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Quantized RSS Based Wi-Fi Indoor Localization with Room Level Accuracy

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ABSTRACT

The prevalent deployment of Wi-Fi infrastructure provides a potentially low-cost way to track Wi-Fi enabled devices in a building. Many indoor Location Based Systems (LBS) aim to get sub-meter precision for grid position estimation, however such accuracy is not necessary for some indoor location-aware applications, such as conference room identification and elder-care alert etc. Our system is designed to track the mobile user at room level granularity with high accuracy and reliability.

In this paper, a probabilistic fingerprint approach is proposed based on quantized Received Signal Strength (RSS) measurements. In the training phase, a histogram based radio map is constructed for each room by storing various levels of RSS. The motion dynamics of the user is modelled as a Markov process and a Hidden Markov model (HMM) is applied to track the mobile user, where the hidden states comprise the possible room locations and the RSS measurements are taken as observations. In the positioning phase, backtracking the trajectory of the user can be carried out by the Viterbi Algorithm.

Our proposed system does not need the prior knowledge of the true scale of the floor plan nor the true coordinate of each reference point (RP) within the room. The experimental results show that the offline labour consumption can be significantly reduced. The proposed approach can give the user location as high as 96.88% room accuracy based on a trajectory that covers 10 rooms and 32 test points.

KEYWORDS: Quantized RSS, histogram probability, Hidden Markov model (HMM), Wi-Fi localization

1. INTRODUCTION

The significant advance of mobile computing and communication techniques has boosted the development of a broad location aware applications, such as security management, intelligent guidance, fire rescues, and elder care monitoring etc.

Global Positioning System (GPS) has been widely used to provide location information in outdoor environments, but it cannot give reliable positioning services under indoor environment (Hightower and Borriello, 2001). Wi-Fi based localization system has attracted continuous attention because of the prevalent deployment of Wireless Local Area Network (WLAN) infrastructure and the extensive availability of Wi-Fi enabled mobile devices, which provides a potentially low-cost way to track a mobile user in a building.

Received signal strength (RSS) based Wi-Fi fingerprinting is a typical method used for location estimation, since it does not need any prior knowledge of access points (APs) deployment, neither explicit distance nor angle. The key idea is to get the best matching between the real time RSS measurements and the fingerprint database previously generated in the offline training phase (Dawes and Chin, 2011). Traditional Wi-Fi fingerprinting method involves a site survey before the test, which needs to grid the area and measure the grid size manually. In addition, fingerprinting method normally averages the Wi-Fi RSS measurements for each AP in stored signatures, assuming a Gaussian distribution of signal strength (Yim *et al.*, 2008, Frank *et al.*, 2009, Youssef and Agrawala, 2005), which is not always true as analysed in (Mirowski *et al.*, 2011, Chen *et al*., 2013, Vaupel *et al.*, 2010). Another drawback for fingerprinting method is that it is not consistent to dynamic environment changes, due to multipath effects and RSS fluctuations in complex indoor environments (Yang and Shao, 2015, Liu *et al.*, 2012, Chintalapudi *et al.,* 2010).

To get a reliable and accurate indoor localization system, advanced algorithms were developed in the recent decades. Differential Wi-Fi (DWiFi) is based on the principle of Differential GPS (DGPS), where positioning corrections can be deduced from reference stations deployed within a wireless network. The major advantage of DWiFi is that correction parameters can be applied in the conversion from RSS to range. Details can be found in (Retscher and Tatschl, 2017)

Bayesian filters are commonly used to fuse inertial sensors with Wi-Fi, and have been studied extensively (Han et al., 2014, Chen et al., 2015). The angular velocity sensed by the gyroscope is applied to obtain walking direction while the acceleration is used to detect each step. Particle filtering is not restricted to linear Gaussian conditions. A new particle is propagated from the motion model, the stride length and stride azimuth is estimated from the inertial sensors. With the aid of map information, the weight will be assigned to be zero if particle passes through the wall (Leppäkoski *et al.*, 2013, Wang *et al*., 2007)

Compared with Bayesian filtering, a HMM has no Gaussian assumptions and is more computational efficient (Seitz *et al.*, 2010). Wi-Fi RSS used as the observations, while the hidden states are the Wi-Fi fingerprints (Liu et al., 2012). Pedestrian Dead-Reckoning (PDR) is also introduced in (Seitz *et al.,* 2010) to generate the state transition matrix.

The vast majority of current indoor localization systems are designed for sub-meter accuracy in position estimation which is unnecessary for most indoor navigation (Pritt, 2013). Room-level or region-level granularity of location is sufficient for most location aware services (Haeberlen *et al*., 2004, Jiang *et al*., 2013, Castro *et al.,* 2001, Jiang *et al*., 2012).

All the systems mentioned above do not take into account the interdependencies among the RSSI measurements at a certain position from the various APs. These interdependencies provide important information about the geometry of the environment (Milioris *et al*., 2010, Mirowski *et al.,* 2014).

By further exploiting the interdependence among the RSS from different APs that are measured for the same cell, the proposed system employs a joint histogram probability distribution model that exploits the spatial correlations of signal strength measurements collected from various APs based on a multivariate quantized state model.

This paper proposes a Wi-Fi indoor localization system based on quantized RSS with room-level accuracy. Our system is implemented to achieve high room localization accuracy and reliability. By segmenting the indoor area into several cells, the system collects RSS from all visible Aps at various RPs within each cell and construct a quantized RSS based radio map for each cell. Unlike other approaches which assume the independency of APs, the proposed system also takes the AP interdependency into account when computing the joint histogram probability.

The remainder of the paper is organized as follows: section 2 depicts the proposed system architecture. Section 3 presents the experiment to verify the validity of the proposed algorithm. Followed by the limitation of the algorithm discussed in section 4. Section 5 draws the conclusion.

2. System Overview

This section presents the framework of Wi-Fi localization system based on quantized RSS measurement. With the segmentation of the floor plan, the area is divided into cells and connects according to the topology of the building. The proposed localization system with room level accuracy which identifies the room a mobile user is in, can be classified into two stages: offline training to construct fingerprint for each room and online positioning to localize the user by providing a sequence of observations.

2.1 Room Fingerprint

2.1.1 Data structure

The offline training phase is also known as calibration phase. A Wi-Fi fingerprint database is created for each cell using the signal strength measurements collected during the training phase.

Cell fingerprint, which involves Wi-Fi RSS collection at multiple RPs for each cell and fingerprint association with manually labelled cell IDs. The RPs are randomly selected within each cell and their location need not known.

Given a building with a set of cells R, and the total number of visible Wi-Fi APs is K. For a given cell $r \epsilon R$, a Wi-Fi measurement is a vector contains signal strength from K APs, denoted as

$$S_{r,j} = \{AP_1: Rss_{1,j}, AP_2: Rss_{2,j}, \dots, AP_{K-1}: Rss_{K-1,j}, AP_K: Rss_{K,j}\}, j = 1, \dots, M$$

M is the total number of measurements at cell r and could vary by rooms. Each AP is identified by its unique MAC address and $Rss_{i,j}$ is the signal strength value from AP_i in the j_{th} measurement. Note the RSS value is replaced with -101dB for those APs not detected in one measurement.

During the offline phase, the signal strength from all visible APs are intensively sampled at multiple RPs within each cell. The training data for cell r fused from all RPs will be stored in a $M \times K$ matrix denoted by $S_r = \{S_{r,j} | \, j = 1, \dots, M\}$.

2.1.2 Multivariate quantized RSS

The histogram is closely related to discretization of continuous values to discrete ones. Currently probabilistic histograms are estimated as marginal probability distributions, one for each AP. Under the assumption of local independence of APs, the quantization method treats the observation variable as one-dimensional (Roos *et al*., 2002, Meng *et al*., 2011).

Unlike other approaches, the proposed localization system aims to exploit the interdependencies among the RSS measurements in a cell from various APs. These interdependencies provide important information about the geometry of the environment as well as the covariance of measurements collected from pairs of APs (Milioris *et al*., 2014). Hence, the multivariate quantized RSS is proposed by taking the AP interdependencies into account.

The quantization requires to fix the number and width of bins, which is a set of non-overlapping intervals that cover the whole range of the RSS measurements. The number of bins is P. The width of each bin is given by $w = (max_{RSS} - min_{RSS})/P$. Here we use equal width-bins for simplicity.

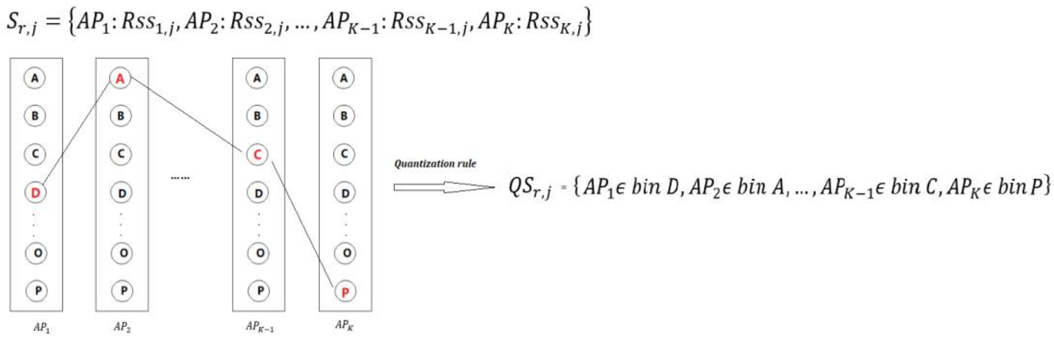

Figure 1. Quantization rule

Figure 1 presents an example of one Wi-Fi measurement quantization. Let $S_{r,j}$ be one measurement taken at cell r. The quantization rule is applied to each of the AP, and get the quantized AP state, i.e. determine which bin the AP belongs to. Note the A, B, C are all integers $\epsilon\ [1, P]$. Then the quantized measurement $QS_{r,j}$ is recorded as the sequence of the quantized AP states. Store all the quantized state tuple that appears in the training data for each cell, which is the quantized RSS fingerprint database for each cell.

The multivariate quantized RSS rule is depicted in Algorithm 1. Fix a cell r and each Wi-Fi measurement is a multivariate vector with dimension of K. Then each AP in one measurement is distributed into P bins. The quantized measurement is recorded as the quantized state for each AP, i.e. which bin the AP belongs to.

Algorithm 1 Multivariate Quantization Rule

Fix a cell $r \epsilon R$
S_r is a data matrix of $M \times K$
P bins with equal bin width of w
Bin Edges = $[min_{RSS}: w: max_{RSS}]$
For j = 1 to M **do**
  $measurement_j \leftarrow j_{th}\ row\ of\ S_r$;
  For i = 1 to K **do**
    $Rss_i \leftarrow measurement_j(i)$;
    Partition Rss_i into P bins $\leftarrow$ **quantization** (Rss_i, Bin Edges);
    Returns $Rss_i\ \epsilon\ p_{th}\ bin$, $1 \leq$ interger(p) $\leq$ P
    $Quantized\ measurement_j(i) \leftarrow Rss_i\ \epsilon\ p_{th}\ bin$
  End for;
  Return $Quantized\ measurement_j$
  $j_{th}\ row\ of\ Quantized\ S_r \leftarrow Quantized\ measurement_j$
End for;
Return $Quantized\ S_r$;

2.1.3 Joint histogram probability

The histogram probability of observing $o_t \in O$ given that the user is in state R_j is estimated as

$$\mathrm{P}(o_t | s_t = R_j) = \mathrm{P}((\mathrm{AP}_1 \epsilon\ bin\ p_1, \mathrm{AP}_2 \epsilon\ bin\ p_2, \dots, \mathrm{AP}_K \epsilon\ bin\ p_K)_t | s_t = R_j)$$

Most current existing probabilistic algorithms assume that the APs are independent where the observation probability becomes the marginal probability distribution of each AP as

$$\mathrm{P}(o_t | s_t = R_j) = \mathrm{P}(\mathrm{AP}_1 \epsilon\ bin\ p_1 | R_j) \times \mathrm{P}(\mathrm{AP}_2 \epsilon\ bin\ p_2 | R_j) \dots \times \mathrm{P}(\mathrm{AP}_\mathrm{K} \epsilon\ bin\ p_K | R_j)$$

By considering the interdependence between APs, a joint probabilistic histogram model is proposed based on the multivariate quantized RSS measurement. The fingerprint of cell r is defined as a set of joint probability distributions (one for each quantized state tuple) that are specific to the cell r. p_i is a set of bins that $\{p_i\} \epsilon\ [1, P]$.

$$P(\mathrm{AP}_1 \epsilon\ bin\ p_1, \mathrm{AP}_2 \epsilon\ bin\ p_2, \dots, \mathrm{AP}_K \epsilon\ bin\ p_K |\ r) = \frac{count(\ p_1, p_2, \dots, p_K)}{M}$$

Where $count(\, p_1, p_2, \dots, p_K)$ is number of times that the quantized state tuple $(\, p_1, p_2, \dots, p_K)$ appears in the entire training set divided by the size of the training set.
The joint histogram probability for the quantized state tuple in figure 1 is estimated as:

$$P\left(QS_{r,j}\right) = P(AP_1 \epsilon\ bin\ D, AP_2 \epsilon\ bin\ A, \dots, AP_{K-1} \epsilon\ bin\ C, AP_K \epsilon\ bin\ P) \tag{1}$$

$$= (count(D, A, \dots, C, P))/(size\ of\ S_r) \tag{2}$$

2.2 Building Topology

The segmentation rule is based on the building topology. Typically there is one cell per one room, and the corridor can be segmented into several cells depends on the length and connections with adjacent rooms. In addition, the segmentation rule classifies the floor plan into 3 categories: rooms, corridors and entrance/ exits. It constructs a logical link between rooms and corridors and provides a constraint of object movement.

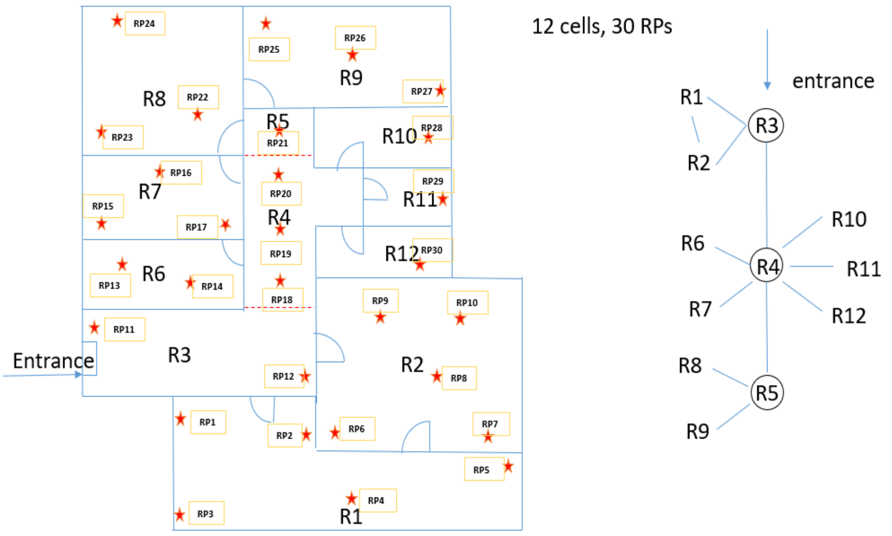

Figure 2. The home floor plan

The segmentation will define the transition matrix in the HMM such that only two adjacent cells would have non-zero transition probability while the transition probability between isolated cells is zero. The system does not attempt to determine the exact grid position of the mobile user but the cell that the user is in. In this scenario, the hidden states of the HMM are the 12 cells that enumerate the possible location of the user.

The example of floor plan and segmentation is shown in figure 2. The whole floor plan is divided into 12 cells, the long corridor is segmented into 3 cells which denote as R3, R4 and R5. There are 30 RPs in total, denoted by the star. The 30 RPs are randomly selected and their location is unknown, thus the number of RPs within each cell, is different. For example, there are only one RP in cell R5 (RP21), while 3 RPs in cell R4 (RP18, RP19, RP20).

2.3 HMM

The motion dynamics of the user can be modelled as a Markov process and a HMM is applied to track the mobile user, where the hidden states comprise the possible cell locations and the RSS measurements are taken as observations.

The formal definition of a HMM is as follows (Rabiner, 1989). The set of states are identical to the set of cells. Let $s_1, s_2, \dots s_T$ be the sequence of hidden states in the state set $\{R_i\}$ during a time sequence $t = 1, \dots, T$, which constitutes the user moving trajectory in specific in our case at time *T*. Given an observed Wi-Fi RSS sequence $O = \{o_1, o_2, \dots o_T\}$ up to time *T*. The model is characterized by parameters $\Lambda = \{A, B, \pi\}$.

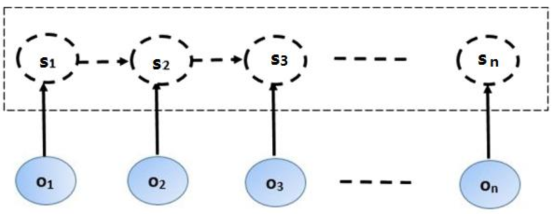

Figure 3. General HMM

A is the transition probability matrix. The segmentation rule based on the building topology is encoded in the state transition probability, which is the probability of the user move from cell R_i to cell R_j. If a given cell is linked to n other cells (including itself), then the probability of moving to one of these cells is defined to be 1/*n*, the probability of moving to other isolated cells is *0*. Here we use equal probability for simplicity.

$$A = [a_{i,j}], \qquad a_{i,j} = P(s_t = R_j | s_{t-1} = R_i)$$

B is the emission probability matrix, which stores the probability of each observation o_t being taken at cell R_j.

$$B = [b_j(o_t)], \qquad b_j(o_t) = P(o_t | s_t = R_j)$$

In the proposed system, the emission probability is a joint histogram probability based on quantized RSS measurement, which is introduced in section 2.1. Let Qo_t is the quantized measurement of o_t, get the emission probability by matching Qo_t with the quantized RSS fingerprint database.

$$b_j(o_t) = Hist(Qo_t) = \frac{count(Qo_t)_{R_j}}{size\ of\ training\ data\ of\ cell\ R_j}$$

π is the prior state probability.

$$\pi = [\pi_i], \qquad \pi_i = P(s_1 = R_i)$$

In HMM-based tracking system, the Viterbi algorithm is applied to find the optimal state sequence with respect to the Maximum a posteriori (MAP) criterion given the observation sequence.

3. Experiments and Results

The proposed approach was evaluated in a home environment in Melbourne, Australia, shown in figure 2.

Figure 4 is the interface of the Wi-Fi signal collection app (Retscher and Hofer, 2017), which shows an example of the total number of visible APs at RP1 in the first scan is 5, and the corresponding sensed AP MAC addresses and RSS values.

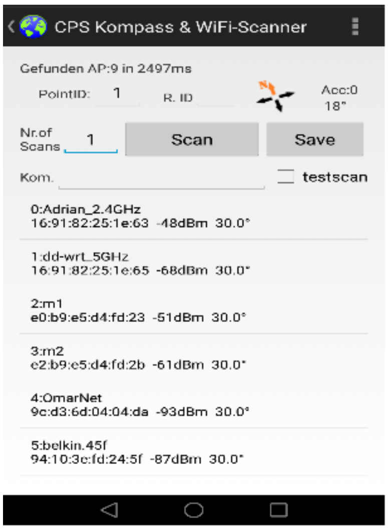

Figure 4. The interface of the collection app

3.1 AP Interdependence Analysis

At each RP, the phone was designed to collect 200 scans in static mode, each scan records the timestamp, point ID, the MAC address, the network name and the RSS values for all the visible APs. Fusing all available RPs' data within each cell to get the training data.

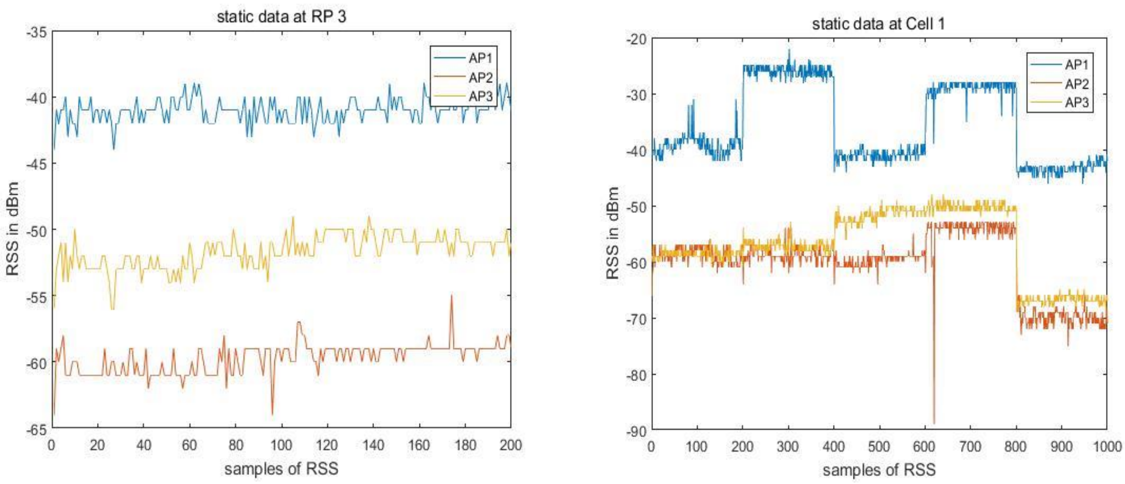

Figure 5. RSS samples from AP 1, 2, 3

To verify the interdependence of multiple RSSs, we compare the static data collected at RP 3 with the training data of cell 1 by fusing 5 RPs' static data. At RP3, the number of visible APs is 8 while the number of visible APs is 10 for the whole training set of cell 1. Intuitively, we chose top 3 APs that appears most of the time both in the RP 3 data and cell 1 data, which are AP 1, 2 and 3. The samples from each AP is shown in figure 5.

From the comparison result shown in table 1, the RSS properties of the three common APs are quite different at a single point and within a room. The RSS samples are more stable during the collection time and have smaller variations at RP 3 compared with the cell 1 data. The correlations between pairs of APs at RP3 are as small as 0.6 which is similar to the results given in work（Kaemarungsi and Krishnamurthy 2004）. However, the correlations between pairs of APs become large after fusing 5 points' data that we can no longer assume the RSS samples from the visible APs are uncorrelated, which also explains the proposed algorithm does not invoke the assumption of AP independence.

	Cell 1	RP3
number of scans	1000	200
number of visible APs	10	8
mean AP1 (dBm)	-35.69	-41.00
mean AP2 (dBm)	-60.33	-59.72
mean AP3 (dBm)	-56.94	-51.70
standard deviation AP1	7.03	0.95
standard deviation AP2	5.47	1.13
standard deviation AP3	5.95	1.26
Correlation (AP1, AP2)	24.39	0.25
Correlation (AP1, AP3)	19.32	0.17
Correlation (AP2, AP3)	27.15	0.60

Table 1. RSS properties comparison result

3.2 Static Test

We chose five scans randomly out of the 200 scans at each RP and exclude them from the training set. The remaining set was used to get the quantized RSS fingerprint database for each cell. The five scans we had removed from the training data are formed as the test set for each RP. We simulated the observation RSS sequences by designing different trajectories connected by several RPs, and randomly chose one scan from the test set to be the real-time RSS measurement at each RP. The distance between two selected RPs is at least 1.5 meters, and the normal walking speed for person is 1.4 m/s (Mohler *et al*., 2007), which matches the scenario that the user is with normal walking speed and the Wi-Fi measuring frequency is about 1 Hz.

In the static test, 6 different trajectories were designed to verify the propose algorithm. The first 4 trajectories were designed to move between adjacent cells, trajectory 5 and 6 were to simulate the situation that the user's location cannot be obtained for a short period of time.

Trajectory 1 was designed to cover 6 cells, connected by 20 RPs. The user always moved between connected cells where the transition probability is not zero. Trajectory 5 repeated trajectory 1 but miss one point. It jumped from RP 9 to RP 18 directly and skipped RP 12, shown in figure 6. Note RP 12 which is in cell 3 worked as a connection cell between cell 2 and 4. Trajectory 4 was a more complex trajectory move across 12 cells. Trajectory 6 was designed to repeat trajectory 4 but miss two points. Due to the limit of space, here we only list the trajectory 1 and 5 as an example.

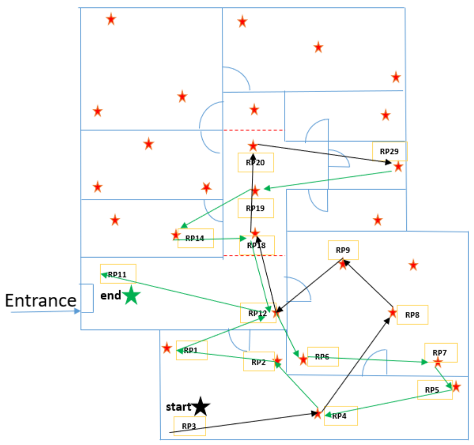

Figure 6a. Trajectory 1

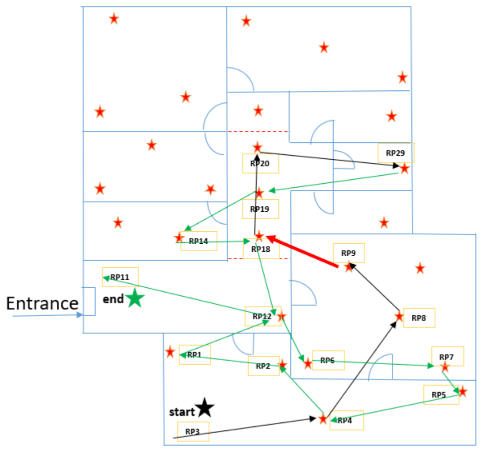

Figure 6b. Trajectory 5

In the following result analysis, we fix the bin number *P*=11.
Matching accuracy is defined as:

$$\text{Accuracy} = \frac{\sum_{n=1}^{N} Equal(s_n^{HMM}, s_n^{True})}{N}$$

Where

$$Equal(a,b) = \begin{Bmatrix} 1 & if\ a = b \\ 0 & otherwise \end{Bmatrix}$$

s_n^{HMM} is the n_{th} cell ID estimated by the HMM, while $s_n^{True}$is the true cell number. *N* is the total number of observations.

Table 2 gives the average accuracy for the 6 trajectories. We performed the experiments 50 times for each trajectory, choosing different scans as test set each time. The proposed algorithm based on HMM can still work properly when the system failed to get updated observation data for a short time. The accuracy decreased if the observation data in the transition cell is missing, however, the HMM based algorithm can always correct the path to the right cell ID in the next scan when backtracking the moving trajectory due to the topology employed in HMM.

Bin number	Trajectory	Cell number covered	RP number in total	Mean matching accuracy
11	1	6	20	94.30%
	2	10	25	93.20%
	3	10	32	96.88%
	4	12	30	95.00%
	5	6	19	91.58%
	6	12	28	87.21%

Table 2. Results for 6 trajectories

The accuracy for the proposed joint histogram probability is also affected by the selection of the bin numbers. Figure 7 gives the result of trajectory 1 by partitioning the RSS measurement into different numbers of bins. The test is also conducted for 50 times to get the average accuracy.

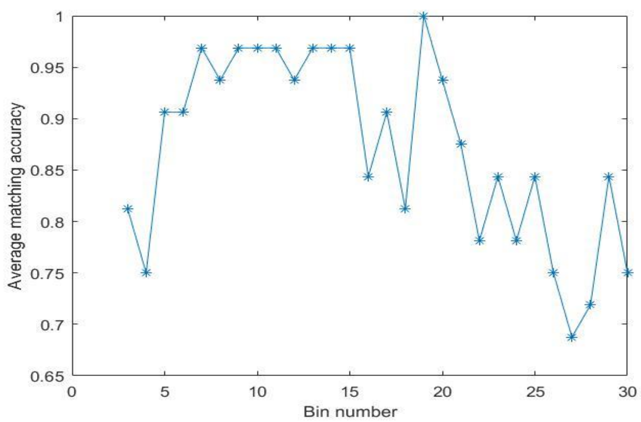

Figure 7. Bin number & matching accuracy

Generally a large number of bins will be more sensitive to the RSS variations while a small number of bins will be not accurate enough to represent the signatures of the cell and distinguish the neighbouring cells. However the relationship between the bin number and the final accuracy is not a simple monotonic increasing or decreasing function. Finding an optimal bin number is still an open question. Similar discussion can be found in (Meng *et al*., 2011).

4. Discussion

As discussed in (Youssef *et al*., 2002), the problem of the joint histogram distribution is that it requires a large training set as the number of possible quantized state tuple is P^K, $11^{\wedge 18}$ in specific for the test that 18 visible APs in the test area. Based on our analysis, currently we can get reasonable accuracy based on a limited number of measurements, there are the two possible reasons: 1. The APs can only be fall into several fixed bins but not all possible combinations.
2. The proposed algorithm gives coarse estimation rather than grid estimation, that we localize a mobile user to a cell instead of a point.

The statistical properties of RSS have been explicitly analysed in (Kaemarungsi and Krishnamurthy 2004). The independency of multiple RSSs from multiple APs is verified based on one-hour RSS measurements collected from three APs. According to their results, the correlation between each pair of RSS data are as small as 0.13, comes with the conclusion that the APs are independent.

However, such a conclusion cannot be made in general case where the number of visible AP is larger than 3 in the changing environment. A simple explanation would be an object moves around a certain position, the RSS measurements from all visible APs at that point will be affected simultaneously. In addition, the independency conclusion is made based on a single point static data which is not true in our case. As presented in section 2.1.1, the training data for each cell is collected by fusing the data collected at multiple RPs. Considering the spatial correlation of the RSS measurements from various APs, we conclude that pairs of the APs are interdependent, which is also coincident with the results presented in section 3.1.

The presented preliminary results indicate that highly successful matching rates up to 96.88% are achievable for observations on reference points in stop-and-go mode. Further analysis is conducted with more RSS measurements using crowdsourcing methods. For that purpose, a new test was conducted at the Ohio State University, U.S.A., in the first week of October 2017.

5. CONCLUSIONS

In this paper, we propose an indoor localization system based on quantized Wi-Fi RSS measurements. By considering the correlation between pairs of APs, the proposed joint histogram probabilistic fingerprinting algorithm can achieve as high as 96.88% matching accuracy and an overall of 94.85% successful matching accuracy with a limited number of training data. The proposed algorithm makes use of the building topology to construct a logical transition between rooms. The HMM is applied to track the movement of the user by taking quantized Wi-Fi RSS as observations. The further research interest will be analysing the interdependencies between the pairs of APs and comparing the performance of the marginal histogram probability based on AP independent assumption with the proposed joint histogram probability.

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