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Wi-Fi Positioning Using a Network Differential Approach for Real-time Calibration

Guenther Retscher
TU Wien – Vienna University of Technology
Phone: +43 1 58801 12847, Fax: +43 1 58801 12894
guenther.retscher@geo.tuwien.ac.at
Yan Li
The University of Melbourne
liy19@student.unimelb.edu.au
Simon Williams
RMIT University
Phone: +61 3 9925 1631
simon.williams2@rmit.edu.au
Allison Kealy
RMIT University
Phone: +61 3 9925 1261
allison.kealy@rmit.edu.au
Bill Moran
The University of Melbourne
Phone: +61 3 8344 4000
wmoran@unimelb.edu.au
Salil Goel
The University of Melbourne
sgoel1@student.unimelb.edu.au
Jelena Gabela
The University of Melbourne
jgabela@student.unimelb.edu.au

ABSTRACT

For Wi-Fi (Wireless Fidelity) Received Signal Strength (RSS) based indoor positioning, fingerprinting is one of the widely-employed methods which can offer relatively high positioning accuracy. However, conventional fingerprinting methods normally do the site survey once, which is not resistant to the dynamic environment change. Continuously updating the fingerprint database is a promising way to enhance the achievable positioning accuracy. For that purpose, a Differential Wi-Fi (DWi-Fi) scheme by analogy to DGPS is developed and applied.

DWi-Fi is a network calibration method based on reference station measurements, which is able to derive the area correction parameters in the triangle network of the three reference station. In this way, the recorded RSS measurements at the user's end are corrected, the fingerprinting database is continuously updated, thus to adapt to the possible changes in the dynamics of the environment,

In this paper, both static and kinematic tests using different devices are conducted to demonstrate the accuracy of the proposed system. Furthermore, the performance of the proposed DWi-Fi based fingerprinting algorithm is compared to the performance of the Hidden Markov Model (HMM) tracking system based on the histogram-probabilistic fingerprinting.

KEYWORDS: Differential Wi-Fi, Calibration, Fingerprinting, Networked approach, Wi-Fi localization

1. INTRODUCTION

Wireless Fidelity (Wi-Fi) is one of the most widely used signal-of-opportunity (Li and Rizos, 2012) which can be employed for positioning and tracking of mobile users if the required infrastructure is already available. In this paper, localization and navigation of a whole group of smartphone users within a neighbourhood is investigated. For that purpose, a fusion of localization technologies is proposed on the example of Wi-Fi positioning. A higher performance is achieved using a meaningful and careful selection of the advantages of location fingerprinting and trilateration. Within the scope of this study, the advantageous qualities of both methods are identified and selected to benefit their combination. The potential of this strategy is demonstrated on the basis of conducted experiments. Furthermore, inertial sensors embedded in smartphones are integrated to form a joint solution.

The paper is organized as follows: In section 2 the operational principle of Wi-Fi positioning based on fingerprinting and trilateration and the technical features of the two methods are identified followed by an assessment of the positioning characteristics and disadvantages as well as the proposed solution strategies in section 3. One of the solutions is the development of a differential Wi-Fi positioning approach termed DWi-Fi. In section 4 fusion approaches and in section 5 probability methods for user localization are discussed more in detail. Section 6 presents the field test site for the experiments and their characteristics. The major results of the experiments and their discussion are described in section 7. Finally, brief conclusions and an outlook on future work are given in section 8.

2. OPERATIONAL PRINCIPLE AND POSITIONING METHODS USING WI-FI

Wi-Fi developed originally for short-range wireless data communication implemented to extend or substitute for a wired local area network, such as Ethernet, it is a flexible protocol with a bandwidth of 11 Mbits operating at 2.4 GHz frequency. IEEE 802.11 is currently the most utilized Wi-Fi technology (Wang *et al.*, 2006). It is typically deployed as an ad-hoc network in a hot-spot fashion. Access points (APs) serve as central control point which forward traffic between terminals of the same cell and bridges traffic to wired LAN in the infrastructure topology (Kotanen *et al.*, 2003). The transmission power is the major factor that has direct influence on the effective range. The received signal strengths (RSS) and MAC (Media Access Control) addresses of the APs are location-dependent information that can be adopted for positioning (Chen *et al.*, 2012). For localization of a mobile device either cell-based solutions, referred to as either cell-ID or cell-of-origin (CoO), or location fingerprinting and trilateration are commonly employed (Retscher, 2016). As CoO can only provide positioning accuracies depending on the size of the signal coverage area (i.e, the cell where the mobile client is currently connected with) which is not accurate enough for the considered application, only the principle of operation of the other two techniques are discussed in the following.

The fingerprint-based localization technique is one of the most common solutions to RSS-based indoor localization where the measured RSS is used directly. It is used to improve indoor localization accuracy by collecting location related data of a scene or signal (i.e., fingerprints) in an off-line training phase. When one positioning request is received, it matches the current RSS fingerprint with the samples. The location of the closest sample is then referred as the location of the current position. The system RADAR developed by Bahl and Padmanabhan (2000) employed this approach for the first time in 2000. A database of measured RSS values is built-up which can be visualized in RSS radio maps. For that purpose RSS measurements on a large number of known reference points (RPs) distributed in the area of interest have to be carried out. Thereby RPs are usually chosen in a regular grid sized distribution. The disadvantage, however, is that this approach leads to high workloads as usually a large number of RPs have to be established to provide a suitable level of positioning accuracy. Thus, an approach introduced by Retscher and Hofer (2016) aimed to reduce the number of required RPs by selecting waypoints along possible user's trajectories to serve as RPs. These waypoints have been referred to as intelligent checkpoints (iCPs) by the authors. A reduction of workload by a factor of four compared to standard Wi-Fi fingerprinting is achieved while still keeping the same level of achievable positioning accuracies. The principle of operation is that the iCPs are the selected RPs which have to be passed along the way while navigating from a start point to the destination. Then always the following iCP is known due to a vector graph allocation in the fingerprinting database and only a small limited number of iCPs needs to be tested when matching the current RSS scans in the positioning phase. For iCPs along a corridor, for instance, constrains can be defined to make sure that iCPs could only be passed in the movement direction. This is to prevent them from being misrecognized, in case they are passed.

Trilateration uses range measurements to known locations where either one- or two-way travel times are converted into ranges between the unknown user's position and the known position (Liu *et al*., 2007). The location of the user is then obtained with the intersection of at least three spherical surfaces where the centres are the known locations and the radii the measured ranges. Apart from direct measurement of travel times ranges can also be derived from RSS measurements. The ranges to the Wi-Fi APs are then derived based on the nature of the RSS. Theoretically, the RSS decreases with the transmitted energy propagating into space. Path loss models can be employed to establish the relationship between the RSS and propagating distances. The limitation, however, is that these theoretical models are subject to free space propagation (i.e., line-of-sight LOS) or signal propagation in a simple environment with a limited number of reflections and obstacles (Retscher *et al*., 2012). Thus, the relationship between the RSS and the range should be derived empirically using RSS measurements in the environment where localization shall be performed.

As RSS measurements vary significantly over time and space in reality trilateration is affected by the current conversion of the RSS to a range tremendously. Due to the propagation media and the surrounding environment, the relationship may not follow the trend of the distance path loss model. To improve trilateration a differential approach is proposed by the first author where the signal variations are modelled in real-time. This approach is described in section 3.2 more in detail.

3. ASSESSMENT OF POSITIONING CHARATERISTICS

The main disadvantage in Wi-Fi positioning with fingerprinting and trilateration, however, is that its performance is significantly affected by the fluctuation and various propagation effects on the scanned Wi-Fi RSS values. Temporal and spatial variations as well as high signal noise caused by the surrounding environment and its changes lead usually to low achievable positioning accuracies on the several meter level (Stojanović and Stojanović, 2014). In this section, firstly the disadvantages and drawbacks of these two techniques are identified followed by solution strategies.

3.1 Challenges, Disadvantages and Drawbacks

As a result of the wide-spread use of Wi-Fi, hundreds of APs may be visible in the area where localization has to be performed. The number of APs are much higher nowadays because everyone can set up his/her own AP. The APs can be deployed using network adapters, PCs or even smartphones. Since many of these APs are not public, they are not promised to be stable. The ones set up by smartphones can even move around. It is hard to use them in localization algorithms if the environment contains many such APs. Thus, the increase in number of APs makes this environment more complex and uncontrollable, which brings several challenges (Chen *et al*., 2014); they are: (1) different types of APs may exist, such as multiple SSIDs where several networks at one physical AP are provided; (2) APs come and go; as time passes by, some APs disappear and new APs may emerge; (3) some APs might be temporarily unavailable due to various reasons; some may be replaced by new ones; and (4) different devices might increase the difficulty of positioning algorithms, as they may receive different RSS readings from the same AP, even at the same position and at the same time. All these cases lead to the variation of the number of APs. When the environment is crowded with hundreds of APs, the variation may become more significant, which might increase the positioning errors. Furthermore, it will be difficult to compare and match the fingerprints collected by other devices. Recent researches have attempted to use crowdsourcing (see e.g. Rai *et al*., 2012; Shen *et al*., 2013; Yang *et al*., 2012) to save the labour of sampling, which will also introduce device diversity to indoor localization algorithms. Chen *et al*. (2014) have investigated five fingerprint-based algorithms and analyzed their performance. The could see that the performance of localization algorithms in a real-world environment with hundreds of APs, could vary significantly due to the number of APs, time variance and different devices. Furthermore, the authors have shown that the number of APs could change significantly after a relatively long period, for example, after several months. Thus, a frequent re-calibration has to be performed.

As described above the IEEE 802.11b standard uses RF signals in the 2.4 GHz band, which is attractive because it is license-free, however, it does suffer from inherent disadvantages. In the 2.4 GHz band, microwave ovens, Bluetooth devices, cordless phones and other devices are sources of interference. Moreover, signal propagation suffers from server multipath fading effects due to reflection, refraction, diffraction and absorption by structures and humans. As a result, a transmitted signal can reach a receiver through different paths, each having its own amplitude and phase. These different components are captured by the receiver and a distorted version of the transmitted signal is reconstructed. Furthermore, changes in the environmental conditions such as temperature and humidity affect the strength of the received signals to a large extent. Consequently, the RSS values received by a Wi-Fi card at a fixed location vary with time and physical conditions of the surrounding environment (Chang *et al*., 2010). Furthermore, the presence of people and the user himself affects the scanned RSS values significantly. Signals of APs may be blocked or the RSS is lowered due to the body of the person to be localized. The main reason for this is that 2.4 GHz signals can be greatly attenuated by water which a human body consists. In general, RSS shows high variations depending on time and space. Non-line-of-sight (NLOS) conditions have server impact on the result for RSS to range conversion. For example, in an office building, metal window frames and pipes passing through rooms can be reflectors of Wi-Fi radio frequency signals. In real terms, the environment can be tremendously complex and therefore, difficult to deal with through the assumptions or conditions listed in the physical or theoretical models. These detrimental effects will degrade the accuracy of the distance estimated using the inversed path loss models (Retscher *et al*., 2012).

In general, location fingerprinting is more robust to environmental effects on the RSS than using the RSS-based trilateration algorithm. This is because the location fingerprinting algorithm constructs a search space according to either a simulated environmental model (e.g., a model of the building) or previously-measured RSS distributions in the radio maps using a site survey. If using only simulated physical environmental models where the distribution of the RSS is simulated by models, such as ray tracing, according to the given environmental conditions, the characteristics of every object in the building have to be defined. The major problem is that physical models cannot accurately represent the reality which leads to inaccurate RSS distributions and consequently degrades the positioning accuracy. Higher positioning accuracies can be achieved when a site survey is conducted in the training phase and with the measured RSS values the database of fingerprints is established. The advantage of constructing the database in that sense is that it can be used to consider a great number of detrimental effects from the surrounding environment, such as reflections and obstructions, into the radio maps and thus increases the accuracy for finding the best matching position based on RSS in the positioning phase (Retscher *et al*., 2012). As identified above the main drawback of fingerprinting is the very labour consuming workload in the training phase for establishing the fingerprinting database. Furthermore, heterogeneous mobile devices measure RSS differently. Spatial interpolation techniques are usually employed for densification of the database and the respective radio map and it is advisable that different mobile devices are used for RSS measurements in the training phase to form a joint database. Because of these disadvantages a new approach has been proposed by the first author where continuous RSS scans at reference stations are conducted.

3.2 Solution Strategies

The aim of this study is to achieve a performance improvement and reduction of the labour intensive RSS site survey in the training phase for indoor Wi-Fi localization and tracking using location fingerprinting and trilateration. Three different solution strategies as well as their combination are proposed; they are: (1) differential Wi-Fi trilateration; (2) use of relative RSS values instead of absolute numbers between consecutive epochs and different APs; and (3) fusion of fingerprinting and trilateration where the benefits of both methods are selected and combined.

In the first strategy, continuous RSS measurements performed at reference stations (RSs) distributed in the area of interest are used to derive and apply real-time corrections at the mobile user side. The differential approach is referred to as Differential Wi-Fi in analogy to the well-known Differential GPS operational principle. Instead of theoretical path loss models this approach utilizes continuous RSS scans carried out during the localization determination of the mobile user to improve the positioning accuracies and reliability of the solution

(Retscher and Tatschl 2016; Retscher *et al*., 2017). For a low-cost realization Raspberry Pi units serve as reference stations and APs at the same time scanning and emitting Wi-Fi signals. Using these devices the RSS scans are recorded together with their MAC addresses of the Wi-Fi APs continuously. On the smartphone the Combined Positioning System (CPS) App developed by Hofer (Hofer and Retscher, 2016) is used for the RSS scanning. The CPS App is able to record RSS values and the smartphones' orientation as well as in a second module RSS values continuously together with the smartphone inertial sensor data, i.e., the accelerations from the accelerometer, direction of movement from a combination of the magnetometer and gyroscope and the altitude with the barometric pressure sensor.

In all common RSS-based approaches scanned absolute RSS values are used either directly in fingerprinting or for the RSS to range conversion using path loss models in trilateration. A second solution strategy is proposed where relative RSS values instead of absolute numbers either between consecutive epochs or different APs are used. If different APs can be received at a certain location the RSS values can be ordered in dependence of their RSS of the AP. At a second location in the area of interest the order is most likely different. Then the difference in order of the AP RSS values between the different locations can be used to match the current RSS measurements to the correct location. Consider, for example, a descending order of RSS where AP1 has higher values than the other APs. On a different location this order might be reverse. If the difference is significant then it is easier to determine where the smartphone is currently located. The difference in order results most likely from physical differences in building structures as in one room the situation is completely different than in another room. Furthermore, different consecutive epochs of RSS measurements might be considered in assignment of the correct location. Due to the significant temporal variation of RSS it is then easier to match the users' location to the correct one. If one considers long-time measurements of RSS at reference stations in real-time the change of RSS of all visible APs can be determined during the current measurements of the user. This approach leads to the third strategy, i.e., the fusion of different localization techniques.

The third strategy is a proposal for the fusion of the location fingerprinting and trilateration techniques combining the advantages of both methods (Retscher, 2017). In short, RSS observations are performed continuously on the aforementioned RSs and used to derive dynamically changing radio maps in real-time. Thus, no training phase requiring high workloads and frequent re-calibration as in standard fingerprinting is required. Further details are discussed in the following section.

4. FUSION APPROACHES

4.1 Integration of Fingerprinting and Trilateration

As aforementioned, a common challenge for all RSS based positioning methods are the large temporal and spatial variations of the radio channel. Thus, dynamically updated radio maps of RSS distribution for the area of interest are derived from continuous RSS observations at deployed RSs. A modelling is performed by derivation of so-called area correction parameters – referred to as Flächenkorrekturparamter (FKP) – as it is done in a Continuous Reference Station (CORS) network for real-time positioning using GNSS. To be able to deduce the FKPs in triangular networks with three RSs each at least three RSs are needed to cover the whole area. If dynamically updated radio maps of the area of interest are derived then it is possible to reduce the signal fluctuations and noise in real-time. If in fingerprinting the radio maps are derived in several training phases at different epochs with a large time period between them only long-time changes of the RSS to the visible APs are considerable, for example, caused by changes in environment. These radio maps cannot account for short-time variations of the signal. Therefore in the new concept the radio maps are always determined and updated in real-time from the RS measurements. This approach can be seen as fusion of location fingerprinting and trilateration as the currently determined radio maps are used to derive the ranges to the APs and RSs. A prerequisite is only that the location of the APs and RSs need to be known. They have to be surveyed only once. As already mentioned in section 3.2 Raspberry Pi units serve at the same time as APs and RSs scanning and emitting Wi-Fi signals. This is a very low-cost solution. As an example, Retscher and Roth (2017) have presented radio maps derived at two different epochs with a time interval of one hour between them. They saw that the RSS distribution has changed and the absolute RSS values are significantly higher in one neighbouring room than in another. Furthermore, the RSS values in the radio maps depend on the hardware of the mobile device. A second smartphone showed a different behaviour. The RSS were not that distinctive as with the first smartphone in the different rooms. This dependence on the used mobile device can be reduced if the radio maps derived from the Raspberry Pi units are used. A requirement, however, is that the device must be calibrated and the relationship of the RSS scans between the mobile devices and Raspberry Pi units at the reference stations must be empirically defined. This can be done on calibration baselines similar as performed for the derivation of the RSS to range relationship.

4.2 Combination with Inertial Navigation (IN) and iCP Detection

Furthermore, an integration with inertial navigation (IN) using the accelerometer, gyroscope and magnetometer available in smartphones is proposed. Then the iCP detection can be employed for absolute positioning to update the inertial smartphone sensors and to reduce their drift rates (Retscher and Hofer, 2017). To use an iCP to correct an IN position obtained via dead reckoning (DR), the passing time has to be determined as precise as possible. The implemented iCP/IN algorithm uses specific information about the structure of a building in the case of indoor navigation. In that, the obtained values of the orientation sensor or the step length are calibrated. Then the step length is automatically corrected if someone climbs the stairs in a building, for instance. The concept of the use of intelligent checkpoints (iCPs) as RPs in fingerprinting was briefly discussed in section 2. In the following the integration with IN is elaborated. Data from smartphone sensors can be used additionally to make the iCPs even smarter and improve the position estimate of the user. For example, also the passing orientation of the iCPs for the recognition can be used because doors can only be passed with a certain orientation. Furthermore, it has to be recognized which iCP is passed at what time. The better the recognition of these waypoints, the higher the positioning accuracy. Using IN a continuous position estimation is achievable via pedestrian dead reckoning (PDR). For that purpose the smartphones inertial sensors; i.e., the accelerometers, gyroscopes and magnetometer, are employed for estimating the distance travelled using step counts and the direction of movement using the heading information from the orientation sensors. If these sensors are integrated with the Wi-Fi position estimates the accuracy for user localization can be significantly improved. The implemented iCP/IN algorithm by Hofer and Retscher (2016) uses specific information about the structure of a building for indoor navigation. For instance, for iCPs selected along a corridor the condition can be formulated that iCPs can only be passed in the movement direction. This is to prevent them from being misrecognized, in case they are passed. In such a way, the obtained values of the orientation sensor or the step length are calibrated. Moreover, DWi-Fi trilateration can be integrated with IN and iCP detection. This approach was firstly presented by Retscher *et al*. (2017). Figure 1 illustrates the integration levels of the three localization methods. As the measurement errors of IN are cumulative the resulting drifts grow with time. A simple trajectory is shown which starts at a known start point or at a previously passed iCP. The growing sensor drift with time and the resulting position estimates from PDR are represented by an envelope around the known trajectory. From DWi-Fi positioning a position estimate is obtained with its corresponding confidence region. The intersection of this confidence region and the possible current IN region defined by the envelope around the trajectory results in the intersecting cell between the DWi-Fi and IN solutions. If the following iCP is reached, an update of the dead reckoned position estimate located in the DWi-Fi and IN intersecting cell can be performed. An iCP location has a sphere of influence around it which is a circular cell whereby the cell size depends on the Wi-Fi RSS difference obtained from RSS observations. This region represents also an accuracy for the iCP detection and the cells can have different sizes depending on the changes of the RSS values of the surrounding visible APs. By intersecting this cell with the DWi-Fi and IN cell a smaller cell (depicted with yellow filling) is obtained describing the current possible user location. For the final position estimate of the users' location the known coordinates of the iCP are then chosen as the user has now reached this cell. Thus, the drift of the IN is corrected and the position estimate is updated as the user passes by the iCP. From this location the user moves on to the next iCP where another update of the position estimate is performed. This process is carried out until the user reaches his desired destination. Thus, navigating along a trajectory becomes more precise and reliable. Even if a user makes a sharp turn, for example at a corner, and an iCP is located there, the approach is capable to determine the turning as the inertial sensors measure the heading of the user.

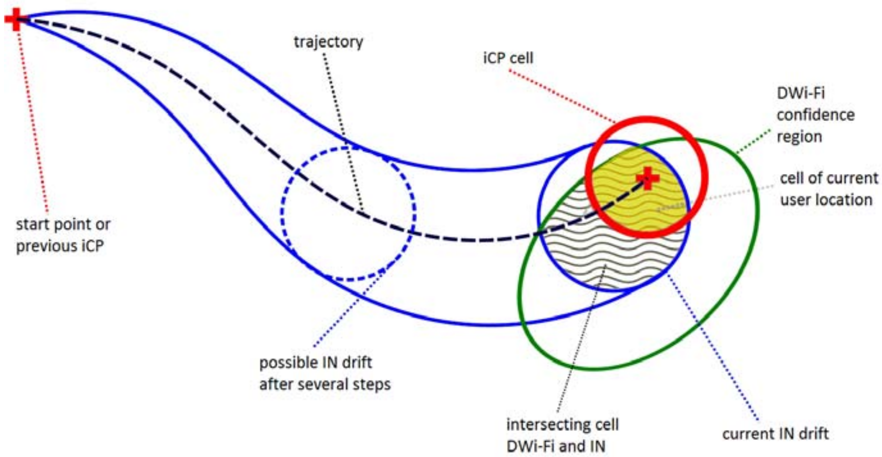

Figure 1. Schematic illustration of the integration of DWi-Fi, IN and iCP detection (Source: Retscher *et al.*, 2017)

5. PROBABILITY METHODS FOR LOCATION ESTIMATION

In a tracking application, estimation of the state of a system is based on a sequence of noisy measurements made on the system. Bayesian filtering employing probabilistic techniques are one strategy to estimates the states of a dynamic system with measurement noise. It is also applicable to sensor integration consisting of many different types of measurements to achieve higher accuracy. In the following, the Hidden Markov Models (HMM) is introduced and discussed for such type of application.

5.1 Principle of the Hidden Markov Model (HMM)

Compared with other Bayesian filtering technologies HMM has advantages of non-Gaussian assumption and computation efficiency (Seitz *et al*., 2010). Wi-Fi RSS is used as the observations, while the hidden states can be Wi-Fi fingerprints (Liu *et al*., 2012) or the reference points (Park *et al*., 2011). PDR is also introduced in (Seitz *et al*., 2010) to generate the state transition matrix. The graph structure which represents the environment, defined by vertices and edges is proposed in (He *et al*., 2015). In particular, the HMM is more feasible to estimate the motion with free moving restrictions (Seitz *et al*., 2010). The formal definition of a HMM is as follows (Rabiner, 1989): Let $s_1, s_2, \ldots, s_t$ be the sequence of hidden states in the state set S, which constitutes the user moving trajectory in specific in the case under consideration at time t. Given an observed Wi-Fi RSS sequence $O = o_1, o_2, \ldots, o_t$ up to time t the model is characterized by parameters $\Lambda = \{A, B, \pi\}$ where A is the transition probability matrix characterizing the state transition probability independent of time and B the emission probability matrix characterizing the observation probability of an observation given its state. They are defined by the following equations (1) and (2), respectively:

$$A = [P(s_t|s_{t-1})] \quad (1)$$

$$B = [P(o_t|s_t)] \quad (2)$$

π is the initial state probability and normally set to:

$$\pi = P(s_1) = \frac{1}{N}, where\ N\ is\ the\ number\ of\ states\ in\ S \quad (3)$$

In the HMM-based tracking system, the Viterbi algorithm (see e.g. Forney, 1973) is applied to calculate the maximum posteriori estimate of the path given the observation sequence.

5.2 Histogram Probability

The fingerprinting method normally averages the Wi-Fi RSS measurements for each AP in stored signatures, assuming a uni-modal distribution of RSS. Another drawback for fingerprinting is that it is not consistent to dynamic environment changes. While using a histogram of signal strength RSS for a signature at a RP instead may offer a more accurate description of the environment as histogram represents various levels of RSS by storing a large number of signatures (Correa et al., 2008). The histogram method is closely related to discretization of continuous values to discrete ones. Firstly, select a room (or a part of the corridor) in a building and take lots of RSS measurements in this room. Then quantize the measurements for each AP into m values, i.e. m bins, which is a set of non-overlapping intervals that cover the whole range of the RSS measurement. Thus, the quantized measurements, i.e., RSS levels for each AP, are received. Here equal width-bins for simplicity are used. Now the probability of each bin given the user is in the room is the normalized count of measurements in that bin from inside the room:

$$P(RSS \in ith\ Bin) = \frac{Count(ith\ Bin)}{size\ of\ training\ data} \quad (4)$$

In this study, a room-based histogram probabilistic method is proposed to estimate the likelihood function $p(z_k|x_k)$. In the training phase, it creates a Wi-Fi fingerprint for each cell of a building. In this way, the labour consuming workload can be reduced relatively since the grid step can be skipped, as it is not necessary to measure or scale the area nor know the true dimension of the floor. Multiple scans, however, are still needed at multiple reference points to create the histogram for each AP. In this stage, RPs within the room are chosen randomly and Wi-Fi signals at each point are collected regardless of the user direction. The online navigation phase matches real-time received Wi-Fi signals to the room fingerprints to determine the user's most likely location. It uses maximum likelihood classification for this matching. Likelihood of a vector of measurements $Z = \{z_1, z_2, \ldots, z_n, n \in N_{ap}\}$ for a hypothesize room within the building $l_k, k \in N_{cell}$ that the user is in, where it is assumed that the AP signal strength are independent, is described according to the Bayes' rule by:

$$p(l_k|Z) = \frac{p(Z|l_k)p(l_k)}{P(Z)} \tag{5}$$

$$\begin{aligned} \max_k(p(l_k|Z)) &= \max_k(p(Z|l_k)) \\ &= \max_{k,i\in m}\left(\prod_{n=1}^{N_{ap}} hist(Z_n \in ith\ Bin)\right) \end{aligned} \tag{6}$$

5.3 Practical Course of Action

Using the histogram matrix computed at the training stage as a look-up table, then the emission (observation) probability for each timestamp is computed. Note, if within one scan, some APs are non-visible, a value of ZERO is assigned to them, and they are not included into the emission probability computation. For example, if a Wi-Fi scan at some timestamp is [-61, -58, -45, 0, -78, 0, 0], where the zero values are added manually, which means that AP 4, 6 and 7 are non-visible, then the probability for the measurement at RP_j is computed as :

- Measurement is a vector of length m at each test point, $m \leq 7$
  $O = (O_1, O_2, ..., O_m)$
- m is visible AP, if non-visible AP, assgin $RSS = 0dB$
- Compute the emission probability for given observation.
  $P(O|RP_j) = \prod_{i=1}^{m} P(O_i|RP_j), j \in 1:10$

  For example, observation in one scan is
  $O = [-61, -58, -45, 0, -78, 0, 0]$,
  AP 4&6&7 is non-visible
  Emission probability:
  $P(O|RP_j) = Hist_{AP1} \times Hist_{AP2} \times Hist_{AP3} \times Hist_{AP5}$

6. FIELD EXPERIMENT SET-UP AND TEST SITE

In the practical evaluation, static and kinematic tests using seven App users carrying different smartphones were conducted in a part of Queen Victoria Market (QVM) in Melbourne, Australia. Seven Raspberry Pi units served as reference stations. In total 16 reference points were distributed along a circular trajectory with a test grid of 4 m around the centre part of shops comprising of four corridors. Figure 2 shows a map of the test bed indicating the location of the sensors and the 16 reference points, referred to as stop points in the Figure. In the experiments stop-and-go as well as kinematic measurements of the moving users were conducted. In the stop-and-go mode up to 10 RSS scans on each reference point were carried out. Each user started at a different RP. In contrast, in the kinematic mode a continuous recording of the RSS scans was performed while the users were moving in the test area. In addition, the inertial sensor observations from the smartphones were recorded with the CPS App. Thus, also inertial navigation could be performed in the kinematic tests. Table 1 summarizes the types of smartphones used and the start reference point for the different users. In another experiment, six static and two moving Ultra-wide Band (UWB) units were used. In this scenario, stationary stations serve as either a reference or in order to be integrated into the overall positioning solution. These observations, however, are not used in the presented solution in this paper. Ground truth for these experiments was measured using a robotic total station.

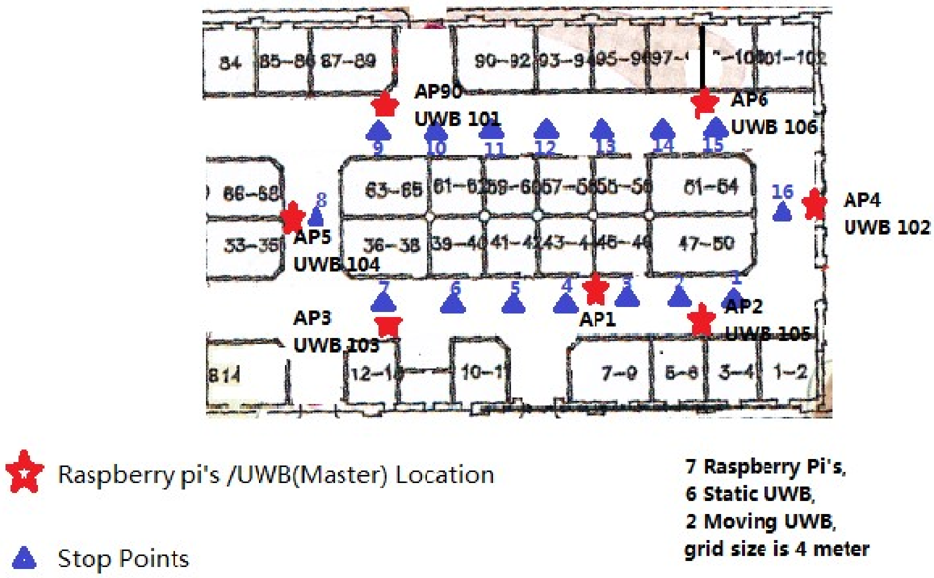

Figure 2. Sensor location in Queen Victoria Market

User ID	Smartphone	Start reference point
1	Sony Xperia Z1	1
2	Samsung Galaxy S3	3
3	Samsung Galaxy S3	5
4	Motorola G3 – MotoG3	9
5	Huawei Mate 7	11
6	Huawei Honor 8	13
7	Samsung Galaxy GT-S7262	15

Table 1. Smartphone user configuration and start reference points

7. EVALUATION AND DISCUSSION OF TEST RESULTS

7.1 Matching Rate for Stop-and-go User Trajectory

1310 stop-and-go observations were recorded in the Queen Victoria Market which were merged as training measurements except for the last epoch. The observations of the last epoch were used to test the positioning performance in the on-line positioning phase. Table 2 summarizes the results. As can be seen the matching results can differ quite significantly as the range from about 76 to 100%. Table 3 shows the detailed results from which can be seen more clearly which points were mismatched.

Bin number	Test data User ID	Matching rate [%]
7	1	100.00
	2	76.47
	3	100.00
	4	88.24
	5	88.24
	6	100.00
	7	82.35

Table 2. Matching rates in [%] for the seven used smartphones

Test data User ID	Start point	Result	
1	1	HMM result is	10 11 12 13 14 15 16 1 1 2 3 4 5 6 7 8 9
		True trajectory is	10 11 12 13 14 15 16 1 1 2 3 4 5 6 7 8 9
2	3	HMM result is	11 12 13 14 14 15 16 1 2 3 3 4 5 6 7 8 9
		True trajectory is	10 11 12 13 14 15 16 1 2 3 3 4 5 6 7 8 9
3	5	HMM result is	11 12 13 14 15 16 1 1 1 2 3 4 5 6 7 8 9
		True trajectory is	10 11 12 13 14 15 16 1 2 3 4 5 5 6 7 8 9
4	9	HMM result is	11 12 12 13 14 15 16 1 2 3 4 5 6 7 8 9 9
		True trajectory is	10 11 12 13 14 15 16 1 2 3 4 5 6 7 8 9 9
5	11	HMM result is	11 11 11 12 13 14 15 16 1 2 3 4 5 6 7 8 8
		True trajectory is	10 11 11 12 13 14 15 16 1 2 3 4 5 6 7 8 9
6	13	HMM result is	10 11 12 13 13 14 15 16 1 2 3 4 5 6 7 8 9
		True trajectory is	10 11 12 13 13 14 15 16 1 2 3 4 5 6 7 8 9
7	15	HMM result is	12 12 13 13 14 15 15 16 1 2 3 4 5 6 7 8 9
		True trajectory is	10 11 12 13 14 15 15 16 1 2 3 4 5 6 7 8 9

Table 3. Detailed results of matching success

The major limitation in these results is that the training size is very small, i.e., only 80 Wi-Fi scans in maximum for each RP, which seems to be not enough for a histogram probability computation. Any route grammar in the data processing cannot be included because of the assumption of the floor plan constrains while only one trajectory was available. Furthermore, it could be seen from the tests – as expected – that the evaluation of the stop-and-go observations is easier to implement because the ground truth is already known while for the kinematic data the true coordinates for those points between two reference points are unknown. Moreover, the stop-and-go observation data does not include inertial sensor data which will be used in the next stage. In further investigations it is planned to segment the test area into four cells. Then more training observations are available per cell other than at the 10 RPs. For these results the HMM will provide then a coarse result that whether the observed Wi-Fi scan is taken within this cell or not.

7.2 RSS Classification

Figures 3 and 4 show box plots illustrating the classified RSS range of one smartphone and all smartphones, respectively, on all 16 reference points. As can be seen from Figure 3 for smartphone ID 1 the RSS readings differ quite significantly for each of the 16 reference points. This fact facilitates positioning as it is then easier to assign the correct RSS scan measurement in the on-line positioning phase as the AP differ in their RSS values. If one looks at all classified RSS range measurements for the 16 reference points in Figure 4 it is not easy to distinguish the different RSS values for each AP. Thus, as expected it is better if the RSS range is more distinctive for a certain smartphone than if not.

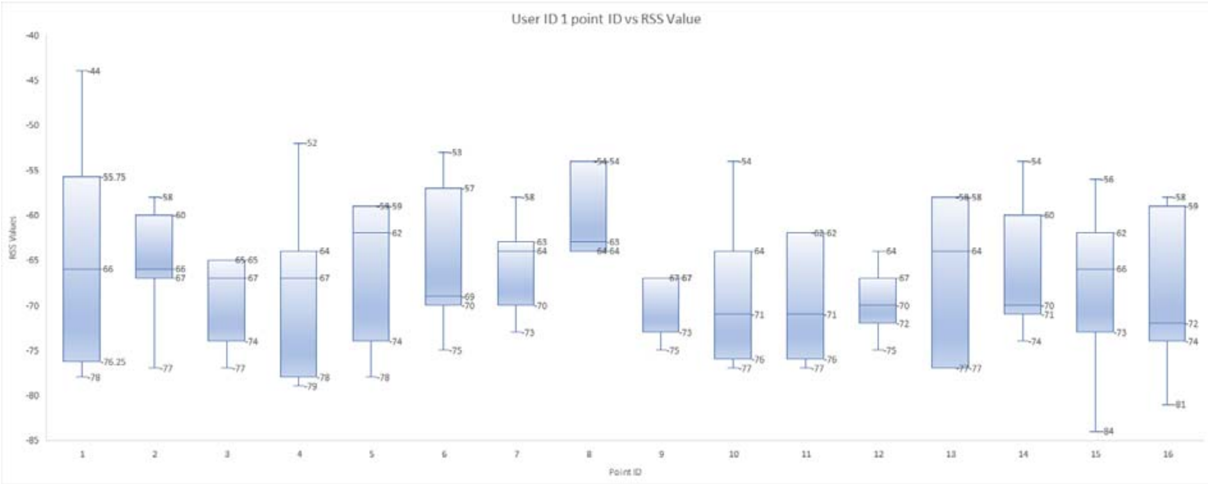

Figure 3. RSS range classification of one smartphone readings on all 16 reference points

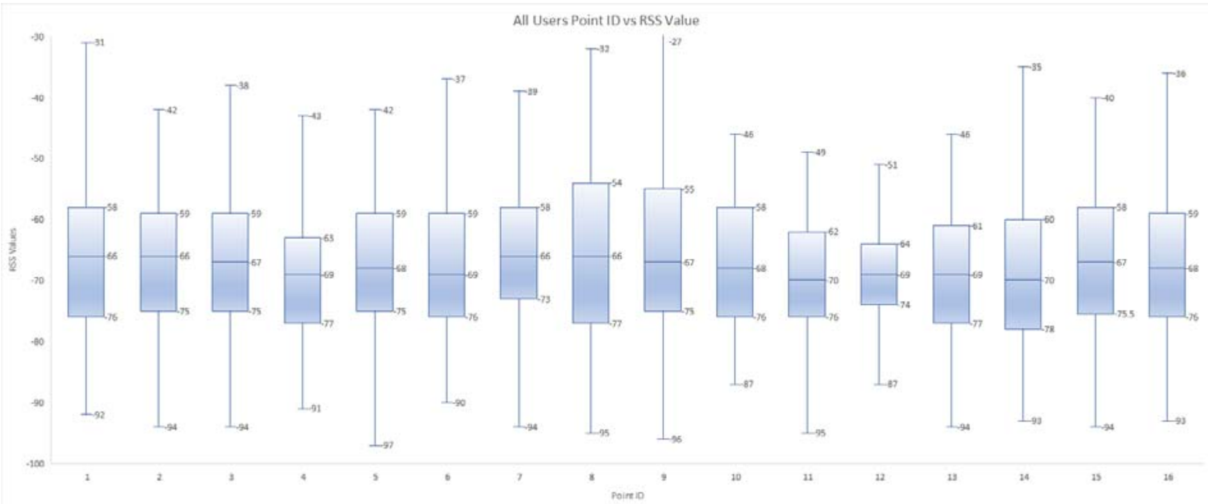

Figure 4. RSS range classification of all seven smartphone readings on all 16 reference points

The vast majority of current fingerprinting positioning methods does not take into account the interdependencies among the RSS measurements at a certain location from the various visible APs. These interdependencies, however, provide important information about the geometry of the environment and can be quantified using the second-order spatial correlations among the measurements (Milioris *et al*., 2010). In further analysis it was investigated if a considered interdependence of AP RSS values needs would lead to be better results. For these results see the paper of Li *et al*. (2018) presented at this conference.

8. CONCLUSIONS AND OUTLOOK

It is a novel method to adapt the temporal radio maps for indoor location estimation by offsetting the spatially and temporally variational environmental factors. Environmental variations, which cause the signals to change from time to time even at the same location, present a challenging task for indoor location estimation in the IEEE 802.11b infrastructure. In such a dynamic environment, the radio maps obtained in one time period in a single off-line training phase may not be applicable in other time periods. To solve this problem, a continuous recording of the RSS in real-time using Raspberry Pi units is proposed.

Experiments validate this approach (see also Retscher *et al*., 2017). The presented preliminary results indicate that highly successful matching rates up to 100% are achievable for observations on RPs in stop-and-go mode. Further analysis is conducted with more RSS measurements with a many more RSS samples of up 10,000 per room (or cell). For that purpose, a new measurement campaign was conducted at the Ohio State University, U.S.A., in the first week of October 2017.

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