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Using Inquiry-based Bluetooth RSSI Probability Distributions for Indoor Positioning

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Abstract

Fingerprinting is a common technique for indoor positioning using short range Radio Frequency (RF) technologies such as Wireless Location Area Network (WLAN) and Bluetooth (BT). It works in two phases: The first phase is a data training phase in which a radio map for the targeted area is generated in advance, while the second phase is the real-time location determination phase using the radio map. Considering the work amount for generating the radio map, only a few samples of the Radio Signal Strength Indicator (RSSI) are typically collected at each reference point. The limited samples are not able to represent the real signal distribution well in the conventional fingerprint approach such as in an occurrence-based solution. This paper presents a new solution using the Weibull function for approximating the Bluetooth signal strength distribution in the data training phase. This approach requires only a few RSSI samples to estimate the parameters of the Weibull distribution. Compared to the occurrence-based solution, the Weibull function utilizes the shape, shift, and scale parameters to describe the distribution over the entire RSSI domain. This study indicates that the reliability and accuracy of the fingerprint database is improved with the Weibull function approach. A Histogram Maximum Likelihood position estimation based on Bayesian theory is utilized in the positioning phase. The test results show that the fingerprinting solution using the Weibull probability distribution performs better than the occurrence-based fingerprint approach.

Keywords: Bluetooth, indoor positioning, RSSI, fingerprint, Baysian estimation

1. Introduction

Location-based Service (LBS) is now becoming one of the standard features in mobile devices. More and more research concentrates on the personal navigation for both outdoor and indoor environments. However, Global Navigation Satellite System (GNSS) technologies are still struggling for indoors due to the unavailability or attenuation of the GNSS signals. There are many radio technologies such as cellular networks, Wireless Local Area Network (WLAN), and Bluetooth (BT) that are now adopted for indoor positioning without modifying neither the user terminals, nor the existing infrastructure. Radio Signal Strength Indicator (RSSI), a standard measure in most radio technologies, has attracted a lot of attentions (Bahl & Padmanabhan, 2000 and Ekahau Inc.) for being adapted as measurements in indoor positioning.

Bluetooth is a technology with low power consumption for short-range wireless data and voice communication (Muller, 2001). It has been utilized in the communication and proximity market (Naya et al., 2005) for a long time. As widely supported by mobile devices, Bluetooth is a potential technology to become an alternative for indoor positioning (Simon & Robert, 2009, Anastasi et al., 2003, Bargh & Groote, 2008, Jevring & Groote, 2008, Huang, 2005, Bruno & Delmastro, 2003, Hallberg et al., 2003, and Pandya et al., 2003). The effective range of the radio signal of a class 1 Bluetooth device (e.g. the Bluegiga Access Point(AP) 3201) is up to 200 meters, while that for the class 2 device (e.g. the Bluetooth module in a smart phone) is about 20-30 meters according to the specifications of Bluetooth 2.0 (Specification of the Bluetooth System, Core Specification v2.0+EDR, 2004).

Bandara et al. (2004) developed a multi-antenna Bluetooth AP for location estimation based on RSSIs. The test obtained 2 meters of error in a 4.5m x 5.5m area with four antennas. Sheng and Pollard (2006) modified the Bluetooth standard to estimate the distance between a reference transmitter and a mobile receiver, using RSSI measurements and a line-of-sight radio propagation model within a single cell. The high-density Bluetooth infrastructure is necessary to acheive an accurate position in the above two approaches. In order to minimize the Bluetooth infrastructure, Damian et al. (2008) used only one class 1 Bluetooth AP for a home localisation system, which combined the measurements of the link quality, RSSI, and celluar signal quality to obtain room-level accuracy. In this paper, we present a Bluetooth locating solution in a reduced Bluetooth infrastructure area by using RSSI only.

2. The RSSI Measurement

There are two types of possible solutions for acquiring the Bluetooth RSSI measurements: the connection-based solution and the inquiry-based solution (Naya et al., 2005). In the connection-based solution, a communication connection between an AP and a mobile phone is needed to establish before carrying out the RSSI measurements. The RSSI measurements can be updated at a frequency of 1 Hz via the established communication channel. However, APs might continually adjust the transmission power of the communication link to reduce the transmission errors and save the energy. The transmission power adjustment makes it impossible to use the RSSI measurement to infer the distance between a mobile phone and an AP. Nevertheless, this is not the case for the inquiry-based solution because it retrives the RSSIs from the inquiry response that utilizes static transmission power instead of the adjustable one. Therefore, the RSSI measurements of the inquiry-based solution reflect the distances between the mobile devices and APs. After the above analyzing, the inquiry-based solution is adopted in our study even though the RSSI update frequency is lower than that of the connection-based solution.

As shown in Figure 1, the components of the proposed inquiry-based Bluetooth locating system in this paper consist of two parts: the Bluetooth network and mobile phones. The server connected with several APs over a WLAN/Ethernet network is responsible for the system kernel functions, especially positioning calculations. The APs are synchronized by the Server when inquiring the mobile phones in their surroundings and relay the positions from the Server to mobile phones.

Whenever RSSI measurements are needed for positioning, the server will send a trigger to all APs to scan the mobile devices in their surroundings.

Mobile device might be miss-detected for three reasons: 1) The time or frequency domain between the mobile device and AP does not overlap during the inquiring process; 2) the mobile device is waiting to answer the inquiry from another AP. One mobile device can only answer one AP at a time; and 3) the inquiring process times out without obtaining a successful measurement for a reason e.g. that the communication between the AP and the corresponding mobile phone is blocked. The probability of being miss-detected for each device will increase when the number of participating APs increases (Peterson et al., 2006a) as shown in Table 1. The occurrence of the miss-detected cases will decrease the number of RSSI measurements in a certain sampling duration.

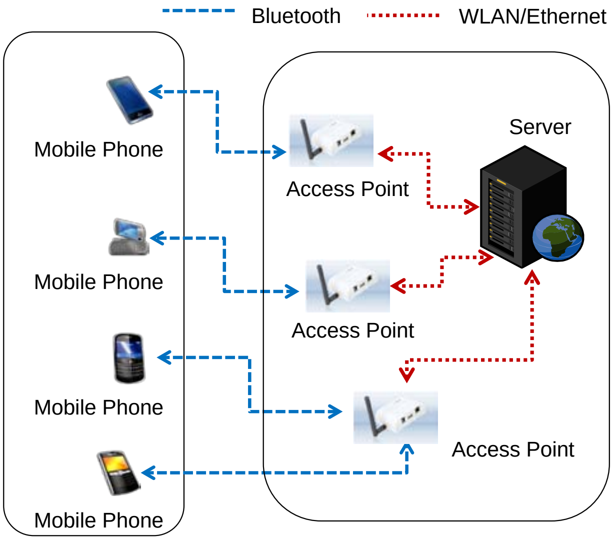

Figure 1: System components of the inquiry-based Bluetooth indoor locating system.

Table 1. Rates of missed-detection

Number of participating APs	***Missed-detection Rate After 6.4 s***
1	0 %
2	7.5%
3	8.3%
6	8.9%

Having completed the inquiring task, all APs will send the RSSI measurements back to the server either for the purpose of calculating the current positions of the mobile devices or generating the radio map database.

3. Fingerprinting with RSSIs

As mentioned above, fingerprinting with RSSIs consists of two phases: the data training phase and the positioning phase as shown in Figure 2. The training phase includes the steps of obtaining a radio map for the targeted area based on a RSSI training data set, while the positioning phase includes the steps of finding a location based on the fingerprints stored in the radio map.

For the data training phase, the targeted area is divided into cells. The center of the each cell is considered as a reference point. The coordinates of the reference points (x_n, y_n) are determined in advance. The RSSI measurements at each reference point from all "visible" APs are collected and stored as fingerprints in the database of the radio map.

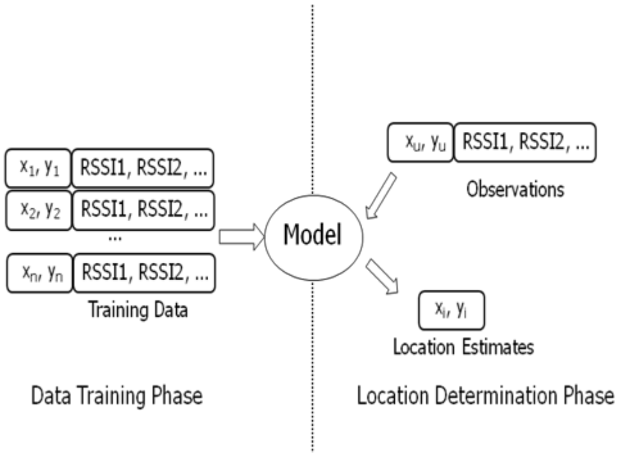

Figure 2: Two phases for Bluetooth positioning

During the positioning phase, the unknown coordinates (x_u, y_u) of a mobile device are estimated by matching the snap shot of the current RSSI measurements to the fingerprints stored in the radio map (Youssef et al., 2003 and Roos et al., 2002).

3.1 Fingerprint Database

At each reference point, the RSSI probability distributions of all APs are stored. If we denote the fingerprint for the i-th reference point as R_i, then, we have

$$R_i = \begin{bmatrix} P(A_1O_1 \mid R_i) & P(A_2O_1 \mid R_i) & \cdots & P(A_kO_1 \mid R_i) \\ P(A_1O_2 \mid R_i) & P(A_2O_2 \mid R_i) & \cdots & P(A_kO_2 \mid R_i) \\ \vdots & \vdots & \ddots & \vdots \\ P(A_1O_v \mid R_i) & P(A_2O_v \mid R_i) & \cdots & P(A_kO_v \mid R_i) \end{bmatrix} \quad (1)$$

where A stands for the AP, while O refers to the RSSI measurement.

In the conventional fingerprinting approach, the probability of a RSSI measurement O_n between the reference point R_i and the AP A_m can be expressed as

$$P(A_mO_n \mid R_i) = \frac{C_{O_n}}{N_i} \quad (2)$$

where C_{O_n} is the number of occurrences that the RSSI measurement O_n appeared in the training data set of the i-th reference point. Here N_i is the total number of training samples collected at the i-th reference point. The entire fingerprint database is expressed as

$$\mathrm{D} = [R_1, R_2, ..., R_w] \quad (3)$$

where w is the maximum number of the reference points in the radio map.

To speed up the computation process, a bin-based solution is adopted. The signal strength distribution is divided into p bins. The fingerprints for the i-th reference point can be redefined as

$$R_i = \begin{bmatrix} P(A_1B_1 \mid R_i) & P(A_2B_1 \mid R_i) & \cdots & P(A_kB_1 \mid R_i) \\ P(A_1B_2 \mid R_i) & P(A_2B_2 \mid R_i) & \cdots & P(A_kB_2 \mid R_i) \\ \vdots & \vdots & \ddots & \vdots \\ P(A_1B_p \mid R_i) & P(A_2B_p \mid R_i) & \cdots & P(A_kB_p \mid R_i) \end{bmatrix} \quad (4)$$

In the conventional occurrence-based solution, at the i-th reference point, the probability of the RSSI measurements within the bin B_n for AP A_m can be expressed as

$$P(A_mB_n \mid R_i) = \sum_{j \geq E_{n-1}}^{j<E_n} \frac{C_{O_j}}{N_i} \quad (5)$$

Where E_{n-1} and E_n are the left and right edges of bin B_n respectively. C_{O_j} stands for the number of occurrences that the value of the RSSI measurement appeared within the range of $[E_{n-1}, E_n)$. All the RSSI measurements in the bin B_n are cumulated for counting the occurance probability.

3.2 Modelling Fingerprints with the Weibull Function

The bin-based solution requires a large training data set in order to obtain a good estimate of the RSSI probability distribution. In this paper, we introduce the Weibull function to proximate the RSSI probability distribution. The Weibull function is a traditional method for modelling the signal strength of radio propagation (Sagias & Karagiannidis, 2005). The probability density function can be expressed as

$$f(x) = \begin{cases} \frac{k}{\lambda}\left(\frac{x-\theta}{\lambda}\right)^{k-1} e^{-\left(\frac{x-\theta}{\lambda}\right)^k}, & x \geq \theta \\ 0, & x < \theta \end{cases} \quad (6)$$

While the cumulate distribution function is defined as

$$F(x) = 1 - e^{-\left(\frac{x-\theta}{\lambda}\right)^k} \quad (7)$$

where x is the variable of the function, k is the shape parameter, λ is the scale parameter, and θ is the shift parameter. When θ=0, this reduces to a 2-parameter distribution.

The parameters of the Weibull function can be estimated with a limited number of RSSI sample measurements (e.g. 20). The function parameters (λ, k, θ) can be calculated with (Papoulis, 2002):

$$k = \delta / \ln(2), \quad 1.5 \le k \le 2.5 \tag{8}$$

$$\lambda = \begin{cases} 2 \times (k + 0.15) & \delta < 2 \\ \delta \times (k + 0.15) & 2 \le \delta \le 3.5 \\ 3.5 \times (k + 0.15) & \delta > 3.5 \end{cases} \tag{9}$$

$$\theta = \overline{O} - \lambda \times \Gamma(1 + 1/k) \tag{10}$$

$$\overline{O} = \frac{1}{n} \sum_{i=0}^{n} O_i \tag{11}$$

$$\delta = \sqrt{\frac{1}{n} \sum_{i=0}^{n} (O_i - \overline{O})^2} \tag{12}$$

where $\overline{O}$ is the mean value of the RSSI measurement set O_i, δ is the standard deviation. Γ is the gamma function. The term $(k + 0.15)$ is an approximation of the expression $1/\sqrt{\Gamma(1 + 2/k) - \Gamma^2(1 + 1/k)}$ when $1.5 \le k \le 2.5$.

For each possible RSSI measurement in this study, the distribution probability can be expressed as

$$P(x) = F(x + 0.5) - F(x - 0.5) \tag{13}$$

Because the RSSI measurements are rounded to an integer. The probability for each bin in the fingerprint database can be generated as

$$P(A_m B_n \mid R_i) = \int_x^{x+w} f(x)dx = F(x + w) - F(x) \tag{14}$$

where w is the width of the bin, x is the RSSI value at the left edge of bin.

In theory, the radio map can be represented by a set of Weibull functions. Each Weibull function has three parameters representing the probability distribution of the RSSI measurements between an AP A_m and a mobile phone at a reference point R_i. The size of the radio map can be reduced in this case because it just requires storing three parameters for each vector between an AP and a reference point.

Using a Weibull function based fingerprint database, we can calculate the probability for any arbitrary RSSI measurement. Considering the computation cost, we still adopt the bin-based solution in this paper by pre-generating the fingerprint database using Weibull functions derived from limited samples.

3.3 Positioning with Bayesian Histogram Maximum Likelihood algorithm

The Bayesian theorem and Histogram Maximum Likelihood algorithm are used for positioning (Youssef et al., 2003 and Roos et al., 2002).

Given the RSSI measurement vector $\vec{O} = \{O_1, O_2 ... O_k\}$ from APs, the problem is to find the location l with the conditional probability $P(l \mid \vec{O})$ being maximized. Using the Bayesian theorem

$$\arg\max_l [P(l \mid \vec{O})] = \arg\max_l [\frac{P(\vec{O} \mid l) P(l)}{P(\vec{O})}] \tag{15}$$

where $P(\vec{O})$ is constant for all l, therefore, the Equation (15) can be reduced as

$$\arg\max_l [P(l \mid \vec{O})] = \arg\max_l [P(\vec{O} \mid l) P(l)] \tag{16}$$

We assume that the mobile device has equal probability to access each reference point, so $P(l)$ can be considered as constant in this case, Equation (16) can be simplified as

$$\arg\max_l [P(l \mid \vec{O})] = \arg\max_l [P(\vec{O} \mid l)] \tag{17}$$

Now it becomes a problem of finding the maximum conditional probability of

$$P(\vec{O} \mid l) = \prod_{n=1}^{k} P(O_n \mid l) \tag{18}$$

where the conditional probability $P(O_n \mid l)$ is derived from the RSSI distribution pre-stored in the fingerprint database. If the RSSI measurement O_n belongs to the bin B_j, Equation (18) can be expressed as

$$P(\vec{O} \mid l) = \prod_{m=1}^{k} P(A_m B_j \mid R_i) \tag{19}$$

while taking Equation (5) and (14) into account. Therefore, the problem becomes to find the maximum $\prod_{m=1}^{k} P(A_m B_j \mid R_i)$ in the fingerprint database.

4. Results and Discussions

In order to evaluate the preformance of the solution proposed in this paper, two test cases have been carried out. The first case is a static test with a long session of collecting 11589 RSSI samples, while the second case is a dynamic test conducted inside the official building of the Finnish Geodetic Institute. The objectives of the first test case are to

- determinate if the shapes of the Weibull functions derived from a limited RSSI samples can approximate the reference shape derived from the long session of 11589 RSSI measurements, and
- compare the positioning performance (in static case) of the Weibull-based solution to that of the conventional occurrence-based solution.

The objective of the second test case is to evaluate the positioning performances of the Weibull-based solution in a dynamic scenario.

4.1 Static Test

In order to establish a reference for comparison, we conducted a long-term measurement campaign. It lasted for 20 hours and 11589 RSSI samples were collected. Considering that the occurrence-based probability distribution derived from 11589 RSSI samples is close to the real RSSI probability distribution, we utilized it as the benchmark distribution for the purpose of comparison.

By using Equations (8)-(12), the parameters of the Weibull function derived from 11589 RSSI samples were calculated as follows: shape k=2.5, scale λ=10.275 and shift θ=61. By using Equation (13), we got the Weibull-based probability distribution as the blue line shown in Figure 3. The red solid line is the benchmark distribution. The shapes of the two lines are similar.

From our experience, it is scarcely bearable for a person collecting samples at one reference point for more than two minutes. About 20 RSSI samples can be obtained over a two-minute sampling duration. Therefore, we selected 20 samples as the limited sampling case for comparison.

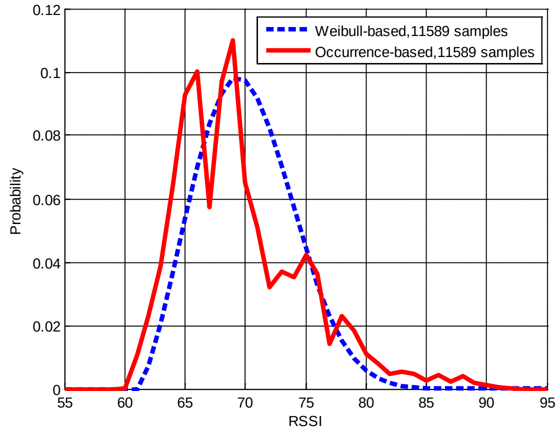

Figure 3: Weibull-based (k=2.5, λ=10.275, θ=61) vs. occurrence-based probability distribution with 11589 samples

In Figure 4, the blue dash line stands for the probability distribution derived from a Weibull-based solution using 20 RSSI samples randomly selected from the large data. The green dash line is the probability distribution derived from the occurrence-based solution for the same data set of 20 RSSI measurement samples, while the red solid line is the benchmark distribution.

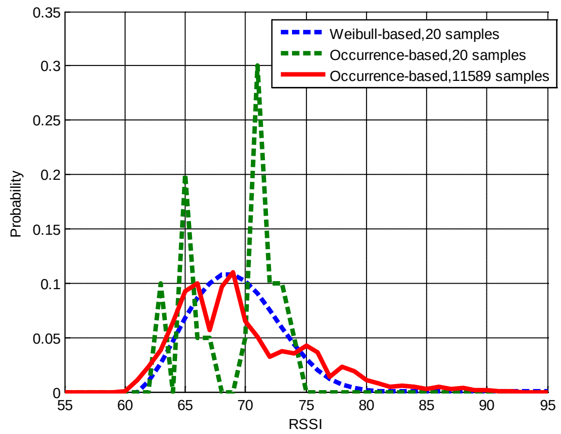

Figure 4: Weibull-based (k=2.5, λ=9.275, θ=61) vs. occurrence-based probability distributions with 20 samples

It is obvious that the shape of the Weibull function derived from 20 RSSI samples is similar to that of benchmark distribution. By comparing the probabilities estimated with the conventional occurrence-based solution for the case of 20 samples to that estimated with the Weibull function, it is obvious that probabilities estimated with the Weibull function are closer to those derived from the benchmark distribution. For example, the true probability for the RSSI measurements values of 68 and 69 should be close to 0.1 based on benchmark distribution. These values are zero while they are estimated with the conventional occurrence-based approach, and about 0.11 if they are estimated with the Weibull function.

Comparing to the benchmark distribution, Figure 5 shows the probability distributions derived from the Weibull-based solution with 11589 samples (red line), Weibull-based solution with 20 samples (blue line), and occurrence-based solution with 20 samples (green line). Table 2 presents the numerical statistics of the probability differences.

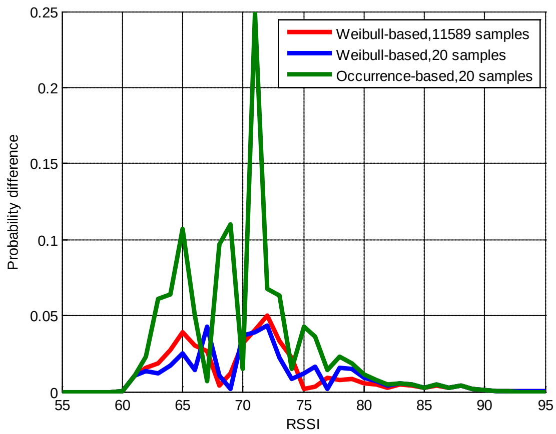

Figure 5: Comparison of the probability distributions.

It can be seen from the results that the Weibull-based probability distributions estimated from 11589 samples and that from 20 RSSI measurement samples have similar shapes. The probability distributions estimated with the Weibull-based solution are significantly better than that obtained from the conventional occurrence-based approach.

Table 2. Statistics of the probability differences

	Weibull-based (11589 samples)	***Weibull-based (20 samples)***	***Occurrence-based (20 samples)***
Mean	0.0105	0.0099	0.0275
Std	0.0136	0.0122	0.0471
Max	0.0502	0.0431	0.2490

For a more detailed investigation, as shown in Figure 6, the large data set of 11589 RSSI measurements is divided into hundreds of sessions that contain 20 samples each (blue lines in Figure 6). The Weibull function for each session is derived and compared with the benchmark distribution (red line in Figure 6).

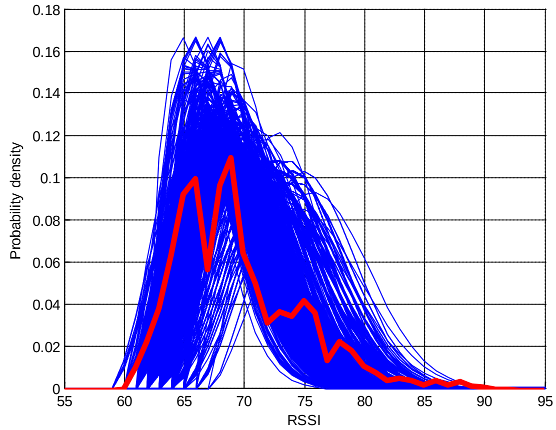

Figure 6: Probability densities estimated with Weibull functions for all sessions of 20 RSSI measurement samples. The red line is the benchmark distribution.

In order to reduce the computation time, the Weibull functions are "digitized". Using Equation (14), the probability densities shown in Figure 6 are cumulated as the bin-based probability in each bin as shown in Figure 7. In our study, the bin edge x is defined as [-55 -60 -65 -70 -75 -80 -85 -90 -95]. The width of the bin w is -5. All the RSSI values lager than -55 belong to the 1st-bin. The minimum possible RSSI value is -95. Thus, there are nine bins designed in our study.

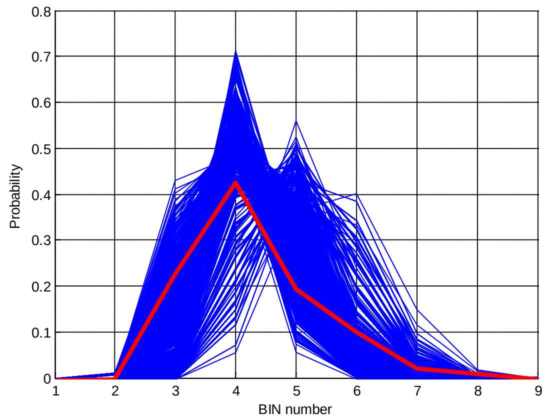

Figure 7: Bin-based probabilities estimated with Weibull functions (blue line) and that estimated with the benchmark distribution (red line).

It is not difficult to see that the shapes of most Weibull functions derived from 20 RSSI samples are close to that of the benchmark distribution (the red line in Figure 7). Table 3 gives the statistics for the differences between the probabilities deriving from the Weibull functions and that from the benchmark distribution. According to the statistics, the Weibull functions derived from 20 RSSI measurement samples effectively approximate the probability distributions. The largest difference of mean value between two probabilities is 0.37 appearing in the 4th-bin. Probability distributions represented with the

Weibull functions obtained from 20 RSSI samples are similar to the benchmark distribution. The maximum difference standard deviation is less than 0.0758.

The static positioning test is intended to evaluate the locating accuracy and stability over time. In this study, two sets of overnight static tests were carried out in two days at the same reference point, one lasted for about 20 hours, while the other lasted for about 24 hours. The test data sets are applied for position estimation using the occurrence-based and Weibull-based fingerprint databases respectively. The occurrence-based fingprint database is generated by using Equation (5), while the Weibull-based solution is derived from Equation (14). The test results are presented in Table 4. We can see that the Weibull-based solution performs significantly better than the occurrence-based solution. The accuracy of the Weibull-based solution in the 20 hours test case is 1.43 meters better than that derived from the occurrence-based solution for the same data set. In 24 hours test case, the error of Weibull-based solution is 1.88 meters lower than that of the occurrence-based solution. Compared to the occurrence-based solution, the Weibull-based solution improves the accuracy by 25.91% and 32.53% respectively for two long-term static positioning test cases.

4.2 Dynamic Indoor Positioning

The dynamic indoor test cases were carried out at the Finnish Geodetic Institute (FGI) with only three Bluetooth APs (red points in Figure 8) mounted inside the office building. The distance between two adjacent APs is about 20 meters. From our field test results, most mobile phones such as Nokia N8, N95, N95 8G, Navigator 6710, Xpress 5800, and HTC Desire can be scanned by the AP in a range of 30 meters without blockage. The length of each corridor is more than 40 meters.

We used a NovAtel SPAN GPS/IMU reference system with 1 Hz output as the reference (green line in Figure 8). The Nokia N95 8G phone was used as the user terminal in the test cases. In order to initialize the SPAN system, the test started from the outside of the building for unobstructed GPS availability. Having initiated the SPAN system, a user who held the Bluetooth-enabled handset (Nokia N95 8G) entered into the building and walked along the corridor. Finally, the user got out of the building from another exit as shown in Figure 8. The purple-circled line in Figure 8 stands for the Bluetooth positioning solutions.

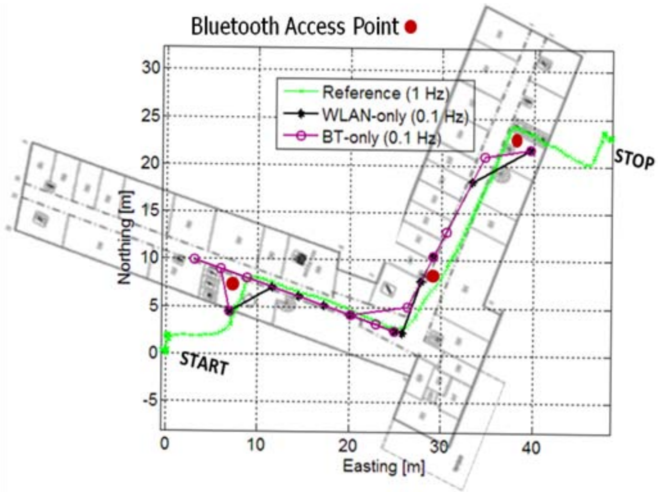

Figure 8: Test route

For comparison, the same location determination algorithms are applied for the WLAN positioning solutions (black-pointed line in Figure 8) using the same mobile device. There are 8 WLAN APs installed in the same test environment. As shown in Figure 9, the horizontal error is 5.1 meters for Bluetooth-based solutions, while that for the WLAN positioning solution is 2.2 meters. It is easy to understand that the Bluetooth-based solution has a lower positioning accuracy compared to the WLAN solution because the number of APs for the Bluetooth-based solutions is much less than that of the WLAN positioning solution.

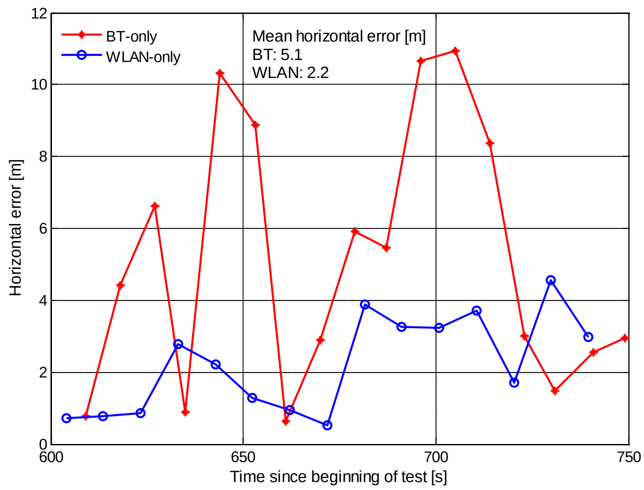

Figure 9: WLAN and Bluetooth locating errors

Table 3. The statistics of the difference between the Weibull-based probability distribution using 20 samples and the occurrrence-based probability distribution using total measurements

BIN number	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***
Mean	0	-0.0001	-0.1299	0.0217	0.1607	0.0194	0.0192	0.0136	0.0006
Std	0	0.0009	0.0684	0.0690	0.0758	0.0500	0.0082	0.0005	0
Max	0	0.0135	0.2293	0.3723	0.3657	0.3002	0.1259	0.0137	0.0006

Table 4. Static locating test

Database	***Weibull-based***		***Occurrence-based***	
Time	20 h	24 h	20 h	24 h
Error	4.09 m	3.90 m	5.52 m	5.78 m

5. Conclusions and discussion

Bluetooth as an existing wireless infrastructure has been widely utilized in personal area network communication. The proximity approaches based on Bluetooth have also been investigated in recent years. To pursue a practical Bluetooth locating solution with sufficient accuracy in a wider area, this study enlightens an inquiry-based Bluetooth indoor locating approach via RSSI probability distributions.

The test result shows that RSSI probabilistic approach is a reasonable way for Bluetooth locating. Since the Weibull function is utilized for approximating the probability distribution of Bluetooth signal strength, the reliability and accuracy of the fingerprint database is improved significantly. It reduces the amount of work needed for generating the fingerprint database.

6. Future work

The following aspects will be considered to improve the locating performance in the related future research efforts: firstly, the Weibull-based fingerprint database will be optimized; secondly, without a timely update, more intelligent position estimation algorithms are needed for better location prediction; and finally, more Bluetooth features such as link quality and celluar signal quality will be studied.

Acknowledgements

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