An Inquiry-based Bluetooth Indoor Positioning Approach for the Finnish pavilion at Shanghai World Expo 2010

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***Abstract*—This paper presents a Bluetooth indoor positioning approach, an inquiry-based solution, that uses Bluetooth access points to inquire the Bluetooth-enabled devices in range via RSSI probability distributions. A practical system architecture is designed after the Bluetooth protocol and profiles are studied. A Weibull function is applied for approximating the Bluetooth signal strength distribution in the data training phase. The Histogram Maximum Likelihood position estimation based on Bayesian theory is utilized in the location determination phase. To verify that the approach will work in the Finnish pavilion at Shanghai World Expo 2010, the proposed solution is merged into a 3D navigation application and tested in the Finnish Geodetic Institute. The results show the feasibility of indoor positioning through inquiring the vicinal handsets. The practicality of the system architecture is also proved by the outcome of a test campaign.**

Keywords - Bluetooth; positioning; indoor; RSSI; Weibull; inquiry

I. INTRODUCTION

Mobile devices are increasingly being equipped with navigation capability and related location based service functionalities. The built-in GPS on the handset is capable of providing location information in open signal-environments. However, satellite based positioning technologies continue to struggle indoors due to the weak satellite signals inside of buildings. To address this shortcoming, there are many technologies utilizing "signals of opportunity" such as telephony networks, Wi-Fi, and Bluetooth and are primarily intended to be used without having to modify the mobile device. At present, positioning utilizing telephony networks is too coarse for indoor location. Wi-Fi as a widely accepted indoor positioning solution has been attracting the researchers for many years. However, the demonstration of this research is targeted to the Finnish World EXPO Pavilion in Shanghai, China where most of the mobile phones do not support Wi-Fi capability due to Chinese wireless communication standard issues nowadays. Instead, Bluetooth has more potential because it is enabled and available in the normal mobile phones in China.

The Bluetooth is devised as an open specification with low power, short range wireless data and voice connections [1] and has been utilized in the communication and proximity market [2] for a long time. As widely supported by mobile devices, Bluetooth has great potential to become an alternative for indoor positioning [3]-[10]. There are two types of possible solutions for Bluetooth indoor positioning: connection-based and inquiry-based [3]. In this paper, we are focusing on a practical inquiry-based Bluetooth indoor positioning approach via RSSI probability distributions.

The roadmap of the paper is organized as follows: in Section II, the motives of this research are highlighted. In Section III, the Bluetooth inquiry process is presented. The interaction of the inquiry hop sequence is discussed. The discovery time with multiple inquiring devices is analyzed. Additionally, the protocol, profiles, connection number, authorization procedure, and time consumption between a pair of Bluetooth devices are discussed. Section IV shows the system architecture for the inquiry-based Bluetooth indoor positioning solution. Then, the RSSI probability distribution database of Bluetooth is established, this is called fingerprinting, and the position estimation algorithms are described in Section V. Finally, Sections VI and VII are devoted to the results and conclusions.

II. MOTIVE

As a part of the 3D navigation and location-based services in the World EXPO, this research is going to provide the indoor position estimations for the visitors with Bluetooth-enabled handsets in the Finnish World EXPO Pavilion in Shanghai. Considering that thousands of people will visit the pavilion per day and hundreds of them are likely to appear in the pavilion simultaneously, it is essential to figure out an efficient solution and establish an achievable architecture to offer stable location services for the mobile users. In this paper, we intend to introduce an inquiry-based Bluetooth indoor positioning approach relying on received signal strength (RSS) fingerprint with the following basic functionalities:

- Administrating the handsets emerging in the pavilion.
- Continually inquiring the signal strengths from all the Bluetooth enabled devices in the pavilion.
- Estimating the locations of the devices which pre-install the positioning application proposed in this paper in the Finnish Pavilion.
- Transferring the location estimation to the mobile device via a Bluetooth connection.

Since Bluetooth is a wireless communication standard considered for low power consumption, the percentage of time that each device is listening inquiry requests is relatively small. Moreover, due to that Bluetooth uses a pseudo-random frequency hopping pattern to transmit

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information, it is necessary to allow some random time to synchronize frequencies between the transmitter and the receiver. Besides, a device can only answer a single inquirer if more than one Bluetooth node is doing the inquiring simultaneously. The number of answers from a detected device is reduced with the number of existing devices in the coverage area and the number of beacons doing the inquiry operations is increasing. The authorization process is always necessary for the communication between two devices. All of the factors lead to more time consumption for updating the position and lower stability of the received signal strength in the inquiry-based solution.

Considering the Bluetooth standard limitations in procedures of inquiry, service discovery, authorization, connecting [3][12][13], and also the characteristics of Bluetooth signal strength [6], this paper mainly focuses on two aspects: (1) the suitable system architecture for Bluetooth positioning, and (2) the reasonable position estimation approach based on inquiry-based Bluetooth RSSI.

III. BLUETOOTH AD HOC NETWORK

Unlike other wireless communication, for example Wi-Fi, Bluetooth is a kind of a short range RF technology with low power consumption. It leads to differences in the protocol and profiles during inquiry and connection phases. To establish a practical architecture, it is essential to look inside of the Bluetooth protocol and signal features.

A. Device Inquiry

Bluetooth uses a slow hop frequency hopping spread spectrum scheme with 79 1-MHz frequency slots (23 in some countries) in the 2.4 GHz band. The master of a Bluetooth piconet coordinates time-division duplex transmissions of up to seven active slaves by alternating between master and slave transmissions in 625 μs time slots. The discovery process requires the piconet master to be in the inquiry substate when a potential slave device is in the inquiry scan substate. The discovery time between an inquiring and scanning device has been fully characterized [13] [14]. Furthermore, the expected inquiry time for multiple devices alternating between inquiring and scanning has been characterized with some simplifying assumptions [15].

In the assumptive scenario of our research, multiple Bluetooth Access Points will inquiry the mobile devices in range in the same period. Due to the relationship between inquiry hop sequences, the impact extends beyond the independent probability that one device delays the discovery of another simply because it discovers a scanning node first. The presence of a second inquirer may in fact prevent an inquiring device from discovering a scanning node until the second node leaves the inquiry substate. As the number of inquiring devices increases, the probability that a specific inquirer will not be able to discover a scanning device usually rises [12]. In Table 1 we can find the trend. Whereas the inquiry time depends on more complex conditions, resulting even with an increasing number of inquirers, the non-detection rate is still lower in the last row of Table I. In this paper, we also attempt to improve the scanning frequency from the default value 1.28 s to 1.25 s, and Table II shows no significant improvement in the inquiry time with three inquirers. Absolutely, the non-detection rates decrease with the timeout increasing.

TABLE I. INQUIRY TIME WITH MULTIPLE INQUIRERS

Inquirers	Mean Inquiry Time	Non-detection Rate
1	5.93 s	0 %
2	5.97 s	7.5%
3	5.96 s	8.3%
5	5.96 s	6.7%

TABLE II. INQUIRY RESULTS WITH DIFFERENT TIMEOUT SETTINGS

Time Out	Mean Inquiry Time	Non-detection Rate
5×1.25 s	5.96 s	8.3%
5×1.28 s	5.96 s	6.7%
10×1.28 s	10.97 s	3.3%

B. Service Discovery Protocol

Bluetooth consists of a set of protocols that constitute a protocol stack. The current version of the specifications defines the Service Discovery Protocol (SDP), RFCOMM (for cable replacement), Logical Link Control and Adaptation Protocol (L2CAP), Host Controller Interface (HCI), Link Manager Protocol (LMP), Baseband and Radio (RF). SDP provides a means for applications on a device to discover services on peer devices and to determine characteristics of the discovered services. Bluetooth SDP has been designed for efficient service discovery on resource constrained devices. The underlying assumption of this design is that devices in a Bluetooth network are resource constrained, primarily in terms of memory and computing power. Thus, Bluetooth SDP provides a simple matching scheme using 128-bit UUIDs. Client applications on devices attempting to discover service(s) must specify the correct service UUID(s) in discovery requests sent to peer devices. The Bluetooth SDP server on each device providing information about services, matches the UUID in incoming discovery requests against existing service UUIDs. SDP also allows service attribute UUIDs to be specified along with service UUIDs. Thus, the server attempts to match against attribute UUIDs if a match on the associated service UUID succeeds [16].

In the proposed inquiry-based solution in this paper, for the purpose of reducing the number of the valid tracking devices, the mobile device takes as slave and creates a *Custom Service* over RFCOMM for the incoming connection from Bluetooth Access Point. The *Custom Service* will use an available channel and register in the SDP record. The Bluetooth Access Points are able to discover the *Custom Service* in SDP and check out the parameters for connecting the mobile device via the *Custom Service*. In this way, only the Bluetooth-enabled devices with *Custom Service* will be tracked in the approach. Therefore, the computing consumption decreases significantly.

C. Connection establishment

The RFCOMM protocol emulates RS-232 serial ports over the L2CAP protocol, and thus the Access Point is able to send the stream to a Bluetooth-enabled device over RFCOMM. A mobile device with Bluetooth takes a role as slave which advertises the *Custom Service* and listens to the incoming connections. The slave can specify a set of security settings which determine if user authorization, authentication, or encryption is required when establishing a connection. These security settings are applied to a specific server, protocol, or channel.

Bluetooth implements confidentiality, authentication and key derivation with custom algorithms based on the SAFER+ block cipher [16]. In Bluetooth, key generation is generally based on a Bluetooth PIN, which must be entered into both devices.

To avoid the delay in the authentication procedure, we use the non-secure settings on the *Custom Service* in this paper. If the user expects a higher security guarantee, the trust relationships have to be enabled between the mobile device and all the Access Points before connecting. In doing so, the mobile user is able to accept the incoming *Custom Service* connections from Access Points without notification and confirmation.

IV. SYSTEM ARCHITECTURE

Following the outputs from Section III, a general architecture for the inquiry-based Bluetooth indoor positioning system is presented. The Distributed Computing, Finite State Machine, and Multi Processes are implemented in this architecture for improving the position update performance.

A. Infrastructure

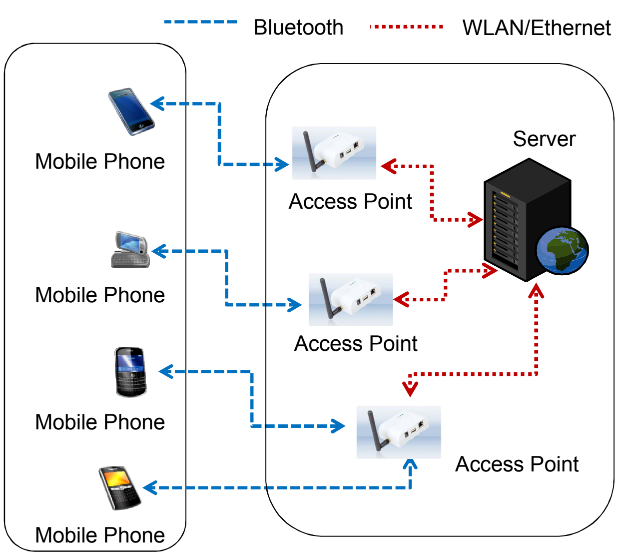

Figure 1. Inquiry-based Bluetooth Indoor Positioning Infrastructure

As shown in Figure 1, the infrastructure of the inquiry-based Bluetooth positioning system consists of two parts: Bluetooth network and mobile devices. A server connected with several access points over Wireless LAN takes charge of kernel functionalities and computing. The access points are synchronized by the Server to inquire the Bluetooth-enabled mobile devices in range and send the messages which wrap the position information to the qualified mobile devices. In another part, mobile devices are scanned by access points and parse incoming positioning messages transmitted by access points over Bluetooth connections.

B. Positioning flow

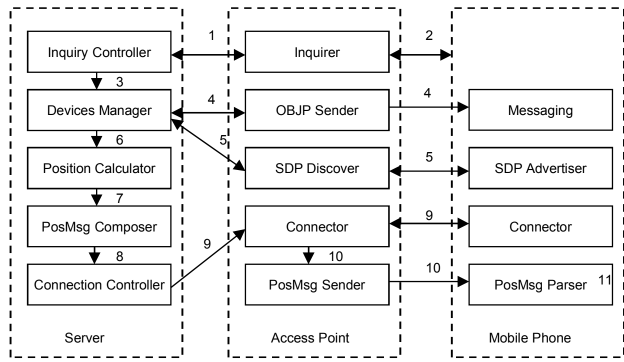

Figure 2. Positioning Flow

Figure 2 demonstrates the architecture of the system. After a mobile user startups the Bluetooth positioning application on the mobile phone, the flow of positioning in each epoch is as follows:

(1) Server: The Server's Inquiry Controller triggers the connected Access Points to perform an inquiry.
(2) APs: The Access Point's Inquirer scans the vicinal mobile devices.
(3) Server: The Devices Manager in the Server filters some found devices out of the inquiry outputs according to the position and service block rules.
(4) APs: The Objp Sender in the Access Point distributes its contents to the visible mobile devices.
(5) APs: The SDP Discover in the Access Point continues to detect the Custom Service broadcasted by the SDP Advertiser on the mobile phone.
(6) Server: On the Server, the Position Calculator computes the position for each mobile phone supporting the Custom Service.
(7) Server: The position information is encoded into the standard NMEA messages by the Message Composer on the Server.
(8) Server: The Server's Connection Controller appoints a connection request to the Access Point which found the mobile phone with Custom Service.
(9) APs: The Access Point's Connector initiates a connection with the mobile phone with security settings.
(10) APs: The Access Point's Message Sender transmits the NMEA massages to mobile phones via the established connection.

(11) Mobile phones: The Message Parser on the mobile phone decodes the messages and extracts the position information.

C. Time consumption

In Figure 2, the communication between the Server and the APs exists in Step 1, 4, 5, and 9. In order to avoid the interaction of the login process, we use the Secure Shell (SSH) protocol with the RSA [22] based authentication to open a secure channel between the Server and APs. According to our experience, it costs 1.5 seconds to establish the SSH channel via a WLAN connection. It means that the system will spend 6 seconds on connecting even if the Server handles all the APs in parallel. To reduce the time consumption on the SSH, we introduce a persistent channel for each AP on the Server, as long as the Bluetooth positioning system starts up.

Due to Steps 3, 6, 7, and 8 are computed on the Server, the time consumptions for these are so tiny that they can be ignored. The most time-costly operation is the inquiry in Step 2. As mentioned above, it takes about 6 seconds to achieve one procedure even if we adopt the 5×1.25 s time out setting.

After the inquiry is completed, the APs will send some contents to the found devices in Step 4. The time cost is up to the content's size because the transfer speed is 20 kbps on average. Fortunately, this task bears a low priority compared to other steps. Thus, we decide to move this process to be run in the background.

However, the system has to spend less than 1 second to discover the protocol broadcast from the emerging devices in the Step 5. Afterward, about one second will be used for position message transfer in Step 10. Considering the Message Parser only contains the simple decoding process, we can also ignore the time consumption of Step 11.

In general, the system costs about 7-8 seconds to serve one complete cycle. Speeding up the inquiry process can further reduce the cycle down to 6 seconds. However, it leads to the non-detection rate to be increased.

V. POSITION ESTIMATION

According to the observation data, we characterize the features of Bluetooth RSSI and create the fingerprint database relying on the features. Afterward, the Histogram Maximum Likelihood Estimation based on Bayesian theory is applied to determine the positions of the Bluetooth-enabled devices.

A. RSSI Probabilistic Approach for Bluetooth Positioning

The RSSI probabilistic approach for indoor positioning, also known as the Fingerprinting Method, consists of two phases: data training phase and location determination phase.

As shown in Figure 3, the measurement campaign is carried out in the data training phase. First of all, to construct the fingerprint database, the indoor area is divided into cells with the help of a building blueprint or layout. The center of the cell is the Reference Point. The RSSIs from "visible" access points at the Reference Points with known coordinates (x_n, y_n) are collected. All the measurements are utilized for calculating the parameters of the RSSI distribution model and creating the fingerprints.

During the location determination phase, the user stands somewhere with unknown coordinates (x_u, y_u), meanwhile the RSSIs from "visible" access points are scanned by the user with a Bluetooth-enabled mobile device. Afterward, the location determination algorithm utilizes the observations to estimate the user's most possible position (x_i, y_i) in the fingerprint database [17][18].

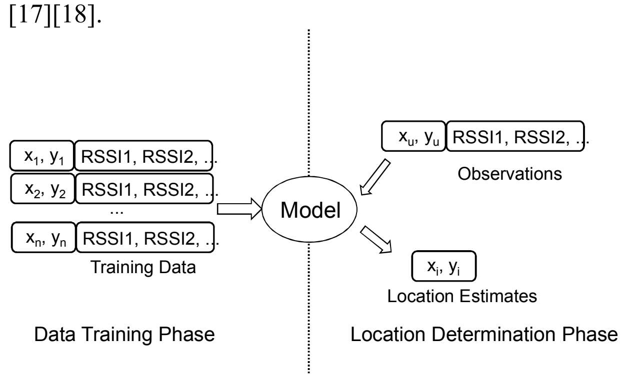

Figure 3. Two Phases for Bluetooth Positioning

B. Weibull Distribution Model for RSSI

At each Reference Point in the set of training data, a fingerprint, model for the joint probability distribution, of Access Points is stored. We denote the fingerprint for the *i*th Reference Point to be R_i and defined as

$$R_i = P(\vec{O} \mid l_i) = \prod_{j=1}^{k} \frac{C_{O_j}}{N_i} \tag{1}$$

where l_i is the location of the *i*th Reference Point, $\vec{O}$ is a set of observations, C_{O_j} is the number of times that a certain signal strength value O_j appeared in the *i*th Reference Point training data set N_i. Then, the entire fingerprint database is

$$\mathrm{D} = (\mathrm{R}_1, \mathrm{R}_2 ... \mathrm{R}_\mathrm{m}) \tag{2}$$

To reduce the computation overhead, a bin-based solution is applied in this paper. The scope of the signal strength distribution is divided into *p* bins.

$$R_i = P(\vec{O} \mid l_i) = \prod_{n=1}^{p} \frac{\sum_{j=1}^{k} C_{O_j}^{n}}{N_i} \tag{3}$$

where $\sum_{j=1}^{k} C_{O_j}^{n}$ stands for the number of times that the signal strength value belongs to the *n*th bin in the entire set of *k* observations.

However, the bin-based solution requires a large training data set in order to obtain a good estimate of the joint distribution. Therefore, we introduce the Weibull function to proximate the real signal strength distribution. The Weibull function is a traditional method for modeling the signal strength of radio propagation [19] and is defined as

$$f(x;k,\lambda,\theta)=\frac{k}{\lambda}\left(\frac{x-\theta}{\lambda}\right)^{k-1}e^{-\left(\frac{x-\theta}{\lambda}\right)^{k}} \tag{4}$$

for $x \geq \theta$, and $f(x;k,\lambda,\theta)=0$ for $x<\theta$, where $k>0$ is the shape parameter, $\lambda>0$ is the scale parameter and θ is the location parameter of the distribution. When θ=0, this reduces to the 2-parameter distribution [20].

The parameters of the Weibull function can be estimated conveniently with the limited sampling measurements. In this study, the RSSI measurements are collected with n samples at every reference point. Using these RSSI samples, the estimation of the parameters (λ,k,θ) is simplified empirically according to the relations of Equation (5) ~ Equation (9).

$$k=\delta/\ln(2),\quad 1.5\leq k\leq 2.5 \tag{5}$$

$$\lambda=\begin{cases}2\times(k+0.15) & \delta<2\\ \delta\times(k+0.15) & 2\leq\delta\leq 3.5\\ 3.5\times(k+0.15) & \delta>3.5\end{cases} \tag{6}$$

$$\theta=\overline{O}-\lambda\times\Gamma(1+1/k) \tag{7}$$

$$\overline{O}=\frac{1}{n}\sum_{i=0}^{n}O_i \tag{8}$$

$$\delta=\sqrt{\frac{1}{n}\sum_{i=0}^{n}(O_i-\overline{O})^2} \tag{9}$$

where $\overline{O}$ is the mean value of the RSSI observation set O_i, δ is the standard deviation, and Γ is the gamma function.

C. Location Determination

The training phase includes the steps of obtaining a radio map for the targeted area with a training data set, while the location determination phase includes the steps of finding a location based on the RSSI observations collected in the current locations. The Bayesian theorem and Histogram Maximum Likelihood algorithm are utilized to search for the most probable location [17] [18].

Given the observation vector $\vec{S}=\{s_1,s_2...s_k\}$, the problem is to find the location l with the conditional probability $P(l\,|\,\vec{S})$ being maximized. Using the Bayesian theorem

$$\arg\max_l[P(l\,|\,\vec{S})]=\arg\max_l\left[\frac{P(\vec{S}\,|\,l)P(l)}{P(\vec{S})}\right] \tag{10}$$

where $P(\vec{S})$ is constant for all l, therefore, the equation (10) can be reduced as:

$$\arg\max_l[P(l\,|\,\vec{S})]=\arg\max_l[P(\vec{S}\,|\,l)P(l)] \tag{11}$$

We assume that the mobile device has equal probability to access each Reference Point, so $P(l)$ can be considered as constants in this paper. Resulting, the equation (11) is simplified as:

$$\arg\max_l[P(l\,|\,\vec{S})]=\arg\max_l[P(\vec{S}\,|\,l)] \tag{12}$$

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

$$P(\vec{S}\,|\,l)=\prod_{i=1}^{k}P(s_i\,|\,l) \tag{13}$$

where the conditional probability $P(s_i\,|\,l)$ is derived from the RSSI histograms stored in the fingerprint database, like described in Equations (2) and (3).

More information on various wireless location technologies can be found from e.g., [21].

VI. RESULTS

To verify the theory proposed in Section V chapter B, a long-term continuous measurement campaign was conducted. As shown in Figure 4, totally 11589 available samples were applied for calculating the Weibull distribution. With Equations (4) to (9), parameters of the Weibull distribution were estimated as follows: shape k=2.5, scale λ=10.275 and shift θ=61. Randomly, we picked up 20 consecutive samples from the entire set of measurements to compute the Weibull distribution. The results are displayed in Figure 5: shape=2.5, scale=11.275 and shift=68. Compared with the probability density derived from the occurrence frequency in 20 samples by Equation (1), the Weibull function with the estimated parameters is a good approximation of the probability distribution of the Bluetooth signal strength over time. Finally, we sliced the entire set of measurements into hundreds of sessions which contain 20 samples each. The Weibull distribution for each session is compared with the one for the total set of measurements side by side. Figure 6 shows the comparison between the distributions.

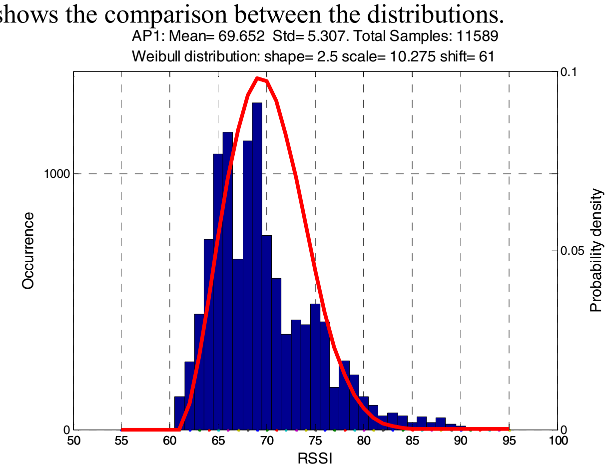

Figure 4. Weibull Distribution for a Long-term Measurement Campaign

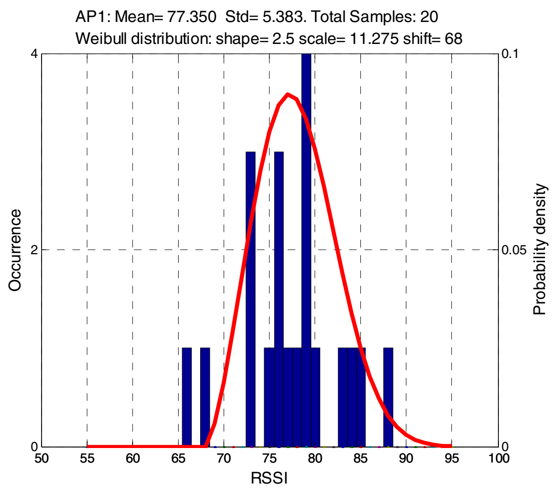

Figure 5. Weibull Distribution for 20 Samples

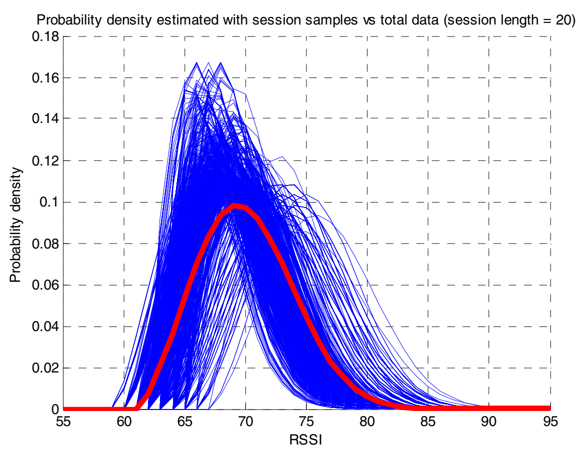

Figure 6. Probability Density Estimated with a 20-Sample Session vs. Total Measurements

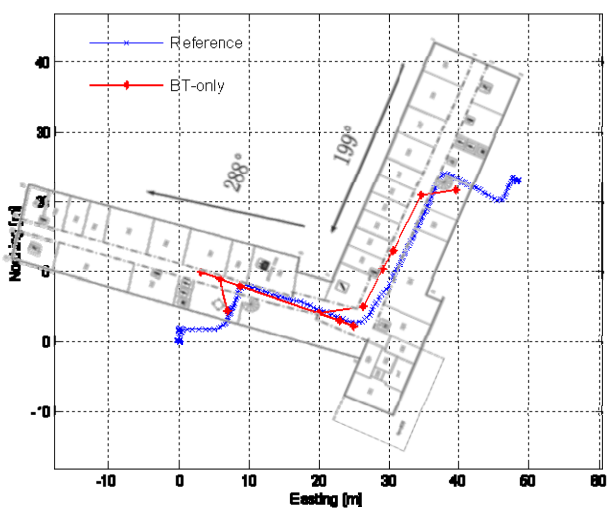

Figure 7. BT Positioning in the Corridor at FGI

The prototype of the Inquiry-based Bluetooth Indoor Positioning is developed and the tests are carried out at the Finnish Geodetic Institute (FGI) with 3 Bluetooth Access Points mounted inside the office building. We used a NovAtel SPAN GPS/IMU reference system with 1 Hz output as the geo-reference. To initialize the SPAN, the test started from the outside of the building and then a user with a Bluetooth-enabled handset entered the building and walked along the corridor. Finally, the user got out of the building from another exit. In Figure 7, the blue starred line indicates the trace of the SPAN. The red starred line stands for the Bluetooth positioning solutions. For comparison, the same location determination algorithms are applied for WLAN positioning in the same test environment with 8 WLAN Access Points. Figure 8 indicates a 5.1 m mean horizontal error obtained in the test from Bluetooth positioning. The results also show that Bluetooth positioning is more inaccurate compared to WLAN positioning.

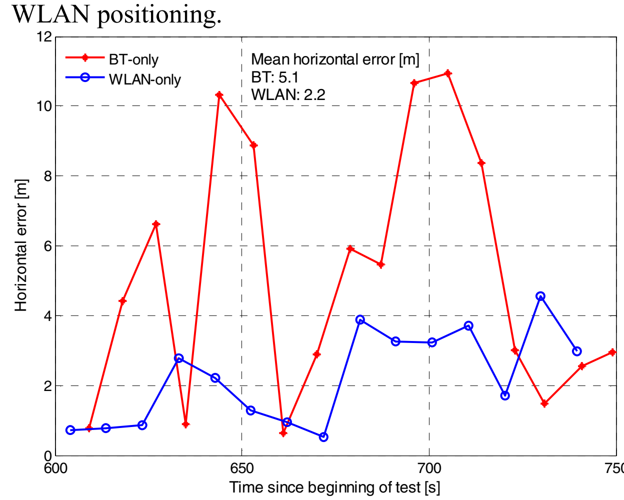

Figure 8. WLAN and BT Positioning Errors

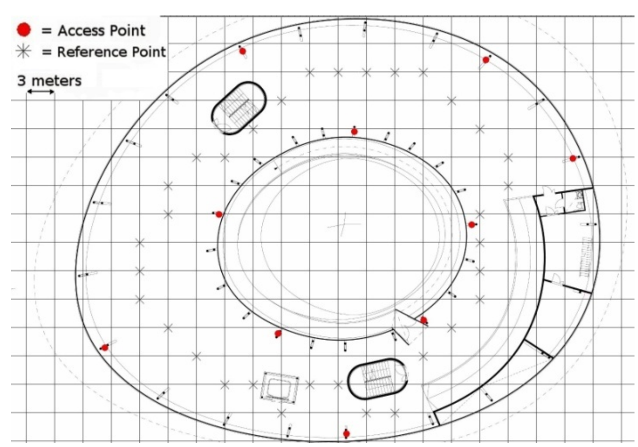

Figure 9. Exhibtion Area in the Finnish Pavilion (From http://www.finlandatexpo2010.fi)

Figure 9 shows the exhibition area floor plan in the Finnish pavilion in the Shanghai World Expo, which will be the final target demonstration environment. Ten pieces of Bluetooth APs (red points) from Bluegiga Ltd. are planned to be distributed in the second floor of the pavilion for the positioning and location based services functionality. Figure 10 demonstrates the 3D navigation application inside the Finnish pavilion based on the Bluetooth positioning solution proposed in this paper. Only the exhibition area is modeled in three dimensions. The textures are absent due to that the decoration of the area is still ongoing.

Figure 10. The 3D Navigation Application on Handset (Left: Front View, Middle: Top View, Right: Inside View)

VII. CONCLUSIONS

Bluetooth as an existing wireless infrastructure has been widely utilized in personal area network communication. The proximity approaches based on Bluetooth are also researched in recent years. To pursue a practical Bluetooth positioning solution with sufficient accuracy in a wider area, this study enlightens an inquiry-based Bluetooth indoor positioning approach via RSSI probability distributions. The architecture of the inquiry-based Bluetooth positioning system is established based on the studies of Bluetooth Ad hoc.

Practically, the performance obtained shows that RSSI probabilistic approach is a reasonable way for Bluetooth positioning. Since the Weibull function is utilized for approximating the probability distribution of Bluetooth signal strength, the reliability of the fingerprint database is improved. The Histogram Maximum Likelihood algorithm is implemented for position estimation. Even though the accuracy of position determination is not very high, the test results still indicate a reasonable performance of the approach proposed in this paper. Compared with WLAN positioning, the Bluetooth signal characteristics and the number of Access Points lead to the lower accuracy obtained in the conducted test. Moreover, considering that the movement of a human being is a consecutive procedure, there is a correlation between the previous and current states. Therefore, $P(l)$ in Equation (11) is not a constant in reality. Proper $P(l)$ estimation will improve the Bluetooth positioning performance significantly.

VIII. FUTURE WORK

Due to the low power consumption protocol, Bluetooth positioning has a significant bottle neck: the updating frequency. In our future research plan, we are going to improve the positioning performance from two aspects. Firstly, optimizing the system architecture is one way to reduce the time consumption in each positioning epoch. Secondly, without a timely update, more intelligent position estimation algorithms are necessary for reasonable location prediction.

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