Autonomous WLAN Heading and Position for Smartphones

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Abstract—**In recent years, indoor positioning systems have become important and WiFi positioning based on fingerprinting has been gaining a lot of attention in this field. However, surveying for the WiFi fingerprints in a specific area is a labor and time consuming process. In this work, an innovative method is proposed to automatically generate geo-referenced radio maps for Wireless Local Area Networks (WLAN). The Trusted Portable Navigator (T-PN) was used to provide an integrated navigation solution using inertial sensors and Global Navigation Satellite System (GNSS), when GNSS is available. The T-PN provided positions were used to automatically build a radio map when the solution was reliable. Building a radio map by using this method alleviates the cost of expensive surveys and does not require additional time or manual labor. After the radio map is built, it is used for typical fingerprinting-based WiFi positioning. The experimental results show that reasonable positioning accuracy can be obtained with this automatic fingerprint collection method in indoor environments. Nevertheless, the positions calculated in this manner are not accurate enough to calculate a useful heading of the user. In this paper, we propose another innovative method that estimates user heading based on WLAN signals. This estimation technique is based on the mathematical relationship between the rate of change of RSS for the different access points (APs) and the user velocities, and consequently the user heading.**

Keywords—WiFi heading; WiFi position; cloudsourcing fingerprint; smartphone navigation

I. INTRODUCTION

Over the last decade, the demand for smartphones has grown exponentially. Smartphones have become an essential tool for daily life and are used for calling, texting, gaming and internet browsing. Technological advancements have facilitated the manufacturing of compact, inexpensive, and low-power consuming receivers and sensors for smartphones; therefore, enabling the development of innovative applications in a multitude of domains. An area expected to grow exponentially as a result of these advancements is smartphone-based navigation applications. Smartphones create limitless possibilities for navigation and positioning applications; due to their sophisticated microprocessors, powerful operating systems, and sensors [1]; and the fact that they are carried everywhere by their users.

The growing demand for navigation applications, especially indoors also promotes the implementation of navigation techniques on smartphones. An indoor navigation system hosted on smartphones would benefit many consumer industries including health care, Location Based Services (LBS), emergency services, tourism and personnel management [2]. A number of techniques [3, 4] have been proposed in the past few years for indoor positioning. The techniques are based on various types of hardware including Micro-Electromechanical Systems (MEMS) sensors, Wireless Local Area Network (WLAN), ultrawideband (UWB), ultrasound, radio frequency identification (RFID), etc. However, unlike outdoor positioning, which is accurately determined by GNSS most of the time, no complete indoor navigation solution exists due to several practical issues, such as complicated infrastructure requirements.

Compared to most indoor positioning techniques; such as UWB, ultrasound and RFID; WLAN (WiFi) positioning has the advantage of not needing special hardware and is only based on ubiquitous WiFi APs. On the other hand, positioning accuracy of the WiFi fingerprinting mechanism does not depend on time, which is different from MEMS sensors. Fingerprinting-based WiFi positioning generally contains two phases of operation. In the offline training phase, a group of Received Signal Strength (RSS) values from available APs is collected with corresponding position information and is stored in a database to create a radio map. In the real-time positioning phase, the user's position is estimated based on the comparison between the observed RSS values and the fingerprints in the pre-built radio map, which is obtained during the offline training phase.

Typically, the offline training phase is classified into two categories: expert surveyor model and crowdsourcing based model. In the first category, trained professionals are employed to survey the area to obtain a robust and precise radio map. Radio maps need sporadic maintenance after they are initially built. Both surveying and maintenance of radio maps cost time and labor, especially for large areas. Recently, a crowdsourcing based model was developed to reduce the cost of building and maintaining radio maps. In this model, regular users collect fingerprints during their daily routine to

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contribute to radio maps in the training phase. However, this process introduces some new issues.

This paper particularly researches two major technical issues in the crowdsourcing indoor positioning system. How to obtain accurate positioning information when building the radio map is the first issue. The T-PN, highly customizable software that converts any quality and grade of inertial sensors into navigation capable sensors, can be used on any of the available smartphone operating systems, including Android. During the training phase, the T-PN running on Android smartphones will be used. Secondly, in the expert surveyor model, professionals must spend a long time at each measurement point to build the precise fingerprint database. However, in the crowdsourcing model, fingerprints are generated automatically, whether the user is walking or static, as long as the software is running in the background. Therefore, while walking a few samples can be collected at each measurement point. Several scenarios are used in this paper to evaluate the performance of WiFi positioning based on crowdsourcing fingerprint model.

Additionally, a method is provided to calculate heading of the platform, where wireless communication systems or wireless networks that enable measurement of RSS are available. The method uses the rate of change of RSS measurements to reduce biasing effects and a low pass filter on the RSS values to reduce noise.

As such, this paper presents a method for enhancing the navigation solution for a device within a platform, wherein the mobility of the device is constrained or unconstrained. This method detects and estimates the absolute heading of the platform using signals received from wireless communication systems when available. Wireless signals used in this embodiment may be obtained from wireless communication systems or wireless networks having an RSS value (e.g. WiFi signals). Beacons of these wireless systems are referred to as APs.

The platform's absolute heading is obtained by using the RSS' rate of change. This makes the present method robust against hardware changes and absolute RSS variations, which commonly occur in harsh indoor environments. Because the RSS values are noisy, low pass filtering or any other de-noising technique can be applied first to these RSS values before using them to calculate the rate of change. The output is the heading of the platform along with its standard deviation or error range.

Following are the contributions of this paper:

- Introduction of an automatic and autonomous crowdsourcing method for fingerprint generation by using the T-PN software on smartphones.
- Performance evaluation of fingerprint-based WiFi positioning by using the automatically generated radio maps in several real-world scenarios.
- Introduction to an innovative WiFi heading estimation algorithm, and verification of its performance in real-world testing scenarios.

II. BACKGROUND

In the past few years, many algorithms have been proposed for WiFi positioning and heading estimation. Several methods are researched for WiFi position estimation based on Time of Arrival (TOA), Time Difference of Arrival (TDOA), Angle of Arrival (AOA) and Received Signal Strength (RSS) [5]. Using signal strength is the most popular method for smartphone WiFi positioning because the other three methods are not supported by typical hardware in smartphones until now. In general, the techniques for WiFi positioning using signal strength are either based on triangulation methods or based on WiFi fingerprinting [5]. Typically, WiFi fingerprint-based positioning has better performance than the triangulation method. In a WiFi fingerprint-based positioning system, an offline training phase is required to collect the fingerprints and build a radio map [3, 6]. The offline training phase usually costs time and labor. Therefore, many methods have been proposed to reduce the costs [7-10]. A system is proposed in [10] to reduce the cost of offline training by collecting WiFi fingerprints automatically utilizing vehicles equipped with GNSS receivers. The system is mainly used for outdoors, and not suitable for indoor applications. A concept that the normal users, not professional surveyors, also can update fingerprints to the radio map in their daily life is discussed in [8]. It is not an automatic system because it needs the active participation of users to update the fingerprints. An automatic system is proposed in [7] for the offline training phase based on an inertial sensors' solution. The inertial sensor's navigation solution is based on basic algorithms; therefore, not as accurate as the T-PN which is robust for any type of use case (such as calling, texting, dangling, etc.) during data collection. In the real-time positioning phase, some methods have been discussed in [6] about probability schemes to improve the positioning accuracy. However, these methods are not suitable for an automatic system because it requires the user to stay in place for a long-time at each collection spot during the training phase.

WiFi SLAM (simultaneous localization and mapping) is another group of algorithms [11-14] for localization and WiFi information mapping (radio map and AP location). Researchers in [11] implemented WiFi SLAM system by using Gaussian Processes Latent Variables Model (GP-LVM). More specifically, the WiFi radio map was generated by using GP-LVM to extrapolate from the existing fingerprints. The result of the paper shows the mean localization error is about 4 meters. It is an iterative algorithm, and has the limitation of large computation load when processing large sets of data. Another WiFi SLAM algorithm was provided in [12], which builds the WiFi radio map based on GraphSLAM. The localization error by using this system is about 2 meters. WiFi radio maps were constructed using the RSS values to differentiate different paths in [13]. [14] proposes a smartSLAM scheme which contains PDR, FEKF, FEKFSLAM and DPSLAM. It also provides the process of building WiFi radio map if it is not readily available. The main problem of WiFi SLAM algorithms [11-14] for radio map generation is the large computation load.

Much research [3, 6, 15] has focused on WiFi positioning solutions. However, there is less research on heading estimation using WiFi techniques. A heading estimation method is proposed for mobile robots in [16]. However, this method needs a special beam antenna, which is not suitable for low cost devices. Research by [17] introduces a method to estimate heading by using four horizontally arranged directional antennas, which also are not used in low cost devices. Another geometrical method is used by [18], in which the accuracy of heading depends on travelled distance after a turn is perceived. This method cannot be used for quick turning situations. In [19] an algorithm to estimate heading by using the rate of change of RSS values from multiple APs is discussed with the assumption that RSS values are Gaussian distributed which is not a valid assumption.

III. SYSTEM OVERVIEW

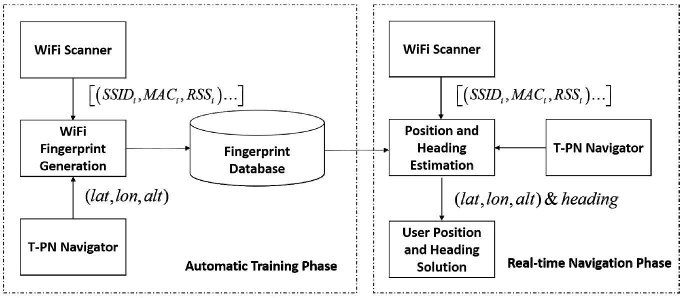


Fig. 1: Proposed System Overview

The proposed system consists of at least one mobile user and a fingerprint server. As shown in Fig. 1, the mobile user automatically collects the fingerprints for the database (radio map) by combining the positioning solution from the T-PN and corresponding RSS values from visible APs in the automatic training phase. The fingerprint server constructs a radio map by integrating fingerprints received from the mobile user at different times. Then, in the real-time navigation phase, the fingerprint database is used to estimate the user's position.

The mobile user measures RSS values with the 'WiFi Scanner' in the smartphone. The user's position is provided by the T-PN. The T-PN estimates the user's position by using the data from inertial sensors in the smartphone. The T-PN also provides user's position accuracy estimates. In sum, the mobile user builds the radio map by providing his/her position, estimated position accuracy and RSS values. To maintain high accuracy of fingerprints, the server filters out unreliable data based upon the estimated position accuracy. In the real-time positioning phase, the mobile user uses the radio map to enhance the positioning accuracy, and reduce the drift errors of the T-PN. Then, the revised T-PN provides reliable information for user heading estimation.

IV. AUTOMATIC RADIO MAP GENERATION

In this section, we discuss how to build the radio map automatically by using smartphones. The mobile user tracks his/her position with the T-PN and measures RSS values from available APs immediately. RSS values are selected and optimized before being added to the radio map. The estimated position errors of the T-PN, as well as optimized RSS values are stored at the corresponding position in the radio map. The estimated position errors are mainly used as an indicator for updating the fingerprints.

A. AP Response Rate

When analyzing preliminary results, we found that some APs with weak signals are not always recorded even when the user is standing still. Therefore, the response rate is introduced to evaluate the stability of AP signals. Our preliminary results show that APs with RSS values of greater than -75dBm provided a response rate of over 90%; APs with RSS values between -75dBm and -85dBm provided a response rate of about 70%; and APs with RSS of less than -85dBm provided a response rate of about 30%. If the user can stand at a specific location for a long time, response rate can be used to determine the quantity and quality of the recorded fingerprint information. However, in this paper, fingerprints are collected as the mobile user goes about their daily life while the software runs in the background of their smartphones. Sometimes, only one sample is collected at a measurement point when the mobile user is walking. In this case, a high response rate was used by setting the threshold to -85dBm to increase the number of RSS values in the fingerprints database, thus potentially increasing the database reliability.

B. Collecting RSS Values

The fluctuation of RSS values also needs to be considered beyond the AP response rate. As we discussed before, a few samples can be recorded at each measurement point when the mobile user is walking. A three-point smoother is used here to improve the reliability of RSS values. Current RSS value is re-determined by averaging previous RSS, current RSS and next RSS. Of course, the averaging can improve the accuracy of measured RSS value if the user is static. If the user is walking, previous RSS and next RSS are measured at different measurement points from current RSS value. However, previous RSS and next RSS are close to current RSS because they only have one epoch's difference for cases with high WiFi data frequency which was the case for this research. Previous and next measurement points are usually located at two opposite sides of the current measurement, and thus these RSS values are usually complementary. This is also helpful as the WiFi measurements are highly noisy. Therefore, no matter whether the mobile user is static or moving, the averaging of three epochs' RSS values will improve the accuracy of the RSS in the radio map.

Designing equally spaced grids is the next issue for RSS collection. The length of grid space is an important factor that affects the performance of WiFi positioning. In a small grid space, the user only stays on the same grid for a short time, which results in insufficient collection of RSS samples. On the other hand, a large grid space results in low positioning accuracy. By considering the normal walking speed of a mobile user, an empirical grid space of three meters is selected as an optimal value.

The tuple stored at each grid has the following form:

$$T=\{p_{llh},\sigma_h,\sigma_a,S\} \quad (1)$$

where, p_{llh} represents the latitude, longitude and height of the grid; σ_h and σ_a represents the horizontal and altitude positioning accuracy; and S is the RSS set received from the observable APs. p_{llh}, σ_h and σ_a are all provided by the T-PN. S is stored as:

$$S=\{(SSID_1,MAC_1,RSS_1),\ldots,(SSID_n,MAC_n,RSS_n)\} \quad (2)$$

where, $SSID$ and MAC presents the SSID name and MAC address of each AP. RSS is the average value of RSS samples. n represents the number of APs. The fingerprint tuples are automatically saved, and if needed can be uploaded to the cloud. The proposed system requires no active participation of the mobile user, which is a substantial improvement over the existing expert survey systems.

C. The T-PN

The T-PN is customizable software that can convert the data from the inertial sensors in smartphones into a navigation solution. This engine improves the navigation results by using any available absolute measurement as an update to the system. Physical movements of the user, such as pedestrian dead reckoning, zero velocity updates, and non-holonomic constraints are used as constraints to improve the navigation solution [20]. The constraints are also tailored to user transit mode to ensure the most robust navigation solution for the user. Mode of transit is automatically detected on a continuous basis. If additional sensors such as a magnetometer or barometer are present and properly calibrated, their readings can be used as optional updates by the T-PN. Most of the smartphones today have both a magnetometer and a barometer. The T-PN provides the 3D position, 3D velocity and attitude of the system. In the case of smartphones, the T-PN also provides the heading of the moving platform in addition to the heading of the device. This gives the smartphone user the flexibility to navigate with the phone in any orientation.

D. RSS Ambiguity Resolution

When the proposed system is running in the background of the smartphone, fingerprint tuples are saved and uploaded to the fingerprint server. The server filters out unreliable tuples based on the estimated position accuracy. Whether the newly updated fingerprint is located in the same grid as a previous fingerprint in the radio map was located, is determined by using the following equation (3):

$$\begin{cases} horizontal\_dis(p_{llh,u},p_{llh,r})<space\_th \\ height\_dis(p_{llh,u},p_{llh,r})<floor\_th \end{cases} \quad (3)$$

where, $p_{llh,u}$ and $p_{llh,r}$ represent the positions of the updated fingerprint and the fingerprint in the radio map. $horizontal\_dis$ and $height\_dis$ are horizontal distance and height distance between the updated fingerprint and the fingerprint in the radio map. $space\_th$ and $floor\_th$ represent the grid space and the floor height of the typical buildings. In this case, the following equation is provided to update the radio map:

$$T_r=\begin{cases} \{p_{llh,r},\sigma_{h,r},\sigma_{a,r},S_r\}, & \sigma_{h,u}>\sigma_{h,r}\,\&\,\sigma_{h,u}>space \\ \{p_{llh,u},\sigma_{h,u},\sigma_{a,u},S_u\}, & \sigma_{h,r}>\sigma_{h,u}\,\&\,\sigma_{h,r}>space \\ E[T_r,T_u], & \sigma_{h,r}\le space\,\&\,\sigma_{h,u}\le space \end{cases} \quad (4)$$

where, $p_{llh,r},\sigma_{h,r},\sigma_{a,r},S_r$ and T_r are the information of the fingerprint. $p_{llh,u},\sigma_{h,u},\sigma_{a,u},S_u$ and T_u are the information of the updated fingerprint. $space$ is the set grid space. $\mathrm{E}[\bullet]$ represents the calculation of averaging. The main idea is to keep the more accurate fingerprint in the radio map. If estimated position errors of the two fingerprints are both less than the designed grid space, the average of the two fingerprints is stored in the radio map. If one of the estimated position errors is greater than the designed grid space, the more accurate fingerprint is kept. Overall, this method tries to keep the high accuracy of fingerprints in the radio map.

E. Position Ambiguity Resolution

We also need to consider the situations where the updated fingerprint has very similar RSS measurements to another fingerprint in the radio map, but has a different position solution. If this situation is not carefully considered when building the radio map, it will affect the accuracy of the real-time position. In this paper, a method is proposed to filter this case out by using:

$$\mathrm{E}\left[\mathrm{abs}(S_r-S_u)\right]<RSS\_th \quad (5)$$

The left part of the equation is calculated by averaging the RSS difference between S_r and S_u for each AP. RSS_th is the threshold for determining whether two RSS sets are collected at the same measurement point. If equation (5) is satisfied, equation (4) is also used as a method for updating the fingerprints.

V. WIFI POSITION ESTIMATION

In the proposed system, the mobile user's position can be calculated by using the RSS fingerprints. The position of the mobile user is adjusted to the average position of the closest matching fingerprints on the radio map. The closest matching fingerprints are the ones that have the smallest differences between the current RSS values and the fingerprints. However, the system does not guarantee that the radio map contains all the fingerprints in the building. Therefore, the smallest differences should be less than a threshold to make sure that the positioning result is reliable. When the WiFi position is calculated, it can be used as a source for the T-PN to improve the accuracy of the mobile user's position estimation.

VI. WIFI HEADING ESTIMATION

The absolute heading of the moving platform (i.e direction of motion) from wireless signals is also estimated by the time rate of change of the RSS values, thereby alleviating any biasing effects in these measurements.

The time rate of change of the RSS of the i[th] AP at time step k, will be called $\left.\frac{dRSS_i}{dt}\right|_k$. This is calculated from the RSS values from APs numerically by formulas that calculate discrete derivative. These numerical formulas can be of any order in time (i.e. with any memory length in the discrete domain) to calculate better and more smooth derivatives. Low pass filtering is applied first to these RSS values before using them to calculate the derivative.

The coordinates used here are Cartesian and are referenced to a starting point within a local level frame, the coordinates are East, North, Up from an initial latitude, longitude, and altitude (this initial point is the origin of the Cartesian coordinate frame under consideration). Since usually in navigation systems latitude, longitude, and altitude are the position coordinates used in the majority of navigation systems, the conversion between this coordinate system and the local Cartesian system used here is as follows:

$$\begin{aligned} North_k &= (\varphi_k - \varphi_0) * (M + h_0) \\ East_k &= (\lambda_k - \lambda_0) * (N + h_0) * \cos(\varphi_0) \end{aligned} \tag{6}$$

M is the Meridian radius of curvature of the Earth's ellipsoid and N is the normal radius of curvature of the Earth's ellipsoid. To simplify the terminology x and y are interchangeably used with East, and North.

The platform or user coordinates at time step k will be referred to as (x_k, y_k), this may be obtained by the integrated navigation solution that uses accelerometers, gyroscopes, magnetometers and barometer, together with absolute navigation information such as GNSS, when available. The i[th] AP coordinates will be referred to as $\left(x_k^{AP_i}, y_k^{AP_i}\right)$. As mentioned earlier, a possible way to obtain the access point coordinates is through a search in a reference database that contains the locations of all wireless access points to determine the locations of each access point from which the RSS was measured. This database is developed in this paper using the T-PN. The platform or user velocity at time step k will be referred to as $(v_{x,k}, v_{y,k})$.

The time rate of change of the RSS of the i[th] AP at time step k is related to the coordinates and velocity as follows:

$$\left.\frac{dRSS_i}{dt}\right|_k = c\left(\frac{\left(x_k^{AP_i} - x_k\right)\left(v_{x,k}\right) + \left(y_k^{AP_i} - y_k\right)\left(v_{y,k}\right)}{\left(\left(x_k^{AP_i} - x_k\right)^2 + \left(y_k^{AP_i} - y_k\right)^2\right)}\right) \tag{7}$$

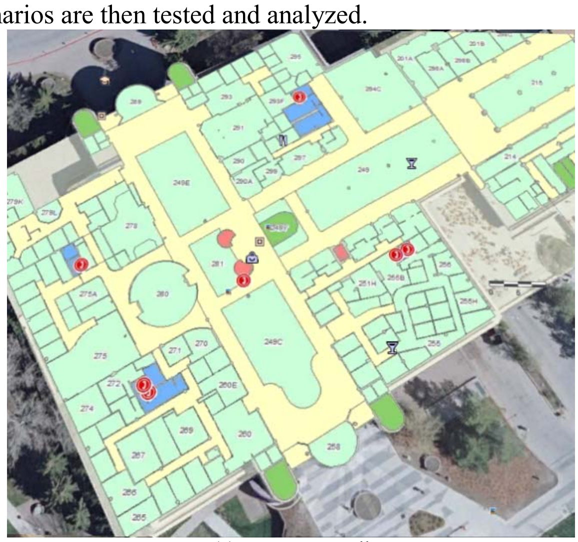
This formula was obtained from the derivative of the logarithmic decay formula that relate the RSS to the user position (i.e. propagation model). . Since the RSS values have no global unit and vary from one system to another, equation 10 has a constant of proportionality term c.

In general, several APs are visible to the platform or user (e.g. n APs are visible), then the rate of change of the RSS of each of these APs is calculated. A measurement model is obtained from the n instances of equation 7. A Least Squares-based technique (measurement-based estimation technique, which does not rely on a system model, but rather on measurement only) is used to obtain the platform or user velocity. The availability of measurements from several APs and the use of an estimation technique tackle and further decrease the effect of the noise in the measurements.

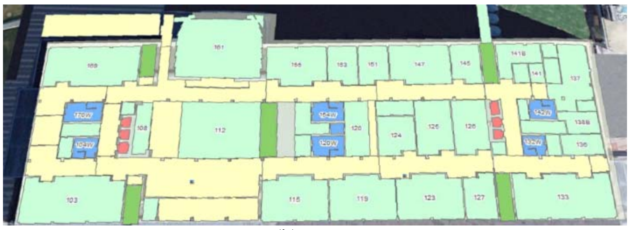
Having the platform or user velocity obtained along the East and North (the x and y directions), the platform heading is obtained as $A_k^{platform} = \text{atan2}(v_{x,k}, v_{y,k})$. It is to be noted that even if the constant of proportionality c is not estimated explicitly, the quantities $c * v_{x,k}$ and $c * v_{y,k}$ are the ones estimated rather than $v_{x,k}$ and $v_{y,k}$; thus the heading is still calculated as $A_k^{platform} = \text{atan2}(c * v_{x,k}, c * v_{y,k})$.

VII. EXPERIMENTAL RESULTS

This section discusses the setup, results and analyses of our experiments to evaluate the performance of the proposed system. We first describe the design and setup of the experiments. Several preliminary results of the real-world scenarios are then tested and analyzed.



(a) MacEwan Hall



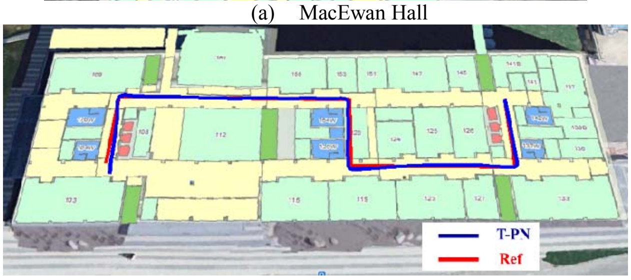
(b) EEEL

Fig. 2: Test scenarios

To evaluate the performance of the proposed system in real-world environments, we implemented the system on a Nexus7, which is an Android device equipped with accelerometers, gyroscopes, magnetometers and a WiFi receiver. For evaluations, we selected two sites which had different environments. As shown in Fig. 2 (a), the first experimental site was the west area (about 90m*70m) of second floor of MacEwan Student Center at the University of Calgary, with a large open area. Another site was the first floor of the Energy Environment Experimental Learning (EEEL) building (about 120m*40m), which has some corridors as shown in Fig. 2 (b).

The T-PN navigation solutions from two scenarios are shown in Fig. 3. The results clearly show that the T-PN solution is accurate and similar to the reference trajectory. Therefore, T-PN is a reliable position provider for automatic fingerprint generation.

(a) MacEwan Hall



(b) EEEL

Fig. 3: Examples of the navigation solution from the T-PN with respect to a hand drawn reference

Fig. 4 illustrates the generation process of the radio map. The mobile user is needed to keep the software running in the background of the smartphone. It is likely that if the building is familiar to the user they will return to the building many times. For example, if the mobile user is a student of the University of Calgary, he/she may go to the MacEwan Student Center many times for food or coffee, etc. In this case, our proposed system will automatically record fingerprints from trajectories in the user's daily routine as shown on the left of Fig. 4. The recorded fingerprints will be recorded in the radio map after some processing, as discussed earlier, and shown on the right part of Fig. 4.

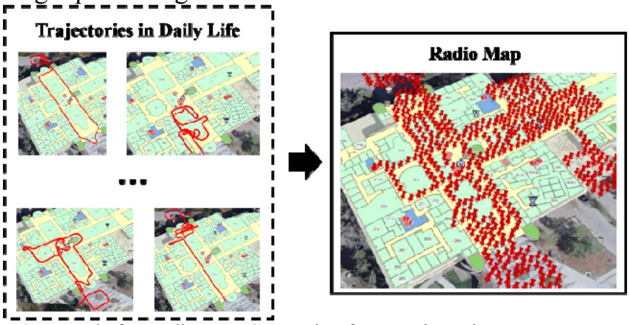
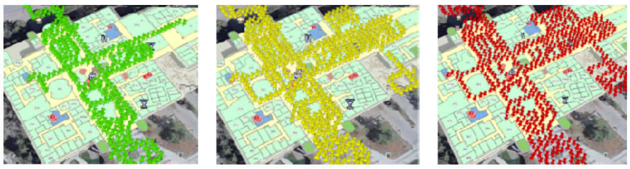


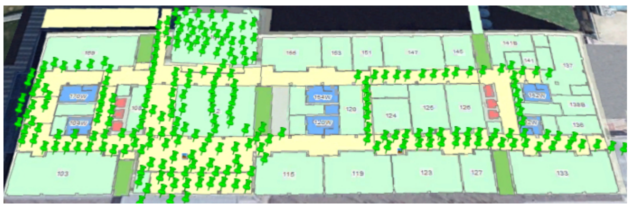
Fig. 4 Example for Radio Map Generation from Trajectories

Fig. 5 and Fig. 6 show the automatically generated radio maps in two scenarios (MacEwan Hall and EEEL) by using different numbers of trajectories from user's daily life usage of the mobile device. Fig. 5 (a), (b) and (c), and 6 (a), (b) and (c) show the radio maps in MacEwan Hall and EEEL building generated from 6, 12 and 16 trajectories. Through the WiFi positioning results, which will be discussed next, the radio maps from different numbers of trajectories will provide different WiFi positioning results. The results are showing that the performance of WiFi positioning becomes better when using the radio map generated from more trajectories.

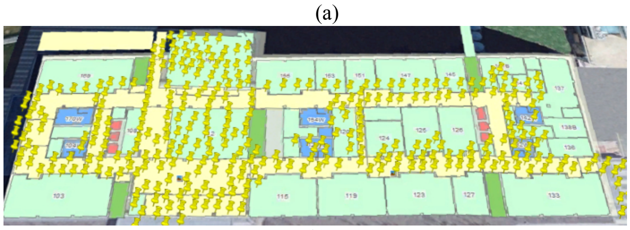


(a) (b) (c)

Fig. 5 Radio Map by Using Different Number of Trajectories (Scenario I: MacEwan)



(a)

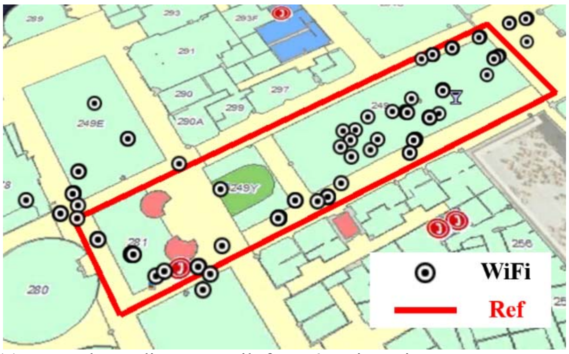


(b)

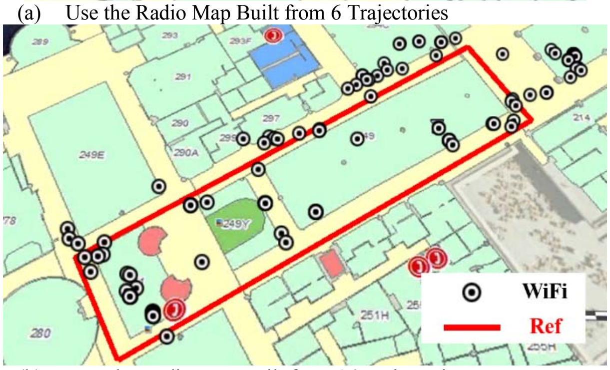
(c)

Fig. 6 Radio Map by Using Different Number of Trajectories (Scenario II: EEEL)

WiFi positioning results based on the automatically generated radio maps are shown in Fig. 7-9. Table I also depicts the statistical numbers of the WiFi positioning results. Through the figures and the table, we found that the WiFi position becomes better and better when more and more trajectories are used for generating the radio map. It is shown that the RMS values of the position errors are less than 5.7 meters when using most available trajectories (16 or 20) for building the radio map. Note that a three-point smoother is also used for the optimization of real-time RSS values before positioning. The results prove that the proposed system can achieve an accuracy of 5.7 meters without professional surveys. When comparing our results with WiFi SLAM algorithms [11-14], we found that our results are slightly less accurate. However, our algorithm requires less computation load and less surveying time for WiFi radio map generation, and this is the main advantage of our system.



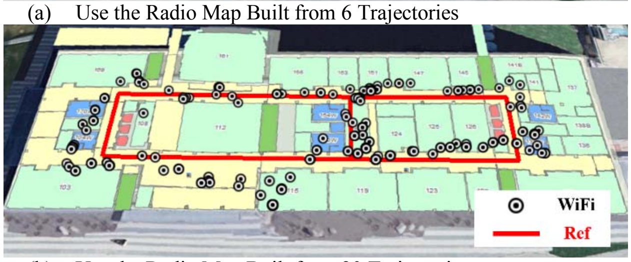
(a) Use the Radio Map Built from 6 Trajectories



(b) Use the Radio Map Built from 16 Trajectories

Fig. 7 WiFi Positioning Results of Trajectory I (Rectangle) by Using Different Radio Maps

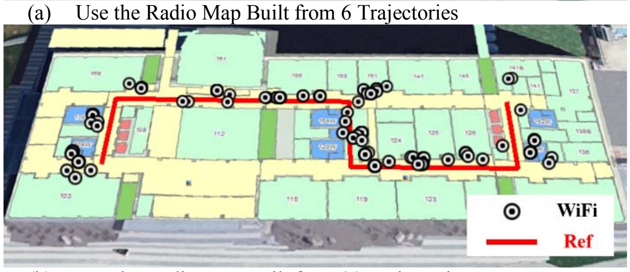
(a) Use the Radio Map Built from 6 Trajectories



(b) Use the Radio Map Built from 20 Trajectories

Fig. 8 WiFi Positioning Results of Trajectory II (Figure-Eight) by Using Different Radio Maps

(a) Use the Radio Map Built from 6 Trajectories



(b) Use the Radio Map Built from 20 Trajectories

Fig. 9 WiFi Positioning Results of Trajectory III (Figure-S) by Using Different Radio Maps

TABLE I. WIFI POSITIONING RESULT BASED ON DIFFERENT RADIO MAPS

Trajectory	Number of Trajectories for Radio Map	Mean Error (meter)	RMS Error (meter)
I	6	9.5	10.7
	12	6.4	7.4
	16	5.1	5.7
II	6	6.0	7.2
	12	4.2	4.8
	20	4.6	5.3
III	6	7.6	8.9
	12	5.5	6.3
	20	4.6	5.5

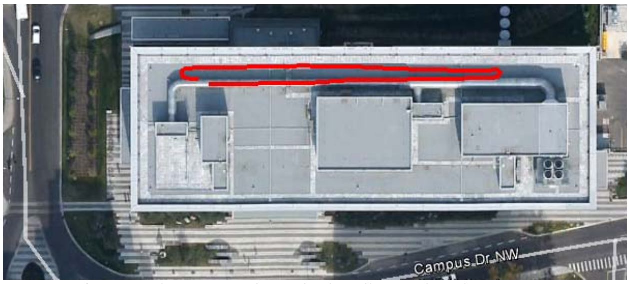


Fig. 10 East/West trajectory to show the heading estimation

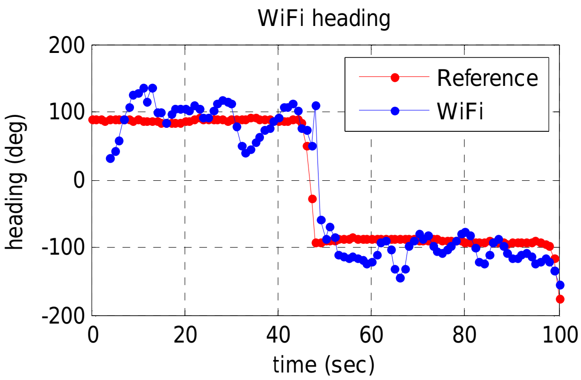


Fig. 11 WiFi derived heading in blue is provided with respect to a reference heading in red.

Fig. 10 shows a simple east west trajectory in EEEL that is used to display the WiFi heading estimation results. Fig. 11 shows the estimated heading from the WiFi algorithm provided in the methodology section of this paper. A reference heading is also provided in red to show that the absolute WiFi derived heading is accurate, though a bit noisy due to the nature of the WiFi measurements.

VIII. Conclusions

The paper presents an approach to WiFi positioning and heading update for smartphones. Firstly, a method of automatically generating fingerprints is presented based on the proposed software and the T-PN, which will run on the background of the smartphone. The fingerprints are used to build the radio map after specific selection and updating algorithms. This radio map generation is carried out by the normal mobile user, not the professional surveyor, which saves the costs of labor and time. Next, WiFi positioning is discussed, and its performance is evaluated through real-world tests. The result shows that the RMS value of WiFi positioning errors is less than 5.7 meters which proves the efficiency of the whole system. Another contribution of this paper is a method for estimating WiFi heading which shows promising results despite the inherent noisy nature of WiFi signals.

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