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Improving indoor positioning precision by using received signal strength fingerprint and footprint based on weighted ambient Wi-Fi signals☆

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ABSTRACT

Positioning is the foremost process in the location based service (LBS). With the GPS signal strength obstructed by the wall, indoor users cannot obtain their positions with the assistance from the global positioning satellites. Most of the indoor positioning systems have relied on received signal strengths (RSSs) from indoor wireless emitting devices, such as Wi-Fi access points (APs). Integrating indoor position information into the application on the modern handheld devices can increase the application diversity and quality in an indoor environment. In this paper, we propose a novel indoor positioning scheme assisted by the RSS fingerprint and footprint. Smartphone users can get their indoor position based on RSSs from the surrounding Wi-Fi APs. With the assistance of collecting ambient Wi-Fi RSSs from not only the intrinsic APs but also the extrinsic APs, filtering RSSs by directions/orientations, and mitigating signal fluctuation, our proposed scheme can overcome the severe signal instability problem in the indoor environment and raise the positioning accuracy. In order to reduce the time complexity of the indoor positioning procedure, we design a close designated location set (CDLS) algorithm that only uses the designated locations with the similar footprints of current user's position to determine the user's location. The proposed RSS fingerprint and footprint matching mechanism can speed up the positioning process. Meanwhile, to lessen the possible negative effect of extrinsic APs, the weighted voting positioning (WVP) algorithm would assign higher reference weights to the signals from the intrinsic APs, and adjust the weights to the signals from the extrinsic APs by their failure probability. The evaluation results show that our proposed scheme can achieve a certain level of accuracy in the indoor environments and outperform other solutions.

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1. Introduction

Location based service (LBS) can help people visit an unfamiliar place. For example, backpackers can easily obtain the local information from LBS while they arrive at a strange place. LBS can also be applied to commercial promotion. For example, when people take a stroll in a shopping mall, a nearby shop they approach can send electronic coupons to them to achieve an effective advertising. However, the foremost issue for LBS is how to accurately obtain visitor's position. The more accurate position can be determined, the more precise information can be provided. The quality of LBS can be therefore raised.

Assisted by Global Positioning System (GPS), people in the outdoors can easily get their positions with a certain level of precision. However, there has been far less improvement

☆ A preliminary version of this paper entitled "Received Signal Strength Fingerprint and Footprint Assisted Indoor Positioning Based on Ambient Wi-Fi Signals," has been presented in The 75th IEEE Vehicular Technology Conference. The video clip for the proposed positioning application can be accessed through http://www.youtube.com/watch?v=Km8Zq4yNsfw.

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on the indoor positioning. Most of past works focusing on indoor positioning intuitively use the radio emitters likes Wi-Fi APs or ZigBee sensor nodes as fixed reference points. Then the positions of the targets which were normally nomadic laptop computers would be estimated based on the RSSs from these points. Nowadays, numerous Wi-Fi APs are established by some network owner or some individuals. Wi-Fi signals are perceived almost everywhere. Hence, the accuracy of the estimated position can be raised by referring to ambient signals from not only the intrinsic Wi-Fi APs, which is self-constructed so that the corresponding referred signals are stable and reliable, but also the extrinsic Wi-Fi APs, which is not self-constructed so that the corresponding referred signals may not be stable or reliable. Meanwhile, with recent developments in mobile communications technologies, smartphones have become an indispensable device than a laptop computer for most people. Intensifying the positioning function on smartphones by adding in the indoor positioning function can realize a ubiquitous LBS concept from outdoors only to almost anywhere.

Based on above, we propose a practical design philosophy for indoor positioning. The proposed positioning scheme is based on the radio strengths from Wi-Fi APs and is mainly composed of two stages. In the first stage, called an offline stage, the positioning system collects the ambient signal strengths at some designated locations to construct the RSS fingerprint. The ambient signals not only come from the intrinsic APs but also from the extrinsic ones. To prevent burst noise signals from affecting the correctness of the RSS fingerprint, filtering out these burst signals is needed. Also, to make a more precise fingerprint as a reference basis for the second stage, the RSS fingerprint is confined in orientation and direction. Meanwhile, the related strengths received from the intrinsic APs in the RSS footprints are also noted for raising the positioning precision.

In the second stage, called an online stage, a Wi-Fi enabled smartphone can be positioned based on the collected information in the offline stage. The strengths of ambient signals from APs surrounding the smartphone are collected by the phone first. The smartphone then forwards the collected signals to the positioning system. In order to reduce the time complexity of the indoor positioning procedure, we design a close designated location set (CDLS) algorithm that only selects the designated locations with the similar footprints of current user's position to determine the user's location. After that, a weighted voting positioning (WVP) algorithm is used to determine the final position based on the collected ambient signals by comparing the RSS fingerprint and footprint database in the positioning system.

The main contribution of the proposed work is the idea of also using extrinsic APs. Since the placement of the extrinsic APs cannot be controlled by the service owner and the extrinsic APs may disappear or be moved after the training phase, so the extrinsic APs may not function stably as intrinsic ones do. Therefore, how to give extrinsic APs suitable weights in the positioning process is important for the proposed system. To lessen the possible negative effect of extrinsic APs, the WVP algorithm would assign higher reference weights to the signals from the intrinsic APs, and adjust the weights to the signals from the extrinsic APs by their failure probability. Thus, extrinsic APs still can facilitate to raise the accuracy of positioning system by the evaluation results. This paper focuses on how to craft the proposed indoor positioning system. Meanwhile, our comprehensive evaluations validate the effectiveness of the proposed scheme in an indoor environment. The rest of this paper is organized as follows. Section 2 illustrates some related works about positioning. Section 3 describes the system architecture and the proposed scheme. Section 4, we theoretically and practically evaluate the performance of the proposed system and conduct a performance comparison with other positioning schemes. A brief conclusion is presented in Section 5.

2. Related works

Recently there has been a shift in attention from a focus on outdoor positing to a concentration on indoor positioning. Using the received signal strengths surrounding the user is the most intuitive way. The authors in [1] utilized the received-signal-strength index (RSSI) of radio signals radiating from fixed reference nodes and reference tags placed at known positions to locate the user. The signals come from the self-established radio radiators only. However, taking other ambient signals for reference may be beneficial to promote the positioning precision. Other reference information may be used to identify the user position, such as a vision based mechanism using prior knowledge about the layout of the indoor environment [2]. However, the positioning system may need a large space to store the sequences of images and image sequence matching could result in more time consumption compared to character sequence matching.

Among many RSS based indoor positioning techniques, the most common wireless signal is Wi-Fi since the IEEE 802.11 APs are pervasively deployed as a wireless local area network (WLAN) nowadays. Before the Wi-Fi technique becomes popular, the radio-frequency (RF) based RADAR system in [3] has been proposed according to empirical measurements by recording and processing signal strength information from multiple base stations to determine user location. Meanwhile, some hybrid indoor location estimation methods were proposed, such as using the two-dimensional marker to complement the Wi-Fi strength [4] or using different wireless technologies involving the cellular GSM, DVB, FM and WLAN to locate the user [5]. However, the network access point with a higher radio coverage, such as GSM, FM base stations, may contribute less to indoor positioning which normally requires a fine scale. Some researchers tried to combine other low-power technologies to build the indoor positioning system, like RFID [6], and ZigBee [7]. However, these technologies need a lot of low-power devices to support the positioning process. Deng et al. [8] pointed out that a multi-source data combined positioning technology can enhance the positioning accuracy, but the cost of the system would also rise significantly. Therefore, we would not use different wireless signals in the proposed indoor positioning system.

The placement of access points can affect the precision of location estimation. A new SNR defined in [9] trying to make the signal maximized and the noise minimized simultaneously is used to deploy APs for reducing positioning errors. However, APs may be displaced unintentionally. Different influence weights should be assigned to different APs with unequal contributions for location estimation [10]. A main challenge for utilizing the strengths of received Wi-Fi signal for estimation in an indoor environment is the multipath effect and signal fluctuation. A machine learning based fingerprinting system was proposed to overcome the impact of the temporal variation caused by the multipath effect [11, 12]. Besides, a genetic algorithm based indoor positioning system [13] without the need of a pre-deployment process was introduced. However, the machine learning or genetic algorithm based scheme may result in a high computation cost.

On the other hand, as the mobile wireless technique has been revolutionized, the personal device for ubiquitous communication has been advanced from a laptop PC to a handheld smartphone. Smartphone users become a good RSS fingerprint collector and can help the positioning server build up a radio map, such as SmartSLAM [14] and SurroundSense [15] use a smartphone to construct its indoor floor plan and radio fingerprint map for buildings. The mobile users can then track their positions with measured RSSs from the surrounding APs by referring the pre-established fingerprint database in the server [16]. Serendipity [17] also used the dissimilarities of collected radio scans between access points and a smartphone to estimate the corresponding position. Meanwhile, the gyroscope bundled in the smartphone can help determine the orientation and direction of the phone. Yang et al. proposed an indoor positioning system with RSS fingerprint and inertial sensors of smartphone. Furthermore, they claimed another possible approach using a backtracking algorithm to calculate the indoor position may result in very high accuracy, but the detail of the algorithm is not exposed in the paper [18]. Li et al. used Wi-Fi and the inertial sensor to implement their indoor navigation system [19]. RSS fingerprint information filtered by the orientation and direction information can facilitate to eliminate the noisy reference information so that the accuracy of the location estimation can be raised [20]. Some previous indoor positioning system also used the similar concept of RSS fingerprint like [21], the authors only used measured RSSs as the fingerprints to calculate the indoor positioning. There exist some prior works only using the important or reliable intrinsic APs for indoor positioning. Nowadays, APs are built almost everywhere by different service providers for offering the Wi-Fi access service to the Wi-Fi users. If the positioning process can refer to more information, the accuracy of positioning can be raised. That is why our system not only refers to the RSS information extracted from intrinsic APs, but the RSS information extracted from extrinsic APs.

The RSS fingerprint and footprint data collected on the smartphone are the combination of RSS data from all APs, including the intrinsic APs and extrinsic APs. We introduced the CDLS procedure and WVP algorithm in the proposed system to lessen the possibly negative effect from extrinsic APs. The evaluation results show that the extrinsic APs indeed can contribute to improve the accuracy of the indoor positioning process even though these APs do not belong to the positioning service provider.

3. System architecture and proposed scheme

Triangulation, scene analysis, and proximity are common location estimation schemes [22]. Our proposed positioning scheme is based on the proximity of received signal strengths at the designated locations and the user's current location. This section illustrates the conceptual processing flow and main application modules in the proposed indoor positioning system. The system mainly contains the two stages shown in Fig. 1, including the offline and online stages.

In the offline stage, Wi-Fi enabled smartphones are used to collect the RSS fingerprint data, which contain the Media Access Control (MAC) information of all scanned APs and their corresponding RSSs after removing the burst noises in terms of the location and the direction of the smartphone at all designated locations. Next, the RSS footprints, which rank the intrinsic APs based on their corresponding received signal strengths, at all designated locations are also built based on the related signal strengths received from the intrinsic APs. The RSS fingerprint and footprint at each designated location are stored in the system for being referred in the second stage. In the online stage, when a new user needs to be located, the mobile user would use the smartphone to scan the surrounding signals and then send the current information including all RSSs and the direction of smartphone back to the system. The positioning system would remove unlikely RSSs by the noise filter and then take the average of the filtered RSSs as the current RSSs for all scanned APs. Based on the current direction of smartphone, the system would calculate the user's location with the assistance from the pre-established fingerprint and footprint databases. In the offline stage, unless the environment is changed, it is unnecessary to update the database once the database is established. However, once the environment is changed, the frequency of updating the database constructed in the offline stage can be adaptively changed based on the demand of positioning accuracy for the online stage. In other words, the frequency of updating the database in the offline stage should be high if the positioning accuracy in the online stage is expected to be high, thus causing a high computation cost. The processing phases as well as the related processes and models are depicted as follows.

3.1. Constructing the RSS fingerprint database

The RSS fingerprint data is used for reference when positioning the user location. To gather RSS fingerprint data for any scanned AP no matter it is intrinsic or extrinsic, a Wi-Fi enabled smartphone is used to gather the RSS information at several designated locations. The more the collected RSS information at each location, the more accuracy the fingerprint data can guarantee. If the system can establish the RSS fingerprint information accompanied with the direction information when collecting, the RSS information can be more elaborately described so that it can more precisely help locate the user by comparing the runtime scanned RSSs to the collected RSSs. In other words, the more specific fingerprint information, the more accurate position the system can conduct.

Filtering the collected RSS data in view of the direction information including orientation and direction can achieve a higher precision for positioning. When collecting the RSS data as Fig. 2 shows, we use the gyrometer on the smartphone to obtain the orientation (shown by (1)) based on

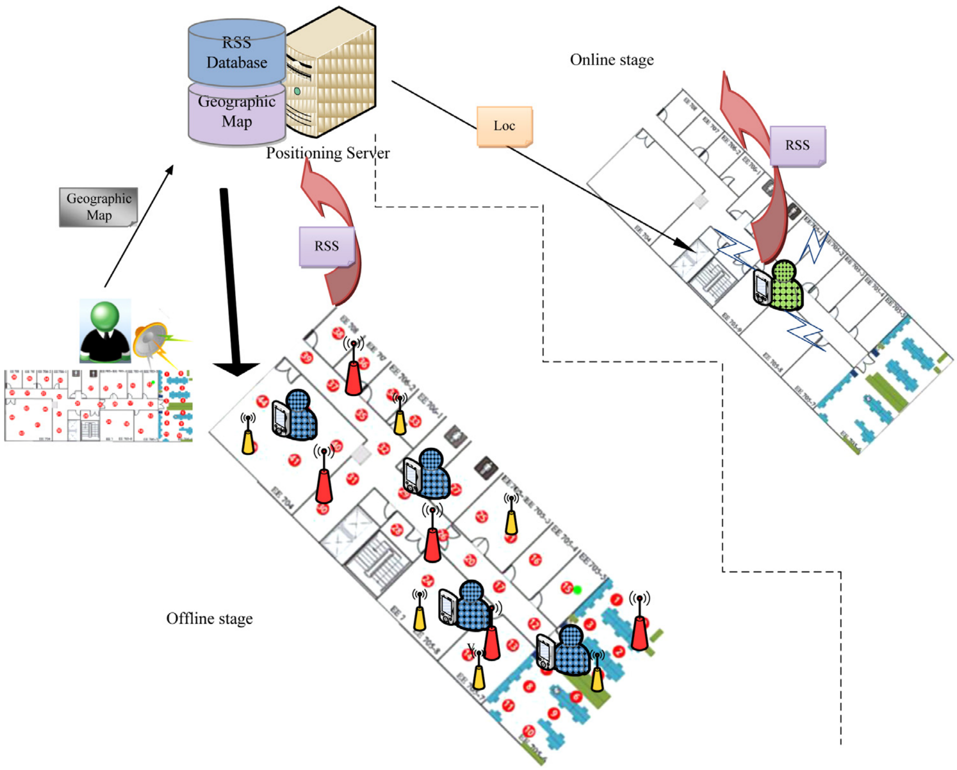

Fig. 1. The conceptual flow of the proposed indoor positioning system.

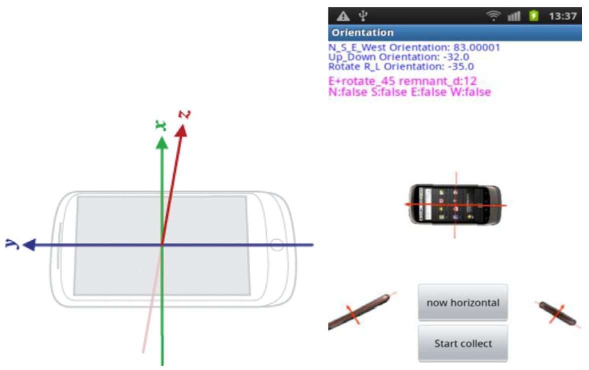

Fig. 2. Filtering the RSS by the direction of RSS smartphone collector.

the azimuth (γ), the angle between the magnetic north direction and the y-axis, around the z-axis (0–359).

$$\text{Orientation} = \begin{cases} North(N), \ if\ 315 < \gamma \le 45 \\ East(E), \ if\ 45 < \gamma \le 135 \\ South(S), \ if\ 135 < \gamma \le 225 \\ West(W), if\ 225 < \gamma \le 315 \end{cases} \tag{1}$$

Also, the direction (shown by (2)) can be obtained based on the pitch (θ), the rotation angle around x-axis (-180 to 180) with positive values when the z-axis moves toward the y-axis.

$$\text{Rotation} = \begin{cases} Horizontal(H), \ if\ -22.5 \le \theta < 22.5 \\ Rotate\,45(R), \ if\ -67.5 \le \theta < -22.5 \\ Vertical(V), \ if -112.5 \le \theta < -67.5 \end{cases} \tag{2}$$

All collected RSSs at each designated location would be sorted in a descending order in the database. To mitigate signal fluctuation by filtering out the burst RSSs, we only consider the middle n RSS values in the strength ordered RSS set for each AP by removing extremely high or low RSSs. If n is small, the range of the referenced RSSs are centralized so that calculating the average RSS for each AP may take less computation time but the result may be more confined. On the other hand, if n is large, the range of the referenced RSSs is wide so that the average RSS result for each AP may be more average but the calculation may consume more computation time. Setting n is a trade-off issue between obtaining a more accurate RSS average and taking a more computation time. Then we take the averages of RSSs from all APs as the RSS fingerprint for each designated location. Also, we calculate the standard deviation of the considered RSSs and set it as a referencing weight for positioning. The less the standard deviation is, the less diverse the considered RSSs are. Fig. 3 contains an example about the signal distribution and RSS calculation before/after signal fluctuation mitigating.

All RSS fingerprint data at all designated locations would be collected to construct the RSS fingerprint database. The fingerprint set is logically modelled as (3).

$$\begin{aligned} FGPS = \{(L, D, S_1 .., S_{|Mac_{in}|}, .., S_{|Mac|}, F) | L \in Loc, \\ D \in Dir, F \subset Mac\} \end{aligned} \tag{3}$$

where

- Loc denotes the location set containing all designated locations where the system learns the ambient signal

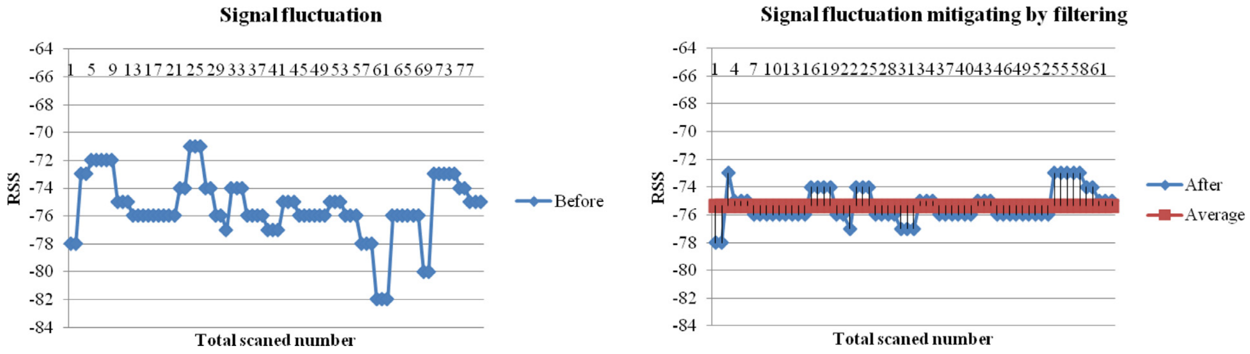

Fig. 3. Signal distribution before/after burst signal filtering.

strengths from all APs; the element *L* belonging to *Loc* is a two-dimensional coordinate$(x,\ y)$.

- *Dir* denotes the direction set; the member *D* belonging to *Dir* is a binary tuple$(o,\ r)$, where $o \in Ori = \{N,\ E,\ S,\ W\}$, $r \in Rot = \{H,\ R,\ V\}$ based on the definitions in (1) and (2).
- $S_1 .., S_{|Mac_{in}|}, .., S_{|Mac|}$ denote the scanned signal information for all APs and each S_i contains three types of information with a ternary tuple $(m,\ ss,\ sd)$, where $m \in Mac,\ ss, sd \in R$.
  - ♦ *Mac* denotes the MAC address set including a MAC address subset Mac_{in}, which includes the MAC addresses of all intrinsic APs, and a MAC address subset Mac_{ex}, which includes the MAC addresses of all extrinsic APs. That means $Mac = Mac_{in} \cup^{M} ac_{ex},\ Mac_{in} \cap^{M} ac_{ex} = \emptyset$; hence, there are totally $|Mac_{in}| + |Mac_{ex}|$ APs in the environment and $S_1 .., S_{|Mac_{in}|}, .., S_{|Mac|}$ denote the learned information about sensed signals emitted from all APs. A special function *Ord*(*mac*) is defined to obtain the ordinal number of a specific AP whose MAC address is *mac*. That means $i = Ord(mac)$ if $S_i.m = mac$.
  - ♦ *ss* is the average scanned signal strength from a specific AP with the MAC address *m* after signal fluctuation mitigating.
  - ♦ *sd* is the standard derivation of all scanned signal strengths from the specific AP with the MAC address *m* after signal fluctuation mitigating;

  For example, $S_i.sd$ expresses the standard derivation (*sd*) of all scanned signal strengths from the specific AP with a MAC address *mac* by pre-obtaining *i*=*Ord*(*mac*).

- *F* denotes a subset of *Mac* containing all MAC addresses whose signals can be scanned and whose signal strengths can achieve a distinguishable level.

Based on above, we define the *LocRetrievingFromFGPS* function to obtain the set containing all designated locations which can sense the signal emitted from the AP with the MAC address *mac* in terms of the direction *dir*. The *LocRetrievingFromFGPS* function can obtain the subset of *Loc* and is defined as (4).

$$LocRetrievingFromFGPS(mac, dir) = \{x.L | x \in FGPS,\ such\ that\ mac\ \in x.F,\ x.D = dir\} \quad (4)$$

where "." represents an operator to retrieve one data member from one element. For example, *x.L* represents retrieving the data member *L* from an *FGPS* element *x* if *x* belongs to *FGPS*.

Besides, we define

$$RSSbyMacFromFGPS(loc,\ dir,\ mac) = x.S_i.ss \text{ and } STDbyMacFromFGPS(loc,\ dir,\ i) = x.S_i.sd \quad if\ x \in FGPS,\ x.L = loc,\ x.D = dir,\ i = Ord(mac) \quad (5)$$

to respectively obtain the received signal strength and the corresponding standard deviation of one AP with the MAC address *mac* in terms of the direction *dir* at the location *loc* from the fingerprint database.

3.2. Constructing the RSS footprint database

Extrinsic APs can provide the additional information to help raise the precision of positioning the mobile user. However, such kind of APs may be randomly placed and controlled by anonymous others so that the signals from them may be unstable whereas the placement of the intrinsic APs is well planned by the implementers so that the signals from them are stable. The RSS footprint data generated based on the signal strengths from the intrinsic APs can conduct a signal strength map so as to further increase the positioning accuracy. Each RSS footprint contains the MAC addresses of the intrinsic APs, which are in a RSS descendant order. All RSS footprint data at all designated locations would be collected to construct the RSS footprint database. The footprint set is logically modelled as (6).

$$FTPS = \{(L, D,\ FT)\ |\ L \in Loc,\ D \in Dir,\ FT \subset Mac_{in}\} \quad (6)$$

where *Loc* and *Dir* are defined as the same in (3); *FT* is an ordered subset of Mac_{in} based on the magnitude of signals received from the scanned APs in a descendant order, where Mac_{in} is defined as the same in (3). That means an *FT* contains an ordered list of MAC addresses of the scanned APs based on the magnitudes of signals received from these scanned APs.

Based on above, we define an *FTRetrievingFromFTPS* function to obtain the footprint in terms of the direction *dir* at the location *loc*. The *FTRetrievingFromFTPS* is defined as (7).

$$FTRetrievingFromFTPS(loc,\ dir) = \{x.FT | x.L = loc,\ x.D = dir,\ x \in FTPS\} \quad (7)$$

Some footprint list examples at some designated locations are shown in Fig. 4.

3.3. Removing the unlikely locations while positioning

When locating a Wi-Fi enabled smartphone user, the user needs to send the current direction of the mobile

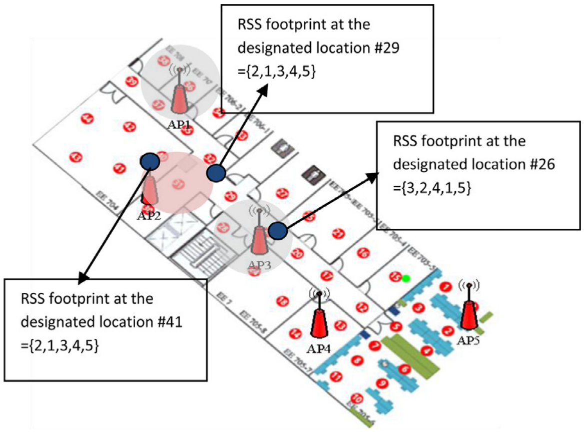

Fig. 4. Generating RSS footprints.

device (D_{cur}) and all raw RSSs from ambient APs to the system. After filtering out the abnormal RSSs, the system would assign all currently scanned signals' information into $S_1^{Cur}.., S_{|Mac_{in}|}^{Cur}, .., S_{|Mac|}^{Cur}$ with the same definition for $S_1.., S_{|Mac_{in}|}, .., S_{|Mac|}$ in (3). Also, the system would also set the user's footprint (FT_{cur}), an ordered subset of Mac_{in} based on the magnitude of signals currently received from the scanned APs in a descendant strength order. Since fully comparing all data in the database is a time-consuming task, the system would only focus on the designated locations where can sense the signals same as the current location. That also means eliminating the unlikely location candidates can reduce the computation cost in the huge database. Hence, calculating the close designated location set (*CDLS*) based on the information sent from the user can narrow down the possible area so as to speed up the positioning process. The *CDLS* is logically modelled as (8).

$$CDLS = \bigcup_{m \in \{S_i^{Cur}.m | \forall i \in \mathrm{N}, 1 \le i \le |Mac|\}} LocRetrievingFromFGPS(m, D_{cur}) \tag{8}$$

3.4. Refining the CDLS by the signal strength pattern similarity with the footprint of locations

The footprint containing a signal strength pattern can help understand the signal pattern similarity between the current user location and the designated locations. The more similar the signal strength patterns at some designated location in *CDLS* and at the current location are, the more weight should be given to the location for that footprint while determining the final position for the user. On the other hand, if the signal strength pattern at some designated location in *CDLS* significantly differs from the one at the current location, such a footprint should not affect the final positioning result too much. That means the system makes the designated location having a low footprint similarity with the current RSS pattern have less influence on the final positioning result.

Meanwhile, the larger the magnitude of signal received from some sensible intrinsic AP, the more the similarity contributed by that AP. Therefore, the weight for a sensible intrinsic AP with the higher signal strength is set higher than the one of a sensible intrinsic AP with the lower signal strength when calculating the footprint similarity. The related footprint similarity calculation is defined as (9).

$$FTSimilarity(FT_a, FT_b) = \frac{\sum_{i=1}^{\min\{|FT_a|,|FT_b|\},} w_i * Compare(FT_{a,i}, FT_{b,i})}{\sum_{i=1}^{\min\{|FT_a|,|FT_b|\}} w_i} \tag{9}$$

where $FT_a, FT_b \subset Mac_{in}$ and $Compare(m_a, m_b) = \begin{cases} 1, & if\ m_a = m_b \\ 0, & if\ m_a \neq m_b \end{cases}$ and $w_i > w_j > 0$ whenever $i > j$;

Note: FT_a means a footprint, which is an ordered subset of Mac_{in} based on the magnitude of signals received from the scanned APs in a descendant order. FT_a is a tuple containing $|FT_a|$ entries and $FT_{a,i}$ means the *i*th entry in the tuple FT_a.

By screening the signal strength pattern similarity, we can get a close designated location set named as $CDLS_s$. The screening process is illustrated below:

> **Close Designated Location Set Refining Procedure:**
> $CDLS_s = \emptyset;$
> $\forall l \in CDLS,$
> **If**
> $FTSimilarity(FTRetrievingFromFTPS(l, D_{cur}), FT_{cur}) >$ 0.5 **Then**
> $CDLS_s = CDLS_s \cap l;$
> **End If**

That means the system would only take those locations having a certain level of footprint similarity with the current user's footprint into consideration. By combining the CDLS procedure, our proposed scheme would use the designated locations with the similar footprints of current user's position to determine the user's location.

3.5. Locating the user's position

When the system locates the user's position, all locations of members in the $CDLS_s$ would be involved in the calculation. Each designated location has a different impact weight on the position determination depending on how similar the signals received by the user and at each designated location are. Meanwhile, since the signals come from ambient APs which may be intrinsic or extrinsic. Compared to the extrinsic APs, the system gives a higher weight to the RSS fingerprint data derived from the intrinsic APs because the intrinsic APs are more reliable than the extrinsic APs. Moreover, when establishing the RSS fingerprint database, the stability of measured signals also should be taken into account. Therefore, the standard deviation of RSSs should be considered as a trustworthy factor. Hence, we propose a Weighted Voting Positioning (WVP) scheme granting different weights to the position determining participants. The weight for each different designated location for positioning is defined as (10) by giving the intrinsic APs a higher weight compared to the extrinsic APs.

$$P_w(l) = \sum_{i=1}^{|Mac|} (AP_w(S_i^{Cur}.m)) * \frac{1}{STDbyMacFromFGPS(l, D_{cur}, i)} * \frac{1}{|RSSbyMacFromFGPS(l, D_{cur}, i) - S_i^{Cur}.ss|} \tag{10}$$

where $AP_w(m) = \begin{cases} T_{in}, & if\ m \in Mac_{in} \\ T_{ex}, & if\ m \in Mac_{ex} \end{cases}$, $T_{in} > T_{ex}$, $T_{in} + T_{ex} = 1$, T_{in} : the normalized weight for intrinsic APs. T_{ex} : the normalized weight for extrinsic APs.

Based on the set of the designated location candidates, we use a weighted interpolation scheme to determine the possible location for the user. The estimated location $(User_x, User_y)$ for the user is calculated as follows:

User's Position Locating Procedure:

$$(x_{avg}, y_{avg}) = \left(\frac{\sum_{l \in CDLS_s} l.x}{|CDLS_s|}, \frac{\sum_{l \in CDLS_s} l.y}{|CDLS_s|}\right);$$

$$Weight_{total} = \sum_{l \in CDLS_s} P_w(l);$$

$$(User_x, User_y) = \left(x_{avg} + \sum_{l \in CDLS_s}\left(\frac{P_w(l)}{Weight_{total}}(l.x - x_{avg})\right), y_{avg} + \sum_{l \in CDLS_s}\left(\frac{P_w(l)}{Weight_{total}}(l.y - y_{avg})\right)\right);$$

The main reason of using the interpolation scheme is its low computation complexity and the simplicity to be implemented. Without considering the complexity and computation cost, other complicated interpolation scheme also can be adopted and replaces this interpolation scheme.

4. Results of theoretical and practical evaluations

This section theoretically analyses the level of participation in positioning for all APs in the environment. Then several practical experiments have been conducted to evaluate the performance of the proposed system and the traditional RSS fingerprint based positioning system.

4.1. Theoretically analysing how the WVP's weights should be adjusted when part of extrinsic Aps disappear

As discussed in the previous sections, extrinsic APs may not stably provide correct information for positioning since they are constructed by others. As defined earlier, Mac denotes the MAC address set including a MAC address subset Mac_{in}, which includes the MAC addresses of all intrinsic APs, and a MAC address subset Mac_{ex}, which includes the MAC addresses of all extrinsic APs. That means $Mac = Mac_{in} \cup^M ac_{ex}$, $Mac_{in} \cap Mac_{ex} = \emptyset$; hence, there are totally $|Mac_{in}| + |Mac_{ex}|$ APs in the environment. Besides, we assume the probability of extrinsic APs disappear in the online positioning phase is $P_{failed,\ ex}$. That means $P_{failed,\ ex} \cdot |Mac_{ex}|$ extrinsic APs may not contribute to the positioning process. The following analysis shows how the contribution weights for different types of APs should be adjusted in case some extrinsic APs cannot provide the information for positioning. In a normal online positioning phase (no extrinsic AP disappears), the average positioning information contributed by all APs is

$$\left(T_{in} \cdot \frac{|Mac_{in}|}{|Mac_{in}| + |Mac_{ex}|} + T_{ex} \cdot \frac{|Mac_{ex}|}{|Mac_{in}| + |Mac_{ex}|}\right) \cdot POS \tag{11}$$

where POS means the coordinate information provided by each AP.

When $P_{failed,\ ex} \cdot |Mac_{ex}|$ extrinsic APs disappear during the positioning phase, in order to maintain the same positioning accuracy, the contribution weights for different kinds of APs need to be adjusted. That means

$$\left(T_{in} \cdot \frac{|Mac_{in}|}{|Mac_{in}| + |Mac_{ex}|} + T_{ex} \cdot \frac{|Mac_{ex}|}{|Mac_{in}| + |Mac_{ex}|}\right) \cdot POS = \left(T'_{in} \cdot \frac{|Mac_{in}|}{|Mac_{in}| + |Mac_{ex}|} + T'_{ex} \cdot \frac{(1 - P_{failed,\ ex})|Mac_{ex}|}{|Mac_{in}| + |Mac_{ex}|}\right) \cdot POS \tag{12}$$

where T'_{in}, T'_{ex} are the new contribution weights for intrinsic APs and extrinsic APs, respectively.

By (12), $(1 - T_{ex}) \cdot |Mac_{in}| + T_{ex} \cdot |Mac_{ex}| = (1 - T'_{ex}) \cdot |Mac_{in}| + T'_{ex} \cdot (1 - P_{failed,\ ex}) \cdot |Mac_{ex}|$.

Hence, $T_{ex} \cdot (|Mac_{in}| - |Mac_{ex}|) = T'_{ex} \cdot (|Mac_{in}| - (1 - P_{failed,\ ex}) \cdot |Mac_{ex}|)$.Finally, we can get

$$T'_{ex} = T_{ex}\left(\frac{|Mac_{in}| - |Mac_{ex}|}{|Mac_{in}| - (1 - P_{failed,ex}) \cdot |Mac_{ex}|}\right) \tag{13}$$

The new contribution weights for extrinsic APs is shown as (13), we can find T'_{ex} should be lowered as $P_{failed,\ ex}$ increases, and T'_{in} therefore is raised.

4.2. Practically evaluating the effectiveness of the proposed system

4.2.1. Evaluation environment setup

To evaluate the proposed system in a real environment, we implemented a positioning application on the Samsung galaxy i9000, which is an Android Smartphone equipped with a gyroscope. To evaluate the performance of the proposed technique, we have collected realistic RSS data in a WLAN environment shown in Fig. 5. The dimension of the environment is 36 m × 15 m. Five intrinsic Wi-Fi APs (D-Link Dir635) were placed and six extrinsic Wi-Fi APs can be detected around the environment. In the offline stage, we collected the RSS fingerprint data at 12 directions (4 orientations times, 3 rotation ranges) and footprint sample data at 44 designated locations. After the databases were established, we validated the positioning accuracy at 30 test locations (each one is denoted by a star sign in Fig. 5).

Meanwhile, we also have successfully implemented one positioning application (shown in Fig. 6) on the smartphone which can connect to our positioning server to evaluate the system performance.

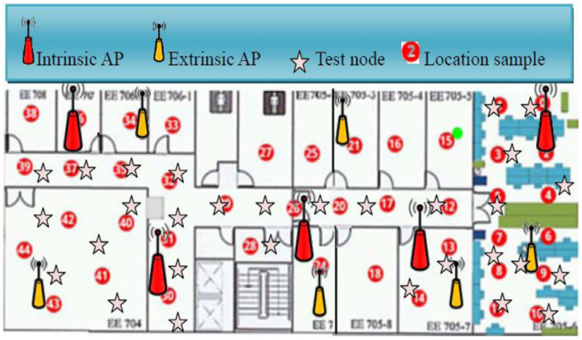

Fig. 5. Experiment environment.

Fig. 6. Snapshot of implemented positioning application on the smartphone.

4.2.2. Evaluation results

First, we are interested in how the RSS data collecting time affects the final positioning accuracy. As Fig. 7 shows, different curves mean the different positioning accuracies in terms of different collecting time (in seconds). The error distance (in meters) means the tolerable distance error between the estimated position and the true one. Once the distance difference between the estimated position and the true one in one positioning test is less than or equal to the error distance, the positioning test could be counted as a valid positioning. The accuracy in the result presents the ratio of the number of valid positioning tests to the number of all positioning tests. We can find that more collecting time to collect the RSS information can increase the accuracy of the fingerprint data so as to raise the positioning accuracy. The result can suggest system implementers to make a tradeoff between the collecting time and the positioning accuracy.

Besides, we tried to compare the positioning accuracy conducted by different positioning schemes. RADAR [3] is the first positioning solution based on the surrounding RSSs. We added the burst noise filtering function into the native RADAR by referring to [9,10] to find how burst noise removing can help raise the positioning accuracy. We compared these two RADAR based schemes to our proposed one with/without a WVP scheme in terms of positioning accuracy on different error distances. As shown in Fig. 8, with the assistance of collecting ambient RSSs, filtering RSSs by directions, filtering burst noises, and matching RSS patterns in the fingerprint and footprint databases, the proposed scheme supported by WVP can outperform others.

Additionally, since the proposed scheme not only relies on the RSSs from the intrinsic APs but also the extrinsic APs for positioning. If the uncontrollable or unstable extrinsic APs disappear while locating the user, the positioning accuracy may be affected. Based on this concept, we conducted an evaluation about how disappeared extrinsic APs would affect positioning accuracy. Shown in Fig. 9, we can find that the accuracies for the proposed schemes with/without a WVP support indeed decreased if the extrinsic APs disappear. However, the proposed scheme supported by WVP still can outperform others.

Furthermore, if the uncontrollable or unstable extrinsic APs are moved after the RSS footprint and footprint databases are created, the positioning accuracy may also be affected while locating the user. Especially, the wrong RSSs from the moved extrinsic APs may deliver wrong information for positioning. However, since the proposed scheme with a WVP always gives a lower weight to the extrinsic APs, the incorrect information from the moved extrinsic APs might have little effect on the final positioning result. Based on this concept, we also conducted an evaluation about how moved extrinsic APs would affect positioning accuracy. Shown in Fig. 10, we can find that the accuracies for the proposed schemes with/without a WVP support indeed decreased if the extrinsic APs were moved. However, the proposed scheme supported by WVP still can outperform others.

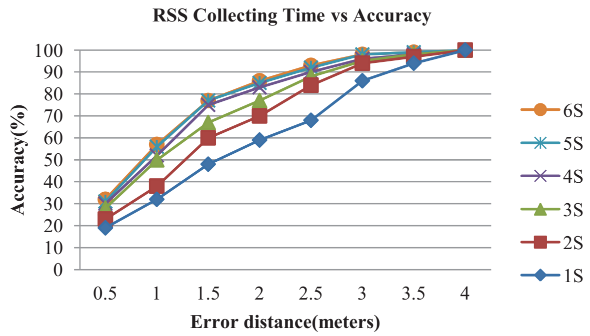

Fig. 7. Positioning accuracy in terms of different RSS collecting time and error distances.

Next, to understand if ambient signals which not only come from the intrinsic APs but also the extrinsic APs can really effectively increase the positioning accuracy, we conducted the accuracy evaluation by two scenarios. One was only referring to the signals from the intrinsic APs only and the other one was referring to the signals from both types of APs. As shown in Fig. 11, we can find the accuracy gap between them is very apparent when the tolerated error distances range from 1 to 2.2 m. Beyond 2.5 m, the accuracies for them are very close because the tolerated error distance is large enough for positioning. However, using ambient signals still can show its benefit for positioning.

From the cross check among the accuracy comparison from Figs. 8 –10, we can find that the accuracy may decline as the extrinsic APs increases due to the unstable condition of the extrinsic APs. Take the 1.0 m error distance as an example, we can find that the accuracy is 57% even when all APs are intrinsic. The accuracy falls to 53% when the extrinsic APs disappear and to 51% even the extrinsic APs provide

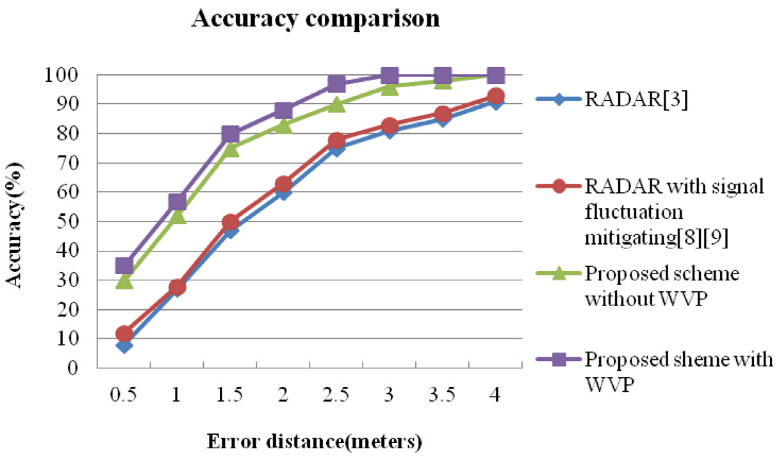

Fig. 8. Different positioning schemes in terms of different error distances.

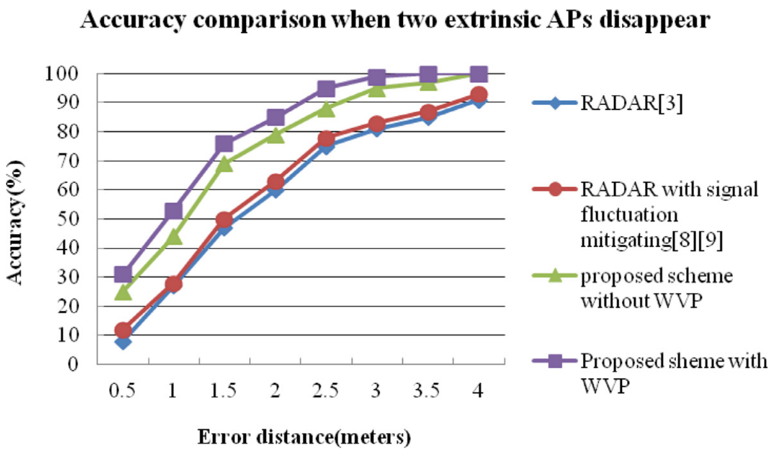

Fig. 9. Affecting positioning accuracy when extrinsic APs disappeared.

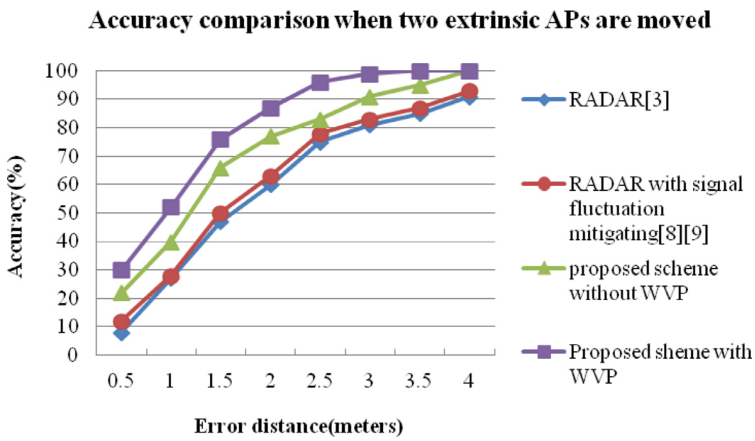

Fig. 10. Affecting positioning accuracy when extrinsic APs were moved.

erroneous position information due to their movements. In an extreme case that there is no intrinsic AP built by the system owner, the accuracy may be very low. However, all positioning schemes based on referring to the APs cannot be controlled by the system operator may encounter the same awkward situation since these APs are out of control by the positioning system operator. However, according to the trend shown from Figs. 8 –10, our proposed solution still surpasses others. Moreover, since the extrinsic APs always provide additional reference information even though they were given

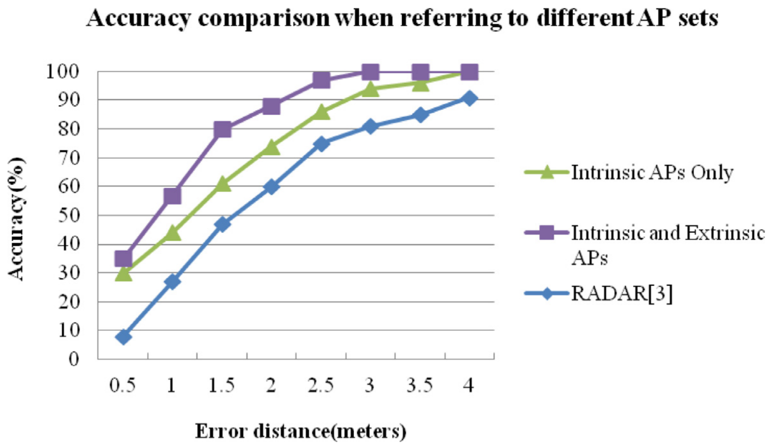

Fig. 11. Accuracy comparison when referring to different types of Aps.

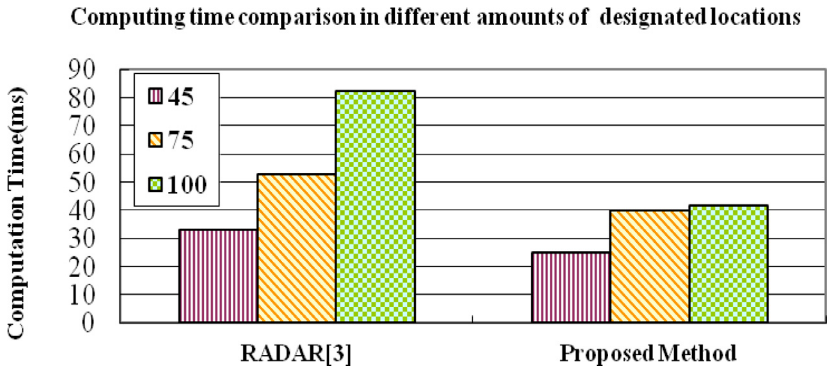

Fig. 12. Computation time cost comparison in terms of different amounts of the designated locations.

a lower weight compared to intrinsic ones, the positioning accuracy can be effectively raise as Fig. 11 depicts. We could also observe from Fig. 11 that our proposed solution could work even in the environment where no any extrinsic AP exists, and still has a better accuracy than the RADAR. Since we have used the burst signal filtering when constructing the RSS fingerprint database and have implemented the indoor positioning support procedure like the CDLS procedure and the WVP algorithm, our proposed scheme can outperform others.

Normally, users are sensitive to the application response time, especially for a real-time interactive application. The response time of positioning plays a hidden role in determining the service quality of a LBS application. Intuitively, increasing the amount of the designated locations which are built in the offline stage and referred for positioning in the online stage can raise the positioning accuracy. As the amount increases, the computation time also increases so that the overhead is also raised. However, our proposed scheme would filter out the unlikely locations and refine the location set based on the signal strength pattern similarity. Consequently, the computation cost for our proposed scheme may not proportionally increase as the amount of the designated locations increased. The evaluation results in Fig. 12 correspond to the phenomenon. By Fig. 12, we can find the computation time of the traditional positioning scheme - RADAR proportionally increased as the amount of designated locations increased. However, the one of the proposed positioning scheme can just slightly increase for the same situation. Specifically, when the amount of designated locations is increased from 75 to 100, the increased computation cost for RADAR is higher than the proposed scheme. This is because RADAR would use all footprints of all designated locations to calculate the indoor position while the proposed scheme with the CDLS procedure only uses the designated locations with the similar footprints of current user's position to determine the user's location.

All in all, the proposed algorithm has the same complexity involving the positioning process - $O(n)$, where n is the number of all APs. However, why our proposed one may outperform the traditional RADAR one is it uses the CDLS procedure and the WVP algorithm to raise the computation efficiency in indoor positioning. The CDLS procedure can reduce the time complexity by only using related APs instead of all APs to calculate the indoor position. The WVP algorithm could use the adaptive weights for the intrinsic APs and extrinsic APs to improve the accuracy of the indoor positioning procedure.

To validate the positioning accuracy of our system in terms of different user devices, we use three different kinds of smartphones or tablets to practically evaluate our system, including a Samsung Galaxy i9000 smartphone, a HTC Sensation smartphone and an ASUS Transformer tablet. Different

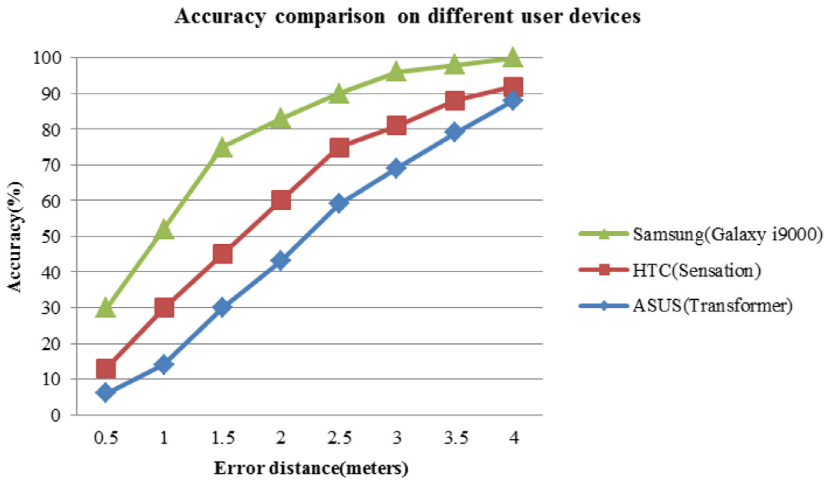

Fig. 13. Accuracy comparison in terms of different types of client devices.

kinds of devices may have different capabilities, such as their hardware conditions and their operating systems. As Fig. 13 shows, the evaluation results may be highly dependent on the devices. However, we still can find the trend of evaluated accuracy in Fig. 13 is consistent with the one in Fig. 8. No matter which user device was used, the accuracy can be raised as the threshold of tolerated error distance increased.

5. Conclusion

In this paper, we point out the problem of indoor positioning and we practically illustrate a skeleton about how to design and implement an efficient indoor positioning system combined with the modern smartphone technique. Compared to other solutions, our proposed scheme constructs the RSS fingerprint and footprint database not only based on the intrinsic APs which are constructed by the system owner but also the extrinsic APs which are constructed by others for positioning. Even though the extrinsic APs may be unstable, our experiment shows these APs still can provide additional reference information for positioning so that the positioning accuracy can be raised. Meanwhile, the proposed WVP scheme based on different contributions from different types of APs can minimize the incorrect influence for the instability of the extrinsic APs. Comprehensive experiment results show that our proposed scheme can perform a higher positioning accuracy with a lower computation cost compared to other solutions.

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