular AP with weights based on RSS values. Based on the criteria mentioned earlier, we chose three rAPs that are positioned at the top, middle and bottom of the line segment, which are marked with arrows in the figure. The corresponding RSS values in the radiomap is drawn in Fig. 4b. During the online phase, RSS values of the three rAPs are measured and used to calculate the best closest location along the line segment. Alternatively, as mentioned earlier, the trend of RSS values in Fig. 4b is used to derive parameters (path loss exponent n, SAF and CAF) for the propagation pattern, which then is used to estimate the client device's location during the online stage. Note that



(a) Diamonds are estimated locations of APs along the line segment and arrows indicate the three rAPs.

(b) RSS patterns of the three rAPs along the line segment

Fig. 4. rAP-based localization method

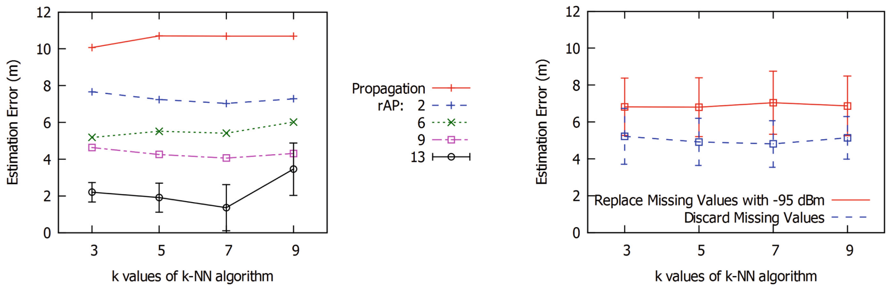
choosing rAPs with different propagation patterns is important because those with similar propagation patterns offer redundant information.

5 Performance Evaluation

This section presents experimental results of rAP-based indoor localization in comparison to conventional Wifi FP-based approach. For the former, we used both propagation model-based approach as well as FP matching method with various number of rAPs (2∼13). For the latter, the entire radiomap is searched to find the closet matching FPs. This is to obtain the optimal performance (least estimation error), which is hardly achieve in reality because it typically searches a subset of radiomap as discussed in Sect. 2.2. In both cases, we applied kNN (k-nearest neighbor) method for matching (see Sect. 2.2), where k varies from 3 to 9. Note that propagation model-based approach does not use kNN because it applies the analytical model mentioned earlier

The measurement was taken to test at 153 test points, which are independent from 2,028 FP collection locations, along the 96 line segments. (For brevity, we skip the test results and the corresponding discussions on the test at intersections.) The performance metric is estimation error in distance. The time taken during the online phase is estimated based on the probing time and the computation time, which are closely related to the number of channels to probe and the size of radiomap to be searched for matching.

Estimation Accuracy: Fig. 5a shows the average estimation error of those at the 153 test points. It is surprising to observe that propagation model-based approach offers the highest estimation error, which is more than 10 m. In a very crowded area like Coex mall with more than 150,000 visitors per day, there exist more obstacles and interferences in addition to complex building structures. Analytical model does not work well due to numerous uncertainties in signal propagation in large-scale venues. On the other hand, rAP-based approach achieves much higher accuracy. With just two rAPs, it achieves 7∼8 m,



(a) rAPs-based method.

(b) Conventional FP-based method.

Fig. 5. Estimation error in distance (For propagation model-based approach, x-axis represents the number of rAPs. In Fig. a, ranges are shown for the case of rAP=13 only for simplicity. Ranges in other cases are usually wider than that.)

which is still on par with the conventional method in Fig. 5b. It is possible to estimate a location with only a few rAPs with a reasonable accuracy because knowing which line segment a client is in simplifies the problem into a small scale localization.

The accuracy gets much better when we uses more number of rAPs. With 13 rAPs, it achieves 1.8∼2.1 m, which is considered one of the best performance reported in the literature. More importantly, the error distance range is restricted to be less than 2.3 m except $k = 9$ as shown in Fig. 5a. Average distance is important but the range is also important because this gives us a higher confidence in the estimated location in the venue. Impact of k values is minimal as observed in previous studies. Note that a large k does not necessarily improve the estimation accuracy because FPs (locations) far from the actual location can also be included in the averaging procedure [2].

Figure 5b shows the average error distance of the conventional Wifi FP-based approach. The figure shows two results that are different in dealing with missing values. To calculate the Euclidean distance, we need to either skip or replace the missing component corresponding to missing APs. As discussed in Sect. 3.2, replacing it with the smallest possible value (i.e., −95 dBm) causes a higher estimation error in large places with many APs because they are missed out not because of the weak signal but because of the probe response explosion problem mentioned above. It achieves the error distance of 6.5∼6.9 m. Just discarding those missing values in calculating the Euclidean distance results in the error distance of 4.8∼5.2 m, which is better than the other. However, this is not usually recommended because discarding missing components in effect reduces the Euclidean distance as discussed earlier. Therefore, it can be summarized that, comparing the former, the rAP-based approach improves the error distance 4.4∼5.1 m or 69∼72 %.

Estimation Delay: Estimation delay can be divided into two parts. First, the time taken to send and receive probe requests and responses. With the conventional method which probes all APs in every channel, the client should wait for *MaxChannelTime* (e.g., 30 ms) and another 9 ms for switching between channels [11]. It takes 420 ms to probe all 11 channels as it observes at least one AP at each channel and thus has very little chance to wait *MinChannelTime* instead of *MaxChannelTime*. With the rAPs method proposed in this paper, on the other hand, the client doesn't need to probe all 11 channels. Instead, only the channels in which the rAPs operate need to be probed. Moreover, it does not have to wait for long because unicast communication is employed. Since each exchange of probe request and response is relatively shorter, it can be deduced that 9 ms $\times$ |rAP| assuming that all rAPs operate in different channels. When rAP=6, it is 54 ms, which is ten-fold reduction compared to the conventional method.

Second, after probing, the client sends the measured FP to the server, which then searches the closest FPs in the radiomap. Because we have a smaller FP, the computational time becomes much smaller, too. With the PC configuration used for this experiment (Intel i7-3770, 3.4 GHz, 8 cores, 12 GB RAM, Windows 7, radiomap Database MySQL version 5, processing tool MATLAB 7), the processing time is about 200 ms and 2 ms with the conventional and the proposed method, respectively. This is a hundred-fold reduction although dimension reduction techniques discussed in Sect. 2.2 may alleviate this problem partially. In summary, the proposed rAP-based method greatly reduces the estimation delay such that it can be useful in applications that need fast localization or navigation.

6 Conclusions

In this paper, we have analyzed the characteristics of the AP-crowded large scale indoor places. In such an indoor venue, a fingerprint becomes imperfect due to the limited time allocated per channel during the scanning process. In order to address this problem, this paper proposes the *representative access points* (rAP)-based method. It probes only the chosen APs among the whole set of access points and thus reduces the estimation delay as well as estimation error.

One of our future work is to develop an AP-based solution, which is based on the selection of rAPs during the online stage. In other words, an AP ignores weak probe request messages (smaller RSS values) and does not send the corresponding probe response message, intentionally giving up its role as an rAP. A client device receives a smaller number of probe responses. Another future work is to develop further with the propagation model-based approach. It has an obvious advantage of demanding less APs for the localization purpose. With a more sophisticated algorithm and the accuracy requirements of different applications, this may offer the cheapest localization solution.

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