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Improving Wi-Fi Based Indoor Positioning Using Bluetooth Add-Ons

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***Abstract*—Location-Based Services (LBSs) constitutes one of the most popular classes of mobile services. However, while current LBSs typically target outdoor settings, we lead large parts of our lives indoors. The availability of easy-to-use and low-cost indoor positioning services is essential in also enabling indoor LBSs.**

Existing indoor positioning services typically use a single technology such as Wi-Fi, RFID or Bluetooth. Wi-Fi based indoor positioning is relatively easy to deploy, but does often not offer good positioning accuracy. In contrast, the use of RFID or Bluetooth for positioning requires considerable investments in equipment in order to ensure good positioning accuracy.

Motivated by these observations, we propose a hybrid approach to indoor positioning. In particular, we introduce Bluetooth hotspots into an indoor space with an existing Wi-Fi infrastructure such that better positioning is achieved than what can be achieved by each technology in isolation. We design a flexible and extensible system architecture with an effective online position estimation algorithm for the hybrid system. The system is evaluated empirically in the building of our department. The results show that the hybrid approach improves positioning accuracy markedly.

I. Introduction

Location based services (LBSs) have experienced exceptional growth over the past decade. LBSs offer great convenience to users and hold the potential for changing peoples' lifestyles. While we in fact spend large parts of our lives in indoor spaces, LBSs have so far primarily targeted outdoor spaces. There is thus a large and so far unrealized potential for indoor LBSs.

Reliable, easy-to-use, and accurate indoor positioning is a key enabler of such indoor LBSs, just as GPS and Wi-Fi and cellular based positioning technologies have enabled outdoor LBSs. Specifically, accurate indoor positioning enables a variety of LBSs in a wide range of indoor spaces, including office buildings, shopping centers, and transportation infrastructures such as airports and metro stations. Examples of indoor LBSs include museum tour guides, and boarding reminders to air passengers far away from their gate, to name only two.

Existing indoor positioning systems are typically built upon a single homogeneous wireless communication technology, such as Wi-Fi [2], [17], RFID [9], [15], Bluetooth [1], [5], or Infrared [6], [16]. Systems that use sensors and receiver/transmitter enhanced indoor GPS are orthogonal to this paper's proposal. In contrast to these single-technology approaches, we argue for a hybrid approach that exploits the different strengths of two existing wireless communication technologies.

Although Wi-Fi is a very widely available infrastructure, its diffusivity in space due to large coverage ranges renders it very difficult to guarantee positioning accuracy. Complex techniques [3], [7], [11] are needed to improve the accuracy of a pure Wi-Fi indoor positioning system.

In contrast, RFID and Bluetooth are able to detect object presence within their relatively short detection ranges that usually vary from a few to tens of meters. However, a large number of RFID readers or Bluetooth hotspots are needed in order to cover an entire indoor space. Therefore, the infrastructure investment on a Bluetooth or RFID based indoor positioning system can be prohibitive. On the other hand, an Infrared based positioning system is constrained by its limited data rate and strict directionality in communication.

We propose a hybrid approach to indoor positioning. Our approach works for mobile user devices with both Wi-Fi and Bluetooth interfaces, which are available in the vast majority of mobile devices nowadays. By introducing a limited number of Bluetooth hotspots into an indoor space with a Wi-Fi infrastructure, we are able to combine the benefits of heterogeneous technologies without paying significant extra cost. In particular, these Bluetooth hotspots are carefully deployed at critical positions such that they partition the indoor space into regions. We then develop an online position estimation algorithm that makes use of the information of these regions to achieve better position estimates. All these techniques are organized in a flexible and open system architecture.

We conduct a series of experiments in an indoor space to test our proposals. The results show that our hybrid approach improves significantly the indoor positioning accuracy in comparison with a pure Wi-Fi based approach.

We make the following contributions in this paper.

- Based on a comparative study, we propose a hybrid approach for indoor positioning with both a Wi-Fi infrastructure and Bluetooth add-ons.
- We design an effective online position estimation algorithm that makes use of both Wi-Fi and Bluetooth in a hybrid indoor positioning system.
- We organize our proposals in a flexible system architecture that is open for useful additions and adaptations.
- We conduct an extensive empirical study to evaluate our hybrid indoor positioning system design.

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To the best of our knowledge, this is the first paper that proposes techniques to exploit both Wi-Fi and Bluetooth simultaneously in achieving improved indoor positioning.

The remainder of this paper is organized as follows. Section II reviews Wi-Fi based positioning and Bluetooth based positioning. Section III proposes our techniques that combine Wi-Fi and Bluetooth in designing a hybrid indoor positioning system. Section IV presents an extensive empirical study on our proposals. Finally, Section V concludes the paper and discusses research directions.

II. Preliminaries on Indoor Positioning

A. Wi-Fi Based Positioning

Wi-Fi is a very commonly used infrastructure in indoor positioning systems [2], [3], [7], [17] because it is a wireless LAN standard and is available in many indoor spaces, including office buildings, conference halls, and transportation facilities like airports. In addition, Wi-Fi covers indoor environments well because of the high radio coverage of an access point—often up to 150 meters indoors. Its wide availability, high coverage, and low cost make Wi-Fi a good choice when building an indoor positioning system.

Wi-Fi based positioning employs a scene analysis technique called *fingerprinting* that is based on received radio signal strengths. Two phases exist in this technique. In the offline phase, which occurs before the online phase, signal strengths from all detectable Wi-Fi access points are collected in a (limited) number of user-specified positions in an indoor space. Such pre-selected positions work as reference positions in the positioning. As a result, a database of all collected fingerprints is created as a *radio map* for the indoor space.

In the online phase, in order to estimate the current position, a user (device) obtains the signal strengths from all detectable Wi-Fi access points and compares the current strengths with the pre-collected fingerprints in the radio map. Consequently, the user-specified reference location associated with the best match is returned as the user's current position.

The estimation methods for finding the best matching fingerprint in the online phase mainly fall into two categories—deterministic methods and probabilistic methods [10]. Deterministic methods make position estimates based on the actual values obtained in radio signal strength measurements. Probabilistic methods make estimates by modeling measurements in all reference positions as random process. As pointed out in the literature [12], probabilistic methods incur higher computation complexity and lower accuracy when compared to deterministic methods. Therefore, we employ a deterministic estimation method.

In particular, we employ the so called Nearest Neighbor in Signal Space method (NNSS) that is commonly used in different Wi-Fi positioning systems [2] due to its simplicity and reasonable accuracy. Suppose there are a total of n Wi-Fi access points in the indoor space of interest where m positions are pre-selected as reference positions. As a result, a signal strength measurement at each (reference or unestimated) position is captured as a n-dimensional vector $s = (s_1, \ldots, s_n)$, where s_i $(1 \leq i \leq n)$ denotes the signal strength from the i-th Wi-Fi access point. Note s_i is set to 0 if the corresponding access point is not detected.

In position estimation, NNSS calculates the Euclidean distance between the current signal strength vector q and each recorded fingerprint s^j $(1 \leq j \leq m)$, i.e., $dist(q, s^j) = \sqrt{\sum_{i=1}^{n}(q_i - s_i^j)^2}$. From all m reference positions, the one whose fingerprint s^j leads to the minimal distance $dist(q, s^j)$ is returned as the estimate for the current position.

Fingerprinting is highly dependent on the infrastructure, i.e., the radio transmitters. In a Wi-Fi based positioning system, any addition, displacement, or removal of a Wi-Fi access point requires an entire update of the radio map before reliable online positioning can take place. Also, the offline phase for radio map creation is a time-consuming process, especially in a large indoor space. Moreover, Wi-Fi based positioning incurs relatively high power consumption. It is pointed out [4] that the Wi-Fi interface on a mobile device consumes approximately 5 times more energy than its Bluetooth counterpart.

B. Bluetooth Based Positioning

Bluetooth is another very popular wireless technology standard. It was designed mainly for voice and data applications and is integrated into many of today's portable electronic devices such as laptops and smartphones. The typical radio coverage range of a Bluetooth hotspot varies from 1 meter to tens of meters, which is considerably shorter than that of Wi-Fi. Due to the relatively small coverage, Bluetooth based indoor positioning employs a technique called *proximity analysis* for position estimations [13], [14].

Thus, the exact positions of all Bluetooth hotspots are recorded beforehand as reference positions. When a mobile user is within the radio coverage range of a particular Bluetooth hotspot, the Bluetooth-enabled mobile device detects the identifier of that hotspot, and the corresponding recorded position is returned as the current position of the user. In some contexts, the detection range of the corresponding hotspot is used to approximate the user's true position.

In cases where more than one Bluetooth hotspot is detected simultaneously, a straightforward way is to take the position of the one with the strongest signal. Alternatively, the intersection of the ranges of all detected hotspots is used to approximate the current user position. The latter, however, requires complex geometrical computations and does not return a point as the estimated position.

In this research, we use Bluetooth hotspots with radio coverage range of only a few meters, and they are deployed such that their ranges do not overlap. This way, we avoid complex computations in approximating user positions. Therefore, the aforementioned complexity is not considered here.

A more detailed explanation of an indoor positioning technique that was designed on top of Bluetooth technology can be found elsewhere [5].

C. Comparison and Motivation

Although a Wi-Fi infrastructure can cover a relatively large indoor region, it incurs higher computational complexity in position estimations that usually deals with fingerprinting in a high-dimensional signal strength vector space. Moreover, the accuracy of fingerprinting relies very much on the radio map, specifically the number of reference positions and the quality of signal strength measurements.

Intuitively, a finer-grained radio map with more reference positions increases the resolution in online positioning and thus results in better accuracy. However, more reference positions render the online distance-based signal strength matching more time-consuming. More seriously, the resolution of Wi-Fi signal strengths in an indoor space is often constrained to the deployment of Wi-Fi access points as well as building features, which in turn critically confine the practical resolution of a finer-grained radio map.

The typical accuracy of an indoor positioning system solely based on Wi-Fi ranges from 2 to 10 meters in a stable environment with no wireless signal strength deviations [3], [7]. In practice, positioning accuracy may sometimes drop due to many factors that cause wireless signal strength variations. Furthermore, some wireless access points are designed in such a way that they increase/decrease the wireless signal power level according to the current load/bandwidth. Such self-adjustments of Wi-Fi access points lowers the reliability of pre-created radio maps.

There are also many other physical factors, such as humidity and temperature, that may affect the quality of the received wireless signals. On the other hand, an indoor space is usually composed of a variety of entities, including walls, floors, and doors, all of which tend to block or reflect wireless radio signals in complex ways.

All these factors have noticeable negative effects on the positioning accuracy of Wi-Fi based indoor positioning systems. In contrast, the shorter range Bluetooth technology is expected to be less sensitive to these factors.

One advantage of Bluetooth over Wi-Fi is that Bluetooth is more lightweight as well as device-oriented, and hence it needs less energy. This way, a user can enjoy a Bluetooth based indoor positioning system installed on the user's mobile device for a much longer period of time. Another advantage is that a Bluetooth device is usually cheaper than a Wi-Fi enabled device.

However, Bluetooth requires a sufficient number of hotspots to be deployed in order to cover an entire indoor space. Because of short coverage ranges, insufficient Bluetooth hotspots in an indoor space can easily leave uncovered regions where no hotspot can be detected by a mobile device, thus rendering indoor positioning impossible. As a result, a Bluetooth based indoor positioning system needs more investment in hardware, which makes such systems much more expensive to build.

Motivated by these observations, it is of interest to build a hybrid indoor positioning system that exploits the benefits of heterogeneous wireless technologies. Finding a novel way to integrate these two distinct infrastructure wireless technologies into one unified system would enable us to have a more robust indoor positioning framework that can combine the advantages of both positioning technologies.

In the next section, we detail how to integrate a Wi-Fi infrastructure with low range Bluetooth hotspots into one single indoor positioning framework.

III. Combining Wi-Fi and Bluetooth in Indoor Positioning

A. Overview

As analyzed in Section II-C, Wi-Fi and Bluetooth technologies have their own pros and cons as infrastructure for indoor positioning. Therefore, it is not reasonable to treat them equally and deploy them in the same way when building a hybrid indoor positioning system. Rather, we deploy these two infrastructure technologies differently so that they complement each other in improving the accuracy of indoor positioning.

Wi-Fi is widely available in today's indoor spaces. The relatively lower price of Wi-Fi access points causes them to be deployed often in redundancy so that an entire indoor space is fully covered. These characteristics are desirable from an investment perspective when a reliable indoor positioning system is to be built. Therefore, we use Wi-Fi as the main infrastructure.

In contrast, it is not economically feasible to deploy many short range Bluetooth hotspots to fully cover an indoor space. Thus, we instead deploy a limited number of Bluetooth hotspots in an indoor space where Wi-Fi is already deployed as the main infrastructure. More importantly, we deploy these Bluetooth hotspots as pivots in that they, together with corresponding indoor space topology, partition the indoor space into different regions. When a Bluetooth enabled object moves from one such region to another, it must be seen by or see a corresponding Bluetooth hotspot. The partitioning by Bluetooth hotspots is further explained in Section III-B.

Several benefits result from this particular arrangement. First, the extra investment in a new infrastructure is controlled and limited. Second, the proximity analysis based on Bluetooth can help narrow down the whereabouts of an object in the online positioning phase. Each Bluetooth hotspot has its exact deployed position and coverage range, as well as corresponding indoor region(s) from partitioning. All these can be exploited to improve position estimation, as to be detailed in Section III-C. Third, fewer Bluetooth hotspots alleviate the possible interference with Wi-Fi signals.

B. Partitioning Indoor Space with Bluetooth Hotspots

The idea of partitioning a given indoor space is proposed elsewhere [8], where RFID readers are assumed. Note that usually RFID readers have shorter coverage range than Bluetooth hotspots. Further, the past work [8] does not take into account heterogeneous wireless technologies, as does this paper.

Because it is prohibitive to build a pure Bluetooth based indoor positioning system, it is important to deploy a limited number of Bluetooth hotspots in appropriate positions. It is important to arrange Bluetooth hotspots in such a way that

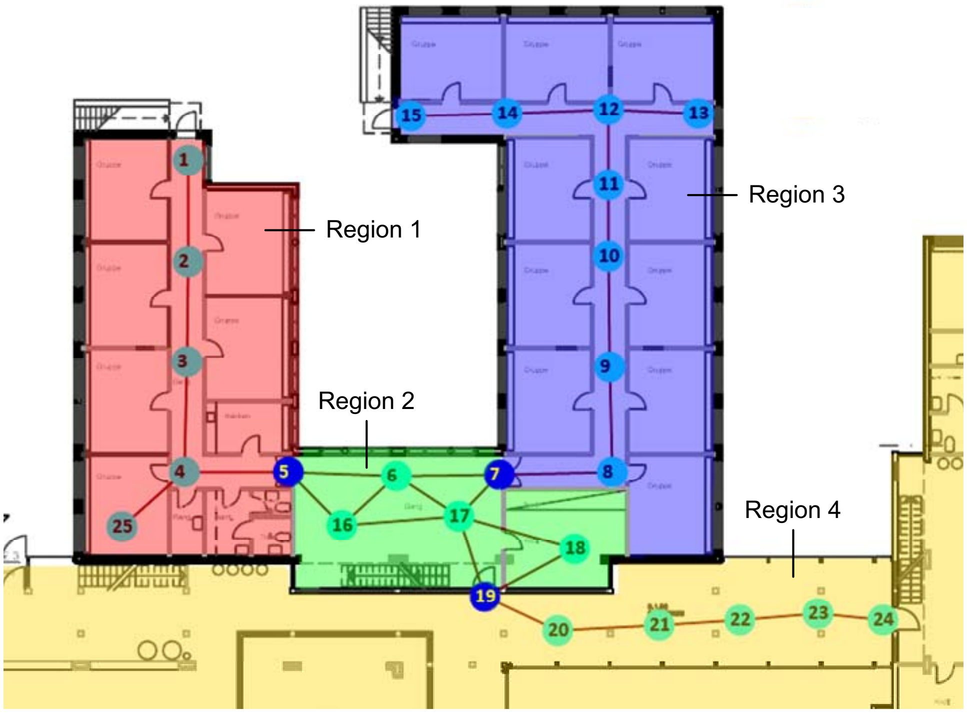

Fig. 1. Partition the indoor space into 4 regions

a user's movement from one region to another is captured. To achieve this partitioning effect, we can place Bluetooth hotspots at doors, staircases, and/or narrow passages that connect different indoor subspaces. This way, such Bluetooth hotspots divide an indoor space into small partitions and thus are able to detect cross-border movements from one partition to another.

For example, Figure 1 shows the floor plan of one cluster in our department building. Each number in a filled circle indicates a reference position in the indoor space. We place three Bluetooth hotspots at three doors in reference positions 5, 7, and 19.[1] Door 5 and door 7 connect to the hallway in the cluster, while door 19 connects the cluster to a large hallway common to all clusters in the building. It is important to make sure that each hotspot's coverage range is large enough to cover the width of the door at which it is placed.

As a result, the cluster is partitioned into four regions. When a user equipped with a Bluetooth device moves from region 1 to region 2, or vice versa, the user's device detects the Bluetooth hotspot at door 5. Similarly, the hotspot at door 19 is detected when the user enters or leaves the cluster. In other words, once a user changes region, a corresponding Bluetooth hotspot is detected.

C. Position Estimation with Hybrid Infrastructures

The position estimation phase in our indoor positioning system needs to be modified with respect to the deployed Bluetooth hotspots. If a Bluetooth hotspot is currently seen by a mobile user, we simply returns the hotspot's position as the estimate for the user. Because of the short coverage ranges of Bluetooth, this can offer much higher positioning accuracy, typically 1 to 2 meters better, than what Wi-Fi usually offers.

Once a Bluetooth hotspot is seen by a user, its identifier is also recorded in our system for later use. When a user sees no Bluetooth hotspot, our system turns to use Wi-Fi, but it still makes use of the previously recorded Bluetooth hotspot identifier. With that identifier, which indicates where the user was previously, we are able to get the possible regions that the user is currently in because each hotspot connects two regions in the partitioning. This tells that the user cannot be elsewhere, which means we do not need to check the current Wi-Fi signal with fingerprints of positions that are in other regions. Therefore, search space in position estimations is reduced. More importantly, this also contributes to improve estimation accuracy as the chance of introducing errors is reduced as well.

The pseudo code of our hybrid indoor position estimation is given in Algorithm 1. It requires an online Wi-Fi signal vector s and two Bluetooth hotspot identifiers id for the previous and current scenario. If the current Bluetooth hotspot identifier id_c is not null, the corresponding position is returned immediately (Line 1–2).

Otherwise, Bluetooth and Wi-Fi are combined to estimate the current user position (Lines 3–17). If the previous Bluetooth hotspot identifier id_p is null, all reference positions are included for consideration (Line 4–5). If id_p is not null, the

[1]For simplicity, we use these reference position labels to identify both the corresponding doors and the Bluetooth hotspots when the context is unambiguous.

relevant regions are obtained as the current regions for the user (Line 7).[2] Subsequently, only those reference positions that are in the current regions are included for consideration (Line 8). From all reference positions under consideration, the one whose fingerprinted signal has the closest Euclidean distance to s is returned as the current position (Lines 9–17).

Algorithm 1 positionEstimation(Online Wi-Fi signal vector s, current Bluetooth hotspot identifier id_c, previous Bluetooth hotspot identifier id_p)

```
1:  if id_c ≠ null then
2:      return the corresponding Bluetooth hotspot's position
3:  L ← ∅                ▷ A set containing relevant reference positions
4:  if id_p is null then
5:      put all reference positions into L
6:  else
7:      get the current region(s) according to id
8:      put all reference positions in the current region(s) into L
9:  minDist ← ∞
10: pos ← null
11: for each reference location p ∈ L do
12:     get the p's fingerprint q from the radio map
13:     dist ← sqrt( Σ_{i=1}^{n} (q_i − s_i)^2 )
14:     if dist > minDist then
15:         minDist ← dist
16:         pos ← p
17: return pos
```

It should be noted that, except during initialization, at most two regions are obtained in Line 5 in Algorithm 1, since a Bluetooth hotspot in our setting partitions a part of indoor space into two regions. Refer to Figure 1 again. Suppose a user's device currently sees no Bluetooth hotspot but it saw hotspot 5 previously. Then the user currently can be in region 1 or in region 2. The user cannot be in other regions because otherwise another Bluetooth hotspot would have been seen. Consequently, position estimation is only conducted against reference positions in regions 1 and 2, rather than against all those in the entire indoor space.

As a matter of fact, we can do better by obtaining a single region as the current region for a user. This is done after the user leaves the range of a Bluetooth hotspot identified by id_p, getting another reference position pos as the estimate position, and before the user sees any other hotspots. Then currently the user must be in the region where position pos is located. Referring to Figure 1, suppose a user's previous Bluetooth hotspot is the one at door 5, and her/his last estimated position is 16. Then before the user is seen by a Bluetooth hotspot, she/he must be in region 2. This can be exploited by subsequent position estimations to further reduce the search space, i.e., the number of reference positions to compare with.

Also, a full Wi-Fi based position estimation against all reference positions happens only when the positioning system initiates, i.e., before any Bluetooth hotspot has been seen by a mobile user's device. This means that the positioning is improved immediately after the first Bluetooth hotspot is seen.

[2]A mapping structure from hotspot identifiers to regions is created in the offline phase. Such a mapping structure is referenced later by the position estimation in the online phase. We omit the details in the algorithm as they are not the focus of our research.

D. System Architecture

Figure 2 shows the architecture of the indoor positioning system based on both Wi-Fi and Bluetooth. The online position estimation works as follows. A user's mobile device, equipped with both Wi-Fi and Bluetooth interfaces, continuously scans for available Wi-Fi signal strength measurements and Bluetooth hotspot identifiers in the indoor space, and it uploads them to the positioning server via the Internet. The server offers online positioning functionality in the form of a Web service that encapsulates the implementation of Algorithm 1. The database contains the radio map created in the offline phase.

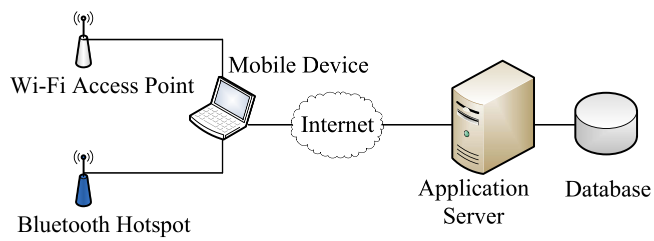

Fig. 2. System architecture

The system architecture is based on a flexible design that imposes only light computational requirements on client devices. Through the standard Web service interface, a user can enjoy the indoor positioning service without installing heavyweight software. We do not assume that the positioning server is tightly coupled with the database. This is consistent with the standard tiered server side architecture. It also allows the positioning server to access different radio maps from different sources. It is possible for radio maps for different indoor spaces to be stored or maintained by different providers.

It is worth mentioning that the client side of the system consists of three main threads running in parallel. They are designed for specific tasks. Two threads are dedicated to continuously scanning for Wi-Fi signal strengths and Bluetooth hotspots. The other thread is responsible for uploading the scanned data to the server and retrieving the estimated positions. It also calls the redraw method to update the user's current position on an interactive map. The diagram of these parallel operations is depicted in Figure 3.

E. Further Discussion

The hybrid nature of the indoor positioning system allows convenient Wi-Fi fingerprint calibration. Wi-Fi signal strength of an access point varies temporally, which causes differences between the fingerprints recorded in a radio map and the actual strength measurements from time to time. We can regard Bluetooth hotspot positions as ground truth and update the radio map accordingly. This desirable feature can be achieved as follows. Whenever the system detects that the user has

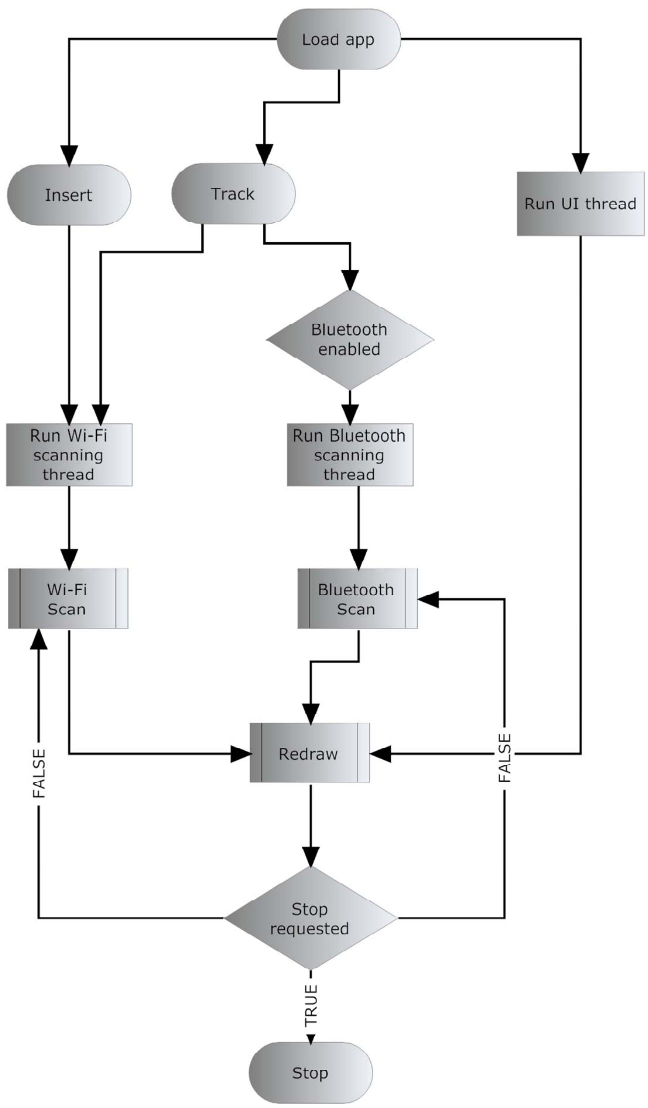

Fig. 3. Multithreading on client side

entered the range of a Bluetooth hotspot, it automatically scans for Wi-Fi signal strengths. The current signal strength vector is subsequently uploaded to the positioning server together with the Bluetooth hotspot's position. The server updates the corresponding radio map in the database by inserting the new fingerprint thus obtained. This yields a more accurate radio map.

In a multi-floor building, separate radio maps may be created for different floors. To cope with this, Bluetooth hotspots with appropriate coverage ranges can be deployed at staircases. This way, adjacent floors are partitioned into regions connected by a hotspot. By keeping track of the previous estimated position, the system can automatically switch radio map when a user passes a Bluetooth hotspot placed at a staircase. Then the online position estimation algorithm detailed in Section III-C still works.

As a last remark, it is usually a good idea to deploy Bluetooth hotspots in regions where Wi-Fi coverage is low. That is because low strength Wi-Fi signals are less stable, which makes it very hard to estimate a user's position.

IV. Empirical Study

A. Settings

We conduct our empirical study in a cluster of our department building. Its floor plan is shown in Figure 1. We perform two kinds of experiments: simulations and walk-throughs. They differ only in the online phase. In the offline phase common to both kinds, we collect real Wi-Fi signals by walking inside the cluster with a laptop. In the simulation online phase, all movements of an object are generated. In the walk-through online phase, we physically walk inside the cluster and use the indoor positioning service from the server in real time.

We select 25 positions in the cluster as reference positions, all of which are shown in labels in Figure 1. The Euclidean distance between each pair of adjacent reference position is approximately 4 meters.[3] When collecting fingerprints in the offline phase, we do 50 scans at every reference position and use the average vector as the position's fingerprint to be stored in the radio map. All those 50 vectors at every reference position are also stored in an *online signal table*.

In the online phase, both real and simulated movements follow three routes in the building (Figure 1). The sequences of all routes are defined in terms of reference positions, and listed in Table I.

Route	Sequence in Reference Positions
I	6, 5, 4, 25, 4, 3, 2, 1, 2, 3, 4, 5, 16, 6
II	6, 7, 8, 9, 10, 11, 12, 13, 12, 14, 15, 14, 12, 11, 10, 9, 8, 7, 6
III	6, 17, 18, 19, 20, 21, 22, 23, 24, 23, 22, 21, 20, 19, 18, 17, 6

TABLE I
Routes in Online Phase

B. Performance Metrics

We consider three performance metrics in the online position estimation phase in all experiments. Each metric is defined with respect to a reference position, since the online phase always returns a reference position as the estimate for the current user position.

First, *hit rate* captures the percentage of correct estimations to all estimations involving a particular reference position. Suppose a user's current true position is closest to reference position pos_i. A correct estimation returns pos_i, while a wrong estimation returns another reference position.

Second, *Euclidean error distance* denotes the Euclidean distance between a user's true position and the reference position that is returned as the estimated position. For each

[3]The density of reference points is determined through a series of pre-experiments with distances from 3 meters to 8 meters. The density of 4 meters gives the most balanced pre-experiment results with respect to the metrics to be introduced in Section IV-B.

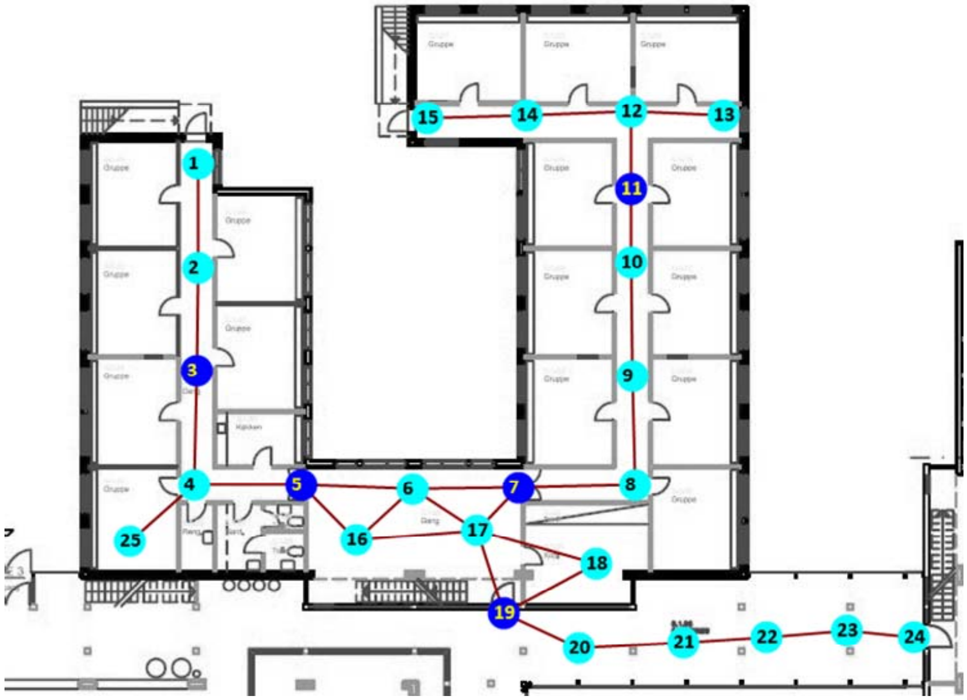

Fig. 4. Partitioning the indoor space into 6 regions

reference position pos_i, we calculate the average error distance from all position estimations involving pos_i.

Third, *walking error distance* is defined similarly, except that indoor walking distance replaces the Euclidean distance between a true position and its estimate. Both error distances are measured in meters. Additionally, we also measure the global average Euclidean error distance for all reference positions. We call this metric the *average error*.

C. Results of Simulation

In simulation we compare our Bluetooth enhanced Wi-Fi based positioning with pure Wi-Fi based positioning. We use two configurations of Bluetooth hotspots to observe the effect of the resulting indoor space partitioning. One configuration has three Bluetooth hotspots that partition the cluster into four regions, as shown in Figure 1 where hotspot identifiers are 5, 7, and 19. The other has five Bluetooth hotspots that partition the cluster into six regions, as shown in Figure 4 where hotspot identifiers are 3, 5, 7, 11, and 19.

A total of 30 routes are used to simulate the movement of a user. Each route is randomly picked from Table I. In each reference position on a route, one signal vector is randomly picked from the position's corresponding online signal table. It is then used as the online signal vector in position estimation.

1) Hit Rate: We first investigate the hit rate in every reference position. Figure 5 reports the results obtained from three settings, namely pure Wi-Fi, Bluetooth with 4 regions, and Bluetooth with 6 regions.

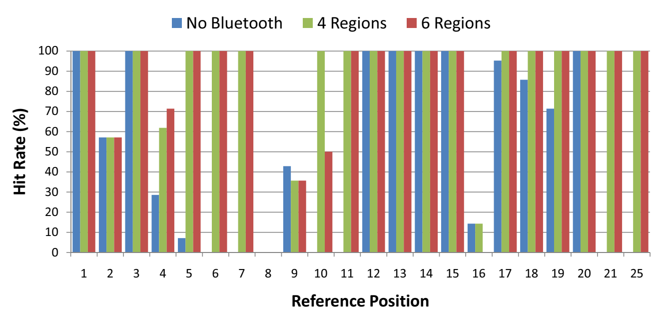

Fig. 5. Accuracy in simulation

From most reference positions, nevertheless, Bluetooth hotspots improve the positioning hit rate markedly. In 11 out of all 25 reference positions, clearly more correct position estimates are observed. The most significant hit rate improvement is seen in positions 5, 6, 7, 10, 11, 21, and 25. Compared with the pure Wi-Fi setting, the positioning hit rate at those places has increased up to 100%. There is only one position, namely 9, where the hit rate has slightly dropped after Bluetooth is introduced. This may be attributed to the fact that position 9 is in a region with more reference positions (see Figure 1). The results demonstrate that our hybrid indoor positioning design considerably improves the positioning accuracy.

2) Error Distance: We also measure the error distances in each setting in our simulation. The results in the pure Wi-Fi setting are reported in Figure 6, whereas Figures 7 and 8 report the results for the settings of Bluetooth with 4 regions and Bluetooth with 6 regions, respectively.

Referring to Figure 6, the Euclidean error distance is quite high in the pure Wi-Fi setting. Particularly, in reference positions 10, 11, and 21, it reaches 19, 20, and 25 meters, respectively. It reaches a maximum error of 40 meters in positions 11 and 21. The average error distance across all the positions is as high as 8.24 meters. These results show that the pure Wi-Fi setting fails to offer acceptable indoor positioning accuracy in the environment of interest.

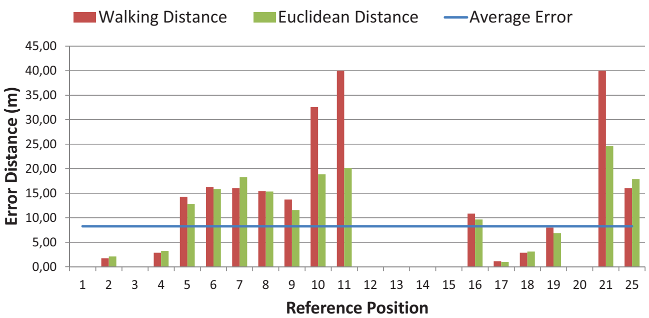

Fig. 6. Error distances without Bluetooth

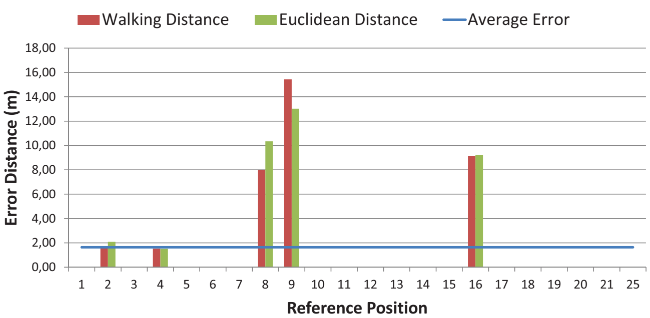

Fig. 7. Error distances with Bluetooth and 4 regions

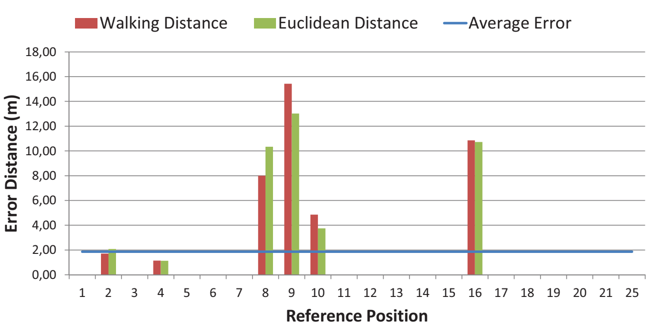

Fig. 8. Error distances with Bluetooth and 6 regions

After we introduce Bluetooth hotspots and partition the indoor space into four regions, the errors are reduced significantly, according to the results reported in Figure 7. Specifically, all error distances stay lower than 2 meters in almost all reference positions, except in positions 8, 9, and 16. The average error distance is now only 1.64 meters, less than one fifth of that in the pure Wi-Fi setting. Even the peaks observed here are much lower than those in Figure 6. Similar results are seen from Figure 8, which is obtained from a Bluetooth setting with six regions. All these clearly show that the hybrid indoor positioning reduces positioning errors considerably.

3) Summary: Our hybrid approach achieves a significant improvement in terms of indoor positioning accuracy. It clearly improves the indoor positioning hit rate, as well as greatly reduces the average error distances. Compared to the pure Wi-Fi approach, our hybrid approach improves the overall hit rate by approximately 35%. Meanwhile, the approach reduces error distances by approximately 80%. However, simply increasing the number of regions by using more Bluetooth hotspots does not guarantee further improvement.

D. Results of Walk-Through

In this section we report on our walk-through experiments. We also conducted pre-tests to study the possible interference between Wi-Fi and Bluetooth signals, considering specifically how Wi-Fi signal strength detection is affected by simultaneous Bluetooth scanning.

1) Wi-Fi and Bluetooth Coexistence: We used two mobile devices to study the coexistence of Wi-Fi and Bluetooth: an Asus EeePC with an external Wi-Fi USB adapter, and a Compaq nw8440 with both built-in Wi-Fi and Bluetooth interfaces. We made them scan for available Wi-Fi signal strengths once every second, and perform a Bluetooth scan every three seconds. Our choice is justified as follows. First, Bluetooth hotspots have smaller coverage ranges, and few hotspots are deployed in our system. Second, the Bluetooth API we used achieves the optimal performance of discovering Bluetooth hotspots at 1/3 Hz in our setting.

On the Asus EeePC, we did 35 scans for Wi-Fi access points with Bluetooth disabled, and another 35 scans with Bluetooth enabled. On the Compaq nw8440, we did 70 scans in either case of Bluetooth availability. We investigate how the detection of each Wi-Fi access point is affected by Bluetooth in terms of average Wi-Fi signal strength and successful Wi-Fi detections.

Figures 9 and 10 report on how the Wi-Fi signal strength is affected by Bluetooth. The results are obtained from the Asus EeePC and the Compaq nw8440. The presence of Bluetooth has no significant impact on the average Wi-Fi signal strength detected by a mobile device in the experiments. However, these results are only on detected Wi-Fi signals, and they do not reflect how often detection of Wi-Fi is successful.

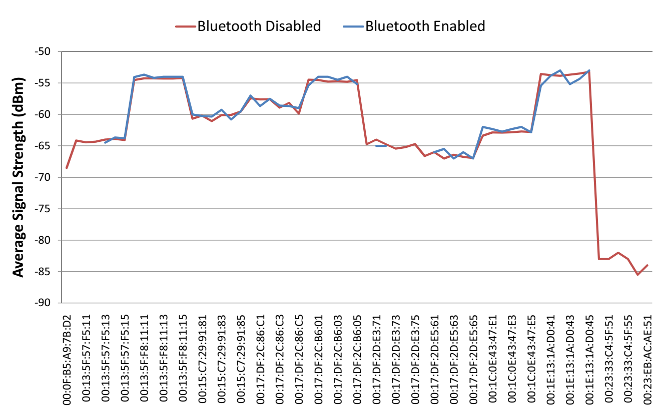

Fig. 9. Average Wi-Fi signal strengths on Asus EeePC

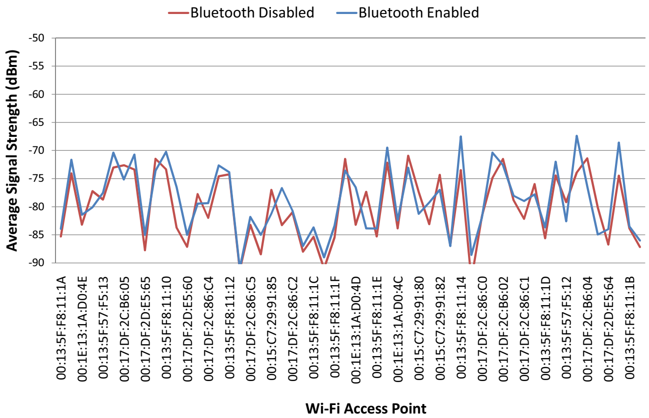

Fig. 10. Average Wi-Fi signal strengths on Compaq nw8440

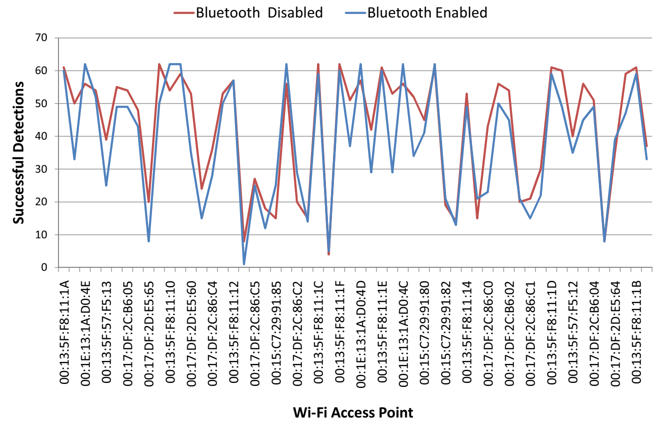

Fig. 12. Successful Wi-Fi detections on Compaq nw8440

The results of successful detections of all Wi-Fi access points are reported in Figures 11 and 12. The relevant results show the Compaq nw8440 device leads to negligible interference between Wi-Fi and Bluetooth. In contrast, the Asus EeePC incurs noticeable interference when Wi-Fi and Bluetooth coexist. The difference occurs because the Asus EeePC's external Wi-Fi USB adapter is much more sensitive to coexisting Bluetooth compared to the built-in Wi-Fi adapter in the Compaq nw8440. Therefore, in the rest of our walk-through experiments, we use the Compaq nw8440 device.

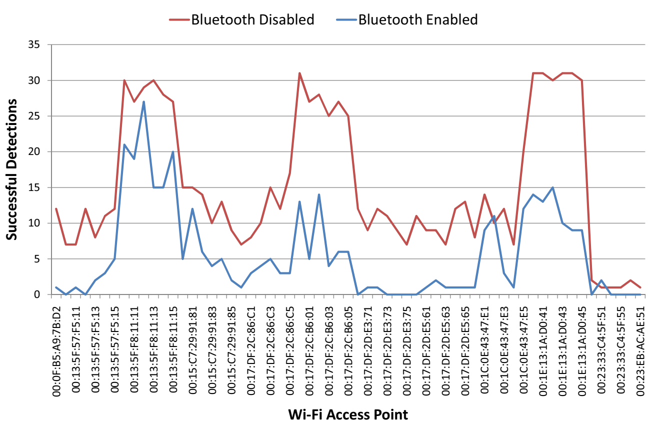

Fig. 11. Successful Wi-Fi detections on Asus EeePC

2) Positioning Performance: We conducted tests in the Bluetooth setting with four regions (see Figure 1), as well as in the pure Wi-Fi setting. The results obtained from the latter show that the pure Wi-Fi setting performs noticeably worse. Due to space limitations, we omit that part of the results. We used the Compaq nw8440 device with built-in Wi-Fi and Bluetooth interfaces. For the same reasons as in Section IV-D1, we scanned for available Wi-Fi signal strengths at 1 Hz and performed Bluetooth scans at 1/3 Hz.

During a walk-through at a quite slow pace, the device holder continuously indicated true positions by clicking on the map shown on the device, which were later used to compare with estimated positions for performance measurement purpose. Position estimation was set at the frequency of 1 Hz, and the walk-through in the cluster took about 10 minutes in total.

Figure 13 presents the results on the positioning hit rate. In reference positions 5, 7, and 19, the hit rate is very high. This is attributed to the fact that we place Bluetooth hotspots in these positions. The average hit rate on all positions in the experiment is about 33%.

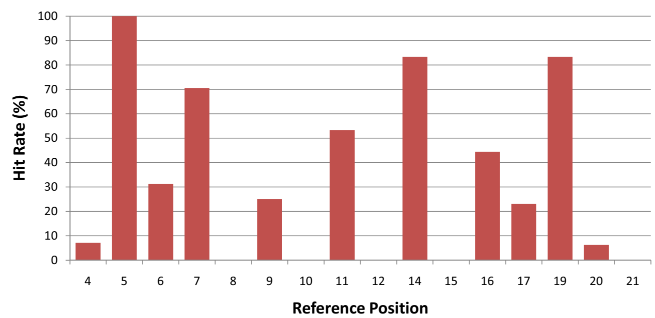

Fig. 13. Accuracy in walk-through

As some reference positions may be visited few times or may even be missed entirely in the walk-through, the hit rate in this set of experiments is less interesting as a positioning accuracy indicator. For example, we can still have low average error distance even if we get a hit rate of 0%. Therefore, it is more interesting to see the error distances shown in Figure 14.

As we can see, the results here are unstable from position to position. Nevertheless, the average error distance remains below 4 meters. The peak Euclidean error distance is 8 meters at reference position 9, and the peak walking error distance is close to 9 meters. The worst cases are actually better than those in the simulation experiments. As a remark, the average error distance result is better than the result reported in a recent study [3] in which various enhancements are employed within a pure Wi-Fi setting. This indicates that our hybrid indoor positioning approach is effective, although it only requires a few Bluetooth hotspots as additions to the original Wi-Fi infrastructure.

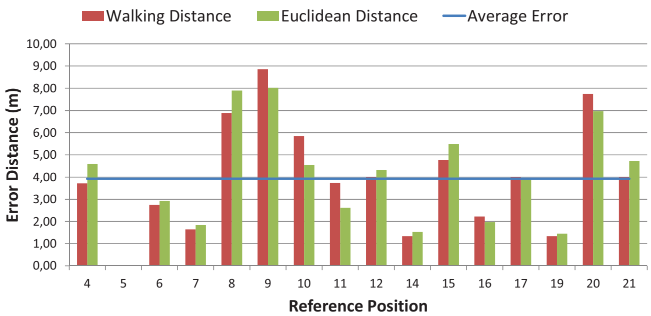

Fig. 14. Error distances in walk-through

Note that position 9 is in a region containing a relatively large number of reference positions (see Figure 1). This indicates it can be a good idea to further partition a region with many reference positions. This is expected to reduce the errors because position estimations are executed in a smaller region, which decreases the chance of wrong estimates.

V. Conclusion

This paper proposes a hybrid approach to indoor positioning. In addition to the widely available Wi-Fi infrastructure, we introduce Bluetooth hotspots into the same indoor space. Using a few Bluetooth hotspots deployed in appropriate positions, the indoor space is partitioned into regions. By making use of such Bluetooth hotspots, the online position estimation in a Wi-Fi based indoor positioning system is able to report more accurate position estimates with reduced search spaces. We conduct an extensive empirical study with both simulation and real-life walk-throughs in an indoor space. The results show that the hybrid approach improves the positioning accuracy markedly. In particular, considerably more correct position estimates are achieved, and error distances are greatly reduced.

The main advantages of the hybrid approach are:

- It improves indoor positioning accuracy. In particular, it achieves more correct hits and reduces error distances in position estimations.
- It offers a framework for additional services and techniques.
- It offers accuracies that are less dependent on Wi-Fi.
- It performs position estimation at lower cost by reducing the number of reference positions that must be considered.

However, the hybrid approach requires an investment in, and deployment of, Bluetooth hotspots. Also, its performance is sensitive to possible Bluetooth device failures.

There exist a few directions for future work. While we have used online position estimation on the server side, it is of interest to implement the enhanced position estimation (Algorithm 1) on the client side under the computational constraints of mobile devices. Interesting issues like power consumption can be studied accordingly. A client-side implementation will require a user to install additional software in her/his mobile device, which may also give rise to security and privacy concerns.

It is relevant to study the optimal setup of Bluetooth hotspots in addition to existing Wi-Fi infrastructure in a given indoor space. Specifically, it is of interest to know the optimal number of Bluetooth hotspots and where they should be positioned such that the overall indoor positioning performance is maximized.

Moreover, it is of interest to generalize the approach in this paper and study the possibilities of combining Wi-Fi with wireless technologies like RFID, ZigBee, and Infrared. Different interferences and effects are expected for different combinations as well as environments.

Yet another direction is to study how tracking of indoor moving objects can be improved in the hybrid indoor positioning proposed in this paper. More efficient tracking algorithms can be designed by exploiting information from both Wi-Fi and Bluetooth.

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