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Collaborative Wi-Fi fingerprint training for indoor positioning

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ABSTRACT:

As the scope of location-based applications and services further reach into our everyday lives, the demand for more robust and reliable positioning becomes ever more important. However indoor positioning has never been a fully resolved issue due to its complexity and necessity to adapt to different situations and environment. Inertial sensor and Wi-Fi signal integrated indoor positioning have become good solutions to overcome many of the problems. Yet there are still problems such as inertial heading drift, wireless signal fluctuation and the time required for training a Wi-Fi fingerprint database. The collaborative Wi-Fi fingerprint training (cWiDB) method proposed in this paper enables the system to perform inertial measurement based collaborative positioning or Wi-Fi fingerprinting alternatively according to the current situation. It also reduces the time required for training the fingerprint database. Different database training methods and different training data size are compared to demonstrate the time and data required for generating a reasonable database. Finally the fingerprint positioning result is compared which indicates that the cWiDB is able to achieve the same positioning accuracy as conventional training methods but with less training time and a data adjustment option enabled.

KEYWORD: collaborative positioning, indoor positioning, Wi-Fi fingerprint, SLAM

1. INTRODUCTION

With the advancement in smartphone technologies nowadays, location based services (LBS) are no longer just a trendy fashion of future fantasies. As LBS applications expand from military and government departments into commercial and normal everyday lives, the positioning and navigation coverage also moves gradually into more complicated environments and out of the working range of conventional Global Navigation Satellite Systems (GNSS). Over the years, different signals and methods have been be explored to achieve robust positioning in diverse environments [1-2]. Low cost inertial sensors, i.e. the accelerometers within smartphones, are handy gadgets to provide basic acceleration and heading data for pedestrian dead reckoning (PDR) navigation. Wireless network signal based positioning, such as Wi-Fi fingerprinting, have become widely applied in indoor positioning due to the high availability of Wi-Fi signals in urban environments [3-4].

A common problem with inertial navigation systems (INS) is the severe gyro drift that becomes increasingly obvious as time increases. Therefore a correction is usually applied [5-6]. On the other hand, Wi-Fi based positioning accuracy is not time related. However wireless signals can be unstable due to hardware and environmental influence, which causes inaccuracy in positioning [7]. A popular positioning method based on Wi-Fi signals is the Wi-Fi fingerprinting method, which provides positioning based on received signal strength (RSS) patterns in designated areas [8-9]. The user is required to train a database during the offline phase by collecting RSS from wireless access points (AP) in a number of selected locations known as fingerprints. During the positioning phase, the user compares the observed RSS to the pre-trained fingerprints for positioning estimation. The positioning accuracy relies on the applied positioning algorithm as well as the accuracy and up-to-date details of the fingerprint database. Therefore, in order to achieve accurate positioning, training for the database can be very time consuming. On the other hand, this method is inconvenient for a new environment or an environment where internal layout or AP locations may change frequently [9-10].

To reduce the time and human labour required for database training, Wi-Fi Simultaneous localisation and mapping (SLAM) has been applied [11-12] to enable a quicker way of learning the signal pattern around a new environment based on inertial measurements and building information. SLAM was originally applied in robotic navigation where robots learn the relative environmental features during navigation and enable quicker and more accurate positioning as the process carries on [13]. It allows the system to navigate in a new environment with no a prior knowledge of the environment. Features could also be learned with respect to maps when available. SLAM has also been applied to learn other features of the building for improved navigation solutions [14].

Whether positioning based on fingerprinting or Wi-Fi SLAM, it is vital that the positions associated with the fingerprints are accurate. Otherwise, the positioning solution could only become more and more biased.

Collaborative positioning improves user positioning accuracy and reliability by applying network constraints when the user has no prior knowledge of the signal fingerprints. A number of nearby users may form a network and the ranging measurements are measured between each user of the network. Corrections are applied to adjust each user position until they all obey the relative ranging constraint [15].

A SLAM-like collaborative Wi-Fi fingerprint database training (cWiDB) approach is introduced in this paper to enable a quicker and more accurate collection of RSS fingerprints. A network of mobile users that are in the same indoor environment achieves position estimations through pedestrian dead reckoning (PDR) measurements obtained from mobile devices. The PDR solutions of the users are constrained by relative ranging measurements among each other, which reduce the inertial measurement errors and biases, improving the positioning accuracy significantly as introduced in [16]. Meanwhile, each user collects Wi-Fi RSS and stores the measurement with the positioning estimation. A Gaussian Process (GP) regression [17] is carried out at certain epochs to generate fingerprints for the whole indoor environment based on the collected data. The collaborative positioning enhances positioning accuracy in a complicated environment thus can provide the positions for fingerprint training. Moreover, positioning robustness and flexibility is improved significantly, while users have the option of performing PDR, collaborative ranging or Wi-Fi based positioning based on available sensors and number of users.

This paper firstly introduces a Wi-Fi fingerprint training method through collaborative positioning. This is compared to a database ground truth to analyse how much data is needed for dynamic training. Various different training data is compared to verify the improvement collaborative positioning and Wi-Fi data collection is proposed to enable quicker data collection and reduce database training time. Finally, the positioning results based on the generated database are compared for analysis on the required amount of data for efficient database training.

2. WI-FI INDOOR POSITIONING

2.1 Wi-Fi positioning methods

Wireless network based positioning generally relies on two different methods: multi-lateration and scene analysis. Lateration requires the user to achieve ranging estimations from the receiver to multiple signal transmitters based on the signal strength path loss model,

$$P_{RX}(d) = P_{d0} - 10n \log_{10} d + a * WAF + \varepsilon \qquad (1)$$

where $\mathrm{P_{d0}}$ is the RSS at a reference distance, usually 1m away from the transmitter, n is the space loss factor which varies in different environments, WAF is the wall attenuation factor and a is the number of obstructions in between the receiver and transmitter, ε is a zero mean normally distributed noise. The position of the receiver is calculated based on the distance and angle between the transmitters and the receiver. Due to interference, multipath and obstruction inside buildings, wireless signals tend to be quite noisy. The actual observation $\widetilde{\mathrm{P}}_{\mathrm{RX}}(\mathrm{d})$ and the estimated $\widehat{\mathrm{P}}_{\mathrm{RX}}(\mathrm{d})$ from the model can differ more than 20dB which could lead to errors up to ten metres. This in result reduces the multi-lateration positioning accuracy, especially in an indoor environment.

A typical scene analysis method is the fingerprinting method, which consists of two steps. The first step is the training phase, where someone must select a number of training points within the area of interest and collect the actual signal strength $\widetilde{\mathrm{P}}_{\mathrm{RX}}(\mathrm{d})$ from all of the transmitters or access points (AP) which forms a signal pattern of the specific location. This not only takes into account the distance between the current location and the AP, but also the obstruction and interference in between, hence is unique for each location. These RSS patterns which indicate a specific location or area of the building are known as fingerprints and stored into a database. During the positioning phase, the user obtains the current set of RSS readings at the location that needs to be positioned and compare it with the fingerprints in the database. Usually the location of k fingerprints with the closest RSS to the current RSS, known as k-nearest neighbours (kNN), is obtained to estimate the current position.

Fingerprinting is able to take into account the fact that signals can be interfered by walls and furniture. As long as the affecting factor remains the same, the signal pattern will remain relatively stable. In fact, the uniqueness of fingerprints gives credit to the varying signal pattern produced by the disturbance from walls etc. Therefore, fingerprinting usually achieves better positioning performance. The biggest problem with fingerprinting is that training for the database requires a huge amount of human labour, which increases the risk of human error and also time cost. Moreover, the database needs to be re-trained and updated each time the infrastructure changes to maintain a valid database for positioning.

The collaborative training method discussed in this paper greatly reduces the training time and human effort by integrating the training data from multiple users at different locations and different training time. The fingerprint database for the building is then generated based on the training data using Gaussian Process (GP) regression. This enables a quick and efficient way of training the fingerprint database, which is also much easier to maintain and update.

2.2 Training the fingerprint database

Usually, the database is trained by selecting a number of locations, known as training points (TPs), which covers the entire area of interest. The user would put a data collection device, e.g. laptop, mobile phones etc., at each TP and collect a series of RSS vectors from each AP in the building. A large number of RSS should be collected at each location to gather enough information on the variance and stability of the signal from each AP over time. Each fingerprint vector is structured as $\{(x_n, y_n)|RSS_{n1}, \sigma_{n1}, AP_1, \ldots, RSS_{nm}, \sigma_{nm}, AP_m\}$. $(x_n, y_n)$is the position of the nth TP, $RSS_{nm}$is the mean RSS of the mth AP at the nth TP, σ_{nm} is the standard deviation of the mth AP at nth TP, AP_m is the unique identification of the AP, usually the MAC address. The uniqueness of the fingerprint is enhanced by the number of APs found and the amount of RSS collected.

Fingerprint-based positioning is achieved by searching through the database and finding the location that is most similar to the current RSS vector. Thus to achieve more accurate positioning results, the fingerprints should cover the floor plan in more detail, i.e. the more TPs the better. However, no matter how much TPs are selected, it is almost impossible to precisely cover the entire floor plan. A common way of selecting TPs is to divide the area into evenly distributed square grids. The RSS data is collected within each grid and assume that the RSS remains the same within the grid. Typical grid sizes are 1m×1m, 2m×2m [18]. Smaller grids ensure a more detailed database. However it will also be more time consuming.

A way of making up the data loss due to large grid size is to select sparse TPs and then generate the RSS at denser grid sizes by applying Gaussian Process (GP) as described in [12]. This is valid based on the assumption that the RSS from a certain AP is spatially correlated within a certain distance according to the path loss model.

If $\{\mathrm{x}, y\}$ are samples drawn from a noisy process

$$y_i = f(\mathrm{x}_i) + \varepsilon \quad (2)$$

where each x_i is an input sample and $y_i$is the target or observation value, ε is assumed to be a zero mean normally distributed noise. Gaussian process estimates the posterior distributions over functions f from the training data which is specified by a mean function $m(x)$ and a covariance function, or kernel $k(x, x')$. This is specified by the kernel which describes the correlation between two input values x_p and x_q . In this paper, the squared exponential kernel is applied,

$$k(\mathrm{x}_p, \mathrm{x}_q) = \sigma_f^2 \exp(-\frac{1}{2l^2}|\mathrm{x}_p - \mathrm{x}_q|^2) \quad (3)$$

where σ_f^2 is the signal variance, l is a length scale that defines the strength of correlation over a distance. The covariance function for observations is defined as

$$\mathrm{cov}(\mathrm{Y}) = \mathrm{K} + \sigma_n^2 I \quad (4)$$

where σ_n^2 is the Gaussian observation noise, K is the $n \times n$ covariance matrix of the input values thus $\mathrm{K}_{(i,j)} = k(\mathrm{x}_i, \mathrm{x}_j)$. The RSS observations and their locations are input into the system to train for the hyperparameters $\theta = \langle \sigma_n^2, l, \sigma_f^2 \rangle$ which define the functions based on the training data. Theses parameters are then used to predict RSS for other locations in the building during the prediction process based on the predicative distribution

$$p(y_*|\mathrm{x}_*, \mathrm{X}, \mathrm{Y}) = \int p(y_*|f(\mathrm{x}_*))p(f(\mathrm{x}_*)|\mathrm{x}_*, \mathrm{X}, \mathrm{Y})\mathrm{d}f(\mathrm{x}_*) \quad (5)$$

The locations of the TPs are input as X while the RSS are the target values Y. The building is divided into 1m×1m grids are included in x_* and the RSS at each location y_* is predicated based on the trained functions. The covariance of the predicted function is given by the covariance function.

3. METHODOLOGY

3.1 Database structure

Wi-Fi SLAM builds a relationship between the RSS of the mobile receiver and its estimated location. The signal measurement noise is assumed to be normally distributed and independent. The receiver scans for the Wi-Fi RSS while moving in the area of interest and associate this data with the location that it was collected. The collaborative training method is a SLAM-like method which performs positioning and trains the Wi-Fi fingerprints simultaneously through multiple users.

The fingerprint positioning solution is achieved by comparing the current RSS from available APs at an unknown location to the fingerprints in the database. Therefore, whether the fingerprints can accurately reflect its position is vitally important. As described in Section 2.2, the fingerprint structure typically consists of a reference location and the RSS from each AP at the location. Signal strength fluctuation means that the signal strength could vary over a range of 5dB to 10dB or even more at any single location when the equipment is static. Thus one single RSS is barely sufficient to act as a precise location indicator.

For gather a general idea of how much signal fluctuation to expect at a specific location, the training time should extend over ten minutes or even hours and days. This increases the time and labour cost. Training for the database collaboratively and during a positioning phase saves a huge amount of time and effort. However it does means that only one RSS will be collected at a specific location, or a scatter of RSS within a small area. Therefore the generated fingerprints will take the form of the basic structure without the signal fluctuation indicator σ_{nm}. Although this could mean that less information is provided as a positioning indicator initially, but further data accumulates quickly as training is operated collaboratively.

3.2 Collaborative training

Training for the fingerprint database is a very time consuming task and has to be redone to maintain positioning reliability when changes have taken place. The collaborative Wi-Fi fingerprint training method is introduced to reduce the training effort by integrating the information collected by a number of users into one system. This method firstly relies on the collaborative positioning among a number of mobile users to produce the reference positions for the RSS fingerprints. Fingerprints record the estimated position of the actual

RSS, the MAC address of each visible AP and the corresponding RSS.

The collaborative positioning algorithm is constrains the measurement error by applying a relative ranging constraint. Each user in the collaborative network propagates forward based on the PDR prediction model as in Eq.(6).

$$\begin{bmatrix} \hat{x}_k \\ \hat{y}_k \end{bmatrix} = \begin{bmatrix} \hat{x}_{k-1} + \hat{s}_{(t|t-1)} \cos \hat{\theta}_{(t|t-1)} \\ \hat{y}_{k-1} + \hat{s}_{(t|t-1)} \sin \hat{\theta}_{(t|t-1)} \end{bmatrix} \tag{6}$$

where $(\hat{x}_{k-1}, \hat{y}_{k-1})$ is the user position at time k, $\hat{s}_{(t|t-1)}$ is the step length estimation between time k-1 and k, $\hat{\theta}_{(t|t-1)}$ is the heading estimation during the step. Ranging estimations between users are obtained from other wireless signals and applied as a constraint to eliminate the inertial measurement error. The position estimation of each user within the network will be forced to a relative geometry which fits the ranging estimation. This in result increases the positioning accuracy and serves as the estimated position of the measured RSS.

The cWiDB method gathers the Wi-Fi RSS data from during the collaborative positioning process and stores the fingerprint data as training data. When a descent amount of training data have been collected to cover a certain area, the data is used to generate a fingerprint database for the area of interest. The GP output mean will be used as the fingerprint RSS for each location.

3.3.1 Fingerprint combination

The ranging measurement builds a link here between the collected RSS data. The training data from the users can be combined and applied in three different ways.

If the distance between the two users is above a separation threshold, it would be regarded that the users are not in the same area of interest. Their training data would be stored separately and used to generate individual database.

If their distance is within the separation threshold but above the integration threshold, their training data would be considered to be within the same area of interest. It would then be applied to generate a single database.

If the any of the collected training data distance is within the integration threshold, they would be regarded as correlated and adjusted to form one fingerprint for the database.

3.3.2 Fingerprint confidence factor

The standard deviations of all history training data that are within the integration threshold σ_{nm} is obtained periodically and acts as a confidence indicator for the fingerprints in the location. If the training data for any location appears to continuously differ from historical data and σ_{nm} remains a high value, it is considered that the Wi-Fi properties at that location have changed. Previous fingerprints will no longer be reliable and valid information for positioning, hence replaced by new fingerprints generated from new training data.

As the users are spread out in various locations within the area, the fingerprint database can be generated fairly quickly. The confidence factor for old fingerprints will be updated based on new data. The procedure is shown as below in Figure 1.

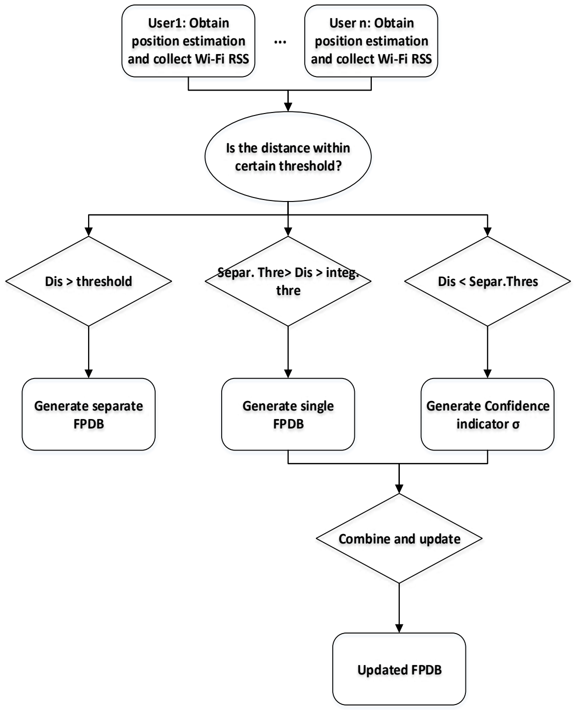


Figure 1 Flowchart for generating a database

4. TRIALS AND RESULTS

4.1 Conventional database

To understand the required density and location setup of the training data to generate an accurate fingerprint database, different training methods are compared. The same Toshiba laptop, where the wireless adapter is Intel® Centrino® Advanced-N 6200, is used throughout the trials. Four APs are located on Floor A of NGB, each transmitting signals at both the 2.4GHz and 5GHz frequency. As the signal characteristics are different on each frequency, thus the two different frequency signals will be treated separately. Hence a full database consists 8 MAC address groups, each denoted as AP1a (2.4GHz), AP1b (5GHz), AP2a, AP2b, AP3a, AP3b, AP4a and AP4b respectively, as indicated in Figure 2.

First of all, the conventional static training method is applied to establish a ground truth for the fingerprint database. These TPs are combined of two groups. The first group of 56 TPs are selected to cover the entire accessible areas in the Nottingham Geospatial Building (NGB) Floor A, which is around two TPs in a small office room and four to six TPs in a large room. The second group of 56 TPs in located in two specific rooms where one room represents an average meeting room with no obstruction and the other a heavily obstructed store room with metal shelves. The density of these TPs is 1m×1m, which is very detailed. During training, a laptop is placed at each location to collect the Wi-Fi RSS data for around fifteen to thirty minutes until at least 100 vectors from each of the four APs on Floor A are collected. The mean and standard deviation of all the collected RSS for each AP at each location is obtained and stored into the database. GP is then applied based on the training data to generate a denser database. The resulting database will be referred to as the static GP fingerprint database, denoted as sDB. This is the best possible solution for fingerprint database training as it covers the entire training area in detail but it is also very time consuming. Training for the 112 points requires almost five days. The selected TPs are shown in Figure 2 and the generated database for the 2.4GHz signal is shown in Figure 3.

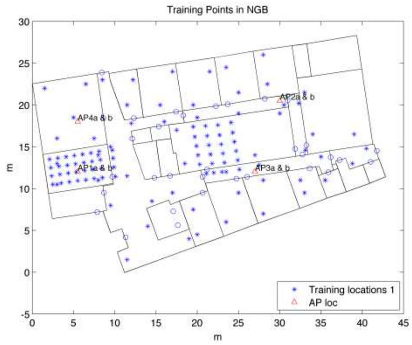
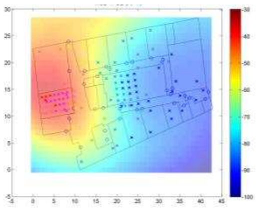
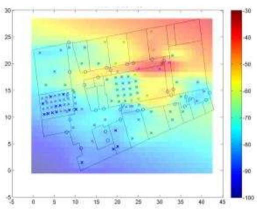


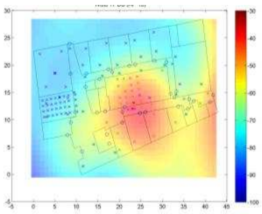
Figure 2 TPs for static DB



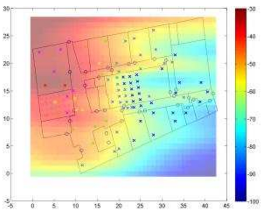
(a) AP1a



(b) AP2a



(c) AP3a



(d) AP4a

Figure 3 GPDB (sDB)

To verify how different the GP fingerprints are compared to the training RSS, the RSS at each TP is compared to the GP generated database fingerprints at various distances from the TP, i.e. from 1m up to 6m. 3 sets of values are listed in Table 1. We can see here that when the GP generated RSS is not over a distance limit from the TP location, the RSS is only slightly different from training data. Thus there is no need for 1m by 1m training. However, when the distance between the TP and the fingerprint is over 6m, the RSS difference does not increase. It actually remains the same level or even reduces slightly, which does not mean that a TP data can be used to generate fingerprints that are 10m away. It simply indicates that there is no correlation due to such a long distance.

Table 1 RSS Difference of TP and sDB (dB)

m	AP1		AP2		AP3		AP4	
	ΔRSS	**σ**	**ΔRSS**	**σ**	**ΔRSS**	**σ**	**ΔRSS**	**σ**
1	3.47	4.52	1.90	2.46	2.61	3.57	12.94	7.83
3	3.62	4.67	4.26	5.67	2.83	3.91	13.13	8.74
6	4.74	5.79	5.36	6.90	4.64	5.94	13.54	9.55

To examine the training quality based on different TP density in different environments, the TPs from the first group that lie in the two rooms mentioned above are extracted to generate a database for each room respectively. The training density for the first group is 4, i.e. 4TPs in a single room. The second group of TP density for the two rooms, R1 and R2, are 24 and 32 respectively. A second set of database is generated for each room based on the second group of TP. Table 2 lists the RSS difference between the first database and second database. Results show that for R1, which is the non-obstruction room, TP density does not affect the database quality too much. Therefore, less TP is required. The database quality for R2 is much worse due to obstructions inside the room. However, the databases for 5GHz signal give better performance in such cases.

Table 2 RSS Difference of different density (dB)

	AP1		AP2		AP3		AP4	
	a	**b**	**a**	**b**	**a**	**b**	**a**	**b**
R1	2.65	2.12	3.19	2.78	1.77	3.34	8.92	2.97
R2	10.94	3.77	8.00	7.65	17.68	12.62	8.16	5.89

4.2 Building the fingerprints

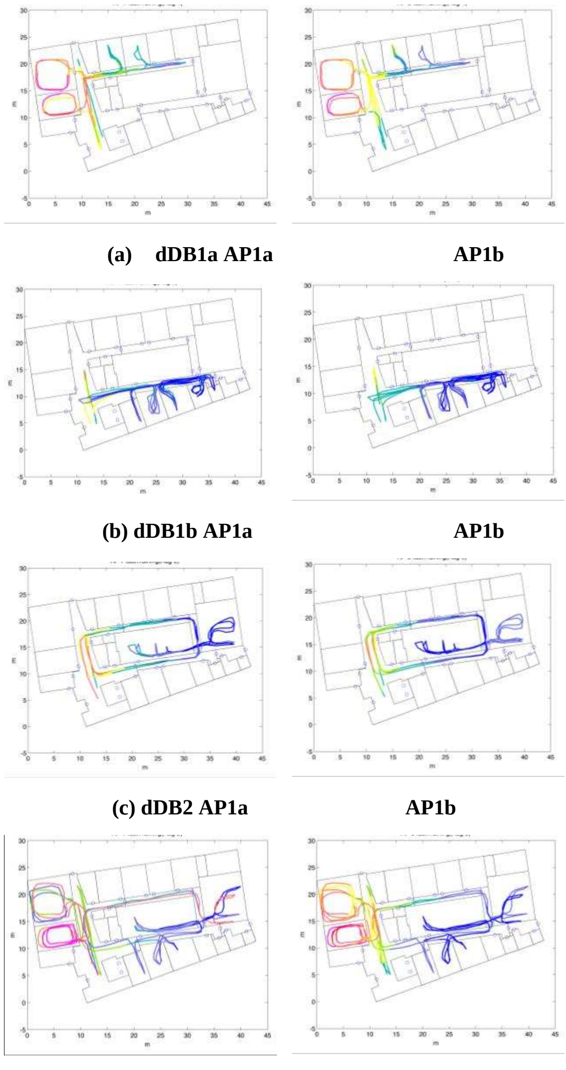
The dynamic training method is applied here, which is part of the collaborative training. Three different trajectories, denoted as T1, T2, T3 and T4, of varying length and locations within NGB Floor A are chosen as the training trajectory where training data will be collected during the collaborative positioning phase. Users follow each of the different routes and collect RSS data using a laptop respectively. GP is then applied to generate a fingerprint database based on the training data, which will be referred to as the dynamic database (dDB), denoted as dDB1a, dDB1b, dDB2 and dDB3 respectively. For experimental purposes, the training data will always be within the separation threshold. Thus they can be applied to generate one database.

The RSS difference between the data from the dynamic TPs and those static TPs from Section 4.1 that are within a certain distance are listed in Table 3. As signal acquisition is less stable while the receiver is moving and more disturbance occurs from the collecting person himself, therefore it can be anticipated that the dynamic training data is noisier. The RSS difference is within 15dB up to 3m between the TPs, which is within the RSS fluctuation range itself. Again, once the distance is over 4m, the variance drops and correlation fails.

Table 3 RSS Difference between dynamic and static TPs (dB)

	1m	2m	3m	4m
ΔRSS	9.85	12.55	13.39	19.36
σ	10.61	10.49	15.91	8.58

Figure 4 show the four different training trajectories where data is collected in 2-3 second intervals along the path and the colours specify the RSS of the collected data. Red indicates high RSS (highest is -30dB) and blue indicates low RSS (lowest -100dB).



(a) dDB1a AP1a **AP1b**

(b) dDB1b AP1a **AP1b**

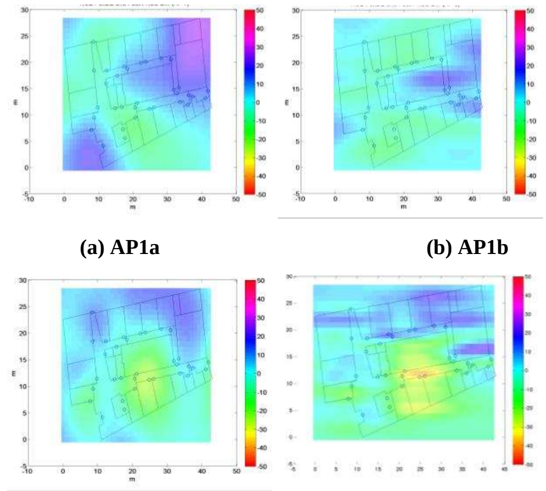
(c) dDB2 AP1a **AP1b**

(d) dDB3 AP1a **AP1b**

Figure 4 Training data from AP1 for all dDB

Due to signal fluctuation, the RSS from one single AP is always a random value that lies within a range when collected at a static point. This is the reason why conventional training requires the receiver to collect RSS data over a long period of time and record the standard deviation. However in dynamic training, only one RSS data can be collected at each location. The final database could be biased if the RSS fluctuation range is not taken into account. Another problem in dynamic training is that some of the signals from certain APs are very weak and unstable at some locations, hence no data is collected during dynamic training, resulting in a fingerprint vector such as $\{(x_n, y_n)|RSS_{n1}, \sigma_{n1}, AP_1, Null, AP_2, \ldots, Null, AP_m\}$. These empty RSS vectors are set to -100dB. A large amount of empty data at a certain location indicates unstable signal which is usually because the AP is too far away or too much disturbance in between, thus should best be ignored in positioning. However, from the training data, we can see that 5GHz signals reflect more accurately the signal strength throughout the building with respect to the AP. On the other hand, the RSS from AP(a) is much more noisier and can be misleading in reflecting the locations. The training data for DB3 from AP1a in one of the rooms varied as much as 30dB, as shown in Figure 4(d).

Figure 5 shows the RSS difference between dDB1a and sDB of AP1 and AP3. Areas that are not covered by dynamic training data can be ignored. We can still see that signal fluctuation and other disturbances cause the RSS to differ and especially in the area near the AP. The difference between the 5GHz signal database is also smaller



(a) AP1a **(b) AP1b**

(c) AP3a **(d) AP3b**

Figure 5 RSS Difference between DB and sDB for dDB1a

To improve the data quality of dDB, the training data from different paths are integrated collaboratively to generate one database. This enables the combination of data collected at different locations and also at different times, denoted as cDB. cDB generates database from more sufficient data and longer time span. This in result captures the RSS fluctuation and environment disturbances.

Collaborative training greatly extends the training data coverage, such as combining the training data of DB1a and DB1b. It also increases the RSS data for a small area of interest. Instead of computing the standard deviation of the RSS at one single TP as in the conventional method, a cluster of RSS data within the integration threshold is regarded to reflect one common location. Therefore, as more collaborative training data is collected, more RSS can be found that are within the integration threshold. This information can then be used to derive the confidence indicator for specific locations.

4.3 Database results

To analyse the training quality of the dynamic database, the RSS difference between dDB and sDB as well as cDB and sDB is compared. First of all, the fingerprint locations and RSS that are covered by training points are extracted. In regards to Figure 5, the RSS difference for all APs between each dDB and sDB is listed in Table 4.

Table 4 RSS Difference between dDB and sDB (dB)

		dDB1a		dDB1b		dDB2		dDB3	
		ΔRSS	σ	ΔRSS	σ	ΔRSS	σ	ΔRSS	σ
1	a	6.60	5.01	8.04	5.28	10.29	5.26	12.85	10.81
	b	5.60	3.88	9.22	6.33	4.59	3.44	4.99	4.70
2	a	4.02	3.26	4.97	4.54	7.42	6.25	6.64	7.64
	b	9.62	8.68	8.40	6.45	16.41	9.52	8.28	6.91
3	a	7.67	5.76	7.36	4.81	9.22	6.32	8.67	8.21
	b	9.52	7.53	9.68	8.90	6.88	5.17	7.07	6.21
4	a	5.49	3.33	14.39	8.99	8.51	6.07	15.97	8.18
	b	7.20	5.14	7.71	5.13	4.28	3.35	5.24	4.07

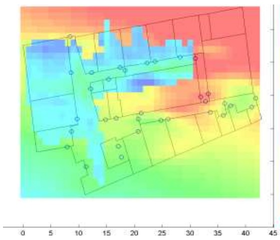
Each dDB lies within the separation threshold therefore can be combined to generate one database. The training data for dDB1a and dDB1b are combined to generate cDB1; dDB1 and dDB2 are combined to generate cDB2; dDB1, dDB2 and dDB3 are combined to generate cDB3.

Table 5 lists the mean RSS difference between each cDB and sDB. The overall RSS difference is reduced when the training data from different path are combined.

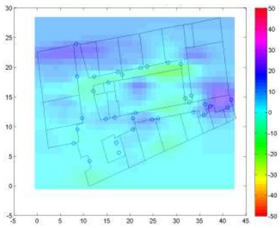
Table 5 RSS Difference between cDB and sDB

		cDB1		cDB2		cDB3	
		ΔRSS	σ	ΔRSS	σ	ΔRSS	σ
1	a	5.75	6.15	8.45	6.38	3.50	7.89
	b	5.48	3.77	4.88	4.23	2.93	4.63
2	a	4.70	3.94	5.30	4.59	1.53	6.52
	b	11.01	7.98	8.18	6.96	5.63	6.65
3	a	7.39	5.42	7.19	7.47	5.25	6.36
	b	3.98	6.27	6.06	4.70	1.67	4.74
4	a	4.55	3.27	5.30	3.22	7.26	6.43
	b	5.70	2.87	6.45	4.74	5.89	4.81

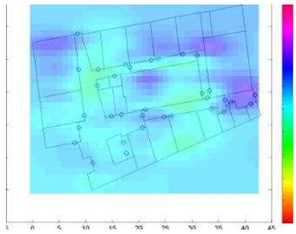
As an example, Figure 6 shows the RSS difference between DB1a, DB1b and sDB, as well as the RSS difference of the combine database cDB1 and sDB. Combining the training data extends the fingerprint coverage and produces overall fingerprints that agree better with the ground truth.



(a) DB1a and sDB



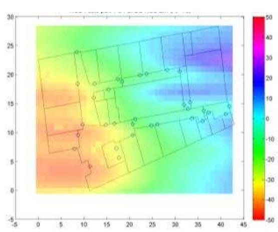
(b) DB1b and sDB



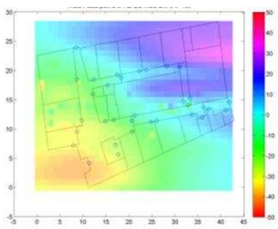
(c) cDB1 and sDB

Figure 6 RSS Difference between dDB and sDB

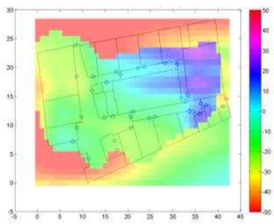
However, users in the collaborative network may come across each other and the collected training data sometimes lie within the integration threshold. This may happen at the same time when two users are very close to each other, or at different times when a user enter an area where previous data has already been collected by another user. These data can be integrated to update the database with a confidence factor based on how much variance is seen in the data. If the data are collected within a short period, the variance will be regarded as signal fluctuation. However, if the timespan lengthens and the RSS difference between new data and history data remains a high level, the system should consider discarding the old data and update the database with new data only. As an example, the training data for dDB3 for collected in two parts. Part1 consists of data collected in the first round in the building and part2 is the collected in the second round. RSS variance can already by identified between the two part data.



(a) dDB3 part1 and sDB



(b) dDB3 part2 and sDB



(c) d- DB3 and sDB

Figure 7 RSS Difference between dDB3 Parts and sDB (AP4a)

Figure 7(a) and (b) shows the RSS difference between the fingerprint database that was generated from each part of the training data and the ground truth. In Figure 7(c), the RSS difference is reduced as the two part training data is combined. The difference for data from each AP is listed in Table 6. The difference between the fingerprints generated from the two parts is also listed. A smaller difference between the two parts results in a better result when the two part data is integrated.

Table 6 RSS Difference between dDB3 parts and sDB (dB)

		p2-p1	p1	p2	dDB3
AP1	a	12.20	12.22	18.23	12.85
	b	5.56	5.70	6.68	4.99
AP2	a	4.59	4.50	19.24	6.64
	b	11.61	9.16	9.64	8.28
AP3	a	15.04	13.35	13.11	8.67
	b	9.90	9.40	6.81	7.07
AP4	a	10.40	18.79	16.60	15.97
	b	4.76	6.24	6.09	5.24

4.4 Fingerprint positioning

Fingerprint based positioning estimates the user position by finding the fingerprint location whose RSS vector matches best with the current user RSS readings. In a scenario where users enter an unfamiliar environment fingerprinting cannot be used as no prior Wi-Fi fingerprints are available. However nearby users can be found to share their location and relative ranging information.

The coarse position of each user in the same environment is estimated based on the inertial measurements, which are obtained from a low-cost inertial sensor. These users may then form a network and obtain ranging estimations between each other. During this process, each user can begin to record Wi-Fi RSS data which will be stored as initial training data. In the following procedure, two different update methods may be carried out based on the available measurements. Collaborative positioning and training is carried out when more than one user is in the network. When the user loses connection with other users, positioning is switched to fingerprinting to maintain position updates.

During the collaborative positioning and fingerprint training process, the measurement update comes from the collaborative ranging measurements as described in Section 3.3. Each user position is forced to remain within the relative ranging constraint. Simultaneously, the users collect RSS data and the range between the users also decides whether the collected RSS from each user are combined to generate a fingerprint database as individual data or to update the confidence factor for the same location.

If collaborative ranging becomes unavailable after an initial fingerprint database has been generated, the Wi-Fi fingerprinting approach will be applied instead and Wi-Fi SLAM can be implemented to maintain the position and environment information.

To compare the fingerprinting accuracy of each different database, a trajectory is defined along the corridor of NGB Floor A. The locations of the potential fingerprints are obtained at each step. Those within 3m of the true location are considered good fingerprints; if the potential fingerprints are 3m away from the true location or cover an area over 15m^2 even if the true location is within this area, they will be considered wrong fingerprints; if no potential fingerprints could be found from the current RSS, the fingerprint information will be empty and the user will simply propagate based on inertial measurements only.

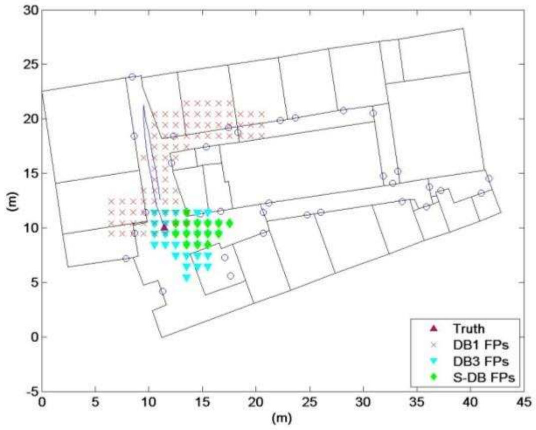


Figure 8 Fingerprint results

Table 7 lists the probability of good, empty and wrong fingerprints for each database based fingerprinting. The fingerprinting result from cDB2 is better than either dDB1 or dDB2 but still worse than dDB3. Therefore improvements can still be made to improve the fingerprint database.

Table 7 Fingerprint quality (%)

	Good	Empty	Wrong
dDB1	60.4	16.4	23.2
dDB2	63.4	9.5	27.1
dDB3	83.3	/	16.7
cDB2	77.4	2.6	20
sDB	83	/	17

The fingerprinting results indicate that building a fingerprint database from very detailed training data, e.g. TP density of 1m by 1m, is unnecessary. Due to signal noise, a set of RSS vectors usually represent more than one location. Therefore in result, no matter how detailed the fingerprint database is, it is always hard to pinpoint the fingerprint to the exact location of the true position. However, this does not mean that ten fingerprints would be enough to cover an entire building. From the different training data densities and the fingerprinting results, we can see that when the user is moving inside the building and data is being collected dynamically, at least two fingerprints is required to cover a regular shaped and sized room. At least one fingerprint is needed to cover an area of $10m^2$ in a corridor or open foyer.

Fingerprint positioning accuracy not only depends on the accuracy of the database but also the fingerprint weighting method. Therefore different fingerprinting methods may vary according to accuracy and positioning requirements. The database generated from this method could be specified according to user needs.

5. CONCLUSIONS AND FUTURE WORK

Indoor positioning faces more challenge due to complicated environment and lack of positioning signals such as GNSS signals. Therefore a robust indoor positioning system needs to cope with different positioning situations adaptively and adjust positioning methods according to available signals. This paper introduces a collaborative Wi-Fi fingerprint database training method which reduces the time and human labour. The collaborative training method is based on a collaborative positioning method which positions users using inertial measurements and relative ranging information. The fingerprint databases that were generated by conventional and dynamic methods and from different training density and location were compared for database quality as well as positioning accuracy.

Results show that training for the fingerprint database simultaneously during collaborative positioning is able to achieve the same accuracy level as conventional training method. The proposed cWiDB training method achieves efficient positioning as multiple users are able to provide reliable positioning and greatly reduce the training time. Furthermore, most indoor PDR positioning relies on the availability of an internal map of the building. This collaborative approach eliminates the need of such information thus saves time and manpower. As Wi-Fi signals develop in recent years, 5GHz signal become more common in both office and home wireless connection. Their signal characteristics differ to those signals in the 2.4GHz band and give better fingerprinting performance in the indoor environment mostly due to their shorter ranging ability.

The application of cWiDB also enables the system to start up without prior knowledge of the Wi-Fi fingerprint which is useful for users who enter a new environment. The training data is collected during the positioning process. Based on the relative distance between the collected data, the system decides whether to combine the training data and generate a database with larger coverage or update old database with new confidence factor.

The system may be further developed so that the RSS difference between users can be applied to update the measurement weight during collaborative positioning and work in a SLAM-like method. This enables further flexibility between collaborative positioning based on inertial measurement or Wi-Fi data. The received signal quality for different devices should also be considered as this directly affects the integration quality of training data from different users.

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